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An Evaluation of Freeway Incident Detection Algorithms Using Field Data

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Abstract

Effective incident detection and management on freeways is vital in order to maximise road system performance and minimise the problems associated with growing traffic congestion. A comparative study of freeway incident detection algorithms was undertaken on the California algorithm, the University of California, Berkeley (UCB) algorithm, the ARRB-VicRoads algorithm, the Detection Logic with Smoothing (DELOS) algorithm, and an artificial neural network (ANN) model. It was found that the ANN model performs better than the other rule-based algorithms. The California and DELOS algorithms performed the best out of the four rule-based algorithms that were evaluated. It is important to note that training an ANN model is far more complex than calibrating a rule-based algorithm. The ratio of incident to non-incident data in training data sets can be critical to the success of the ANN model. On the other hand, the calibration of rule-based algorithms is more straight forward. An optimisation software FRIO has also been developed to optimise the calibration and, thus, maximise the performance of rule-based algorithms

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Introduction

Effective incident detection and management on freeways is vital in order to maximise road system performance and minimise the problems associated with growing traffic congestion. This paper contains a review and evaluation of four Freeway Incident Detection algorithms: the California algorithm, the ARRB-VicRoads algorithm, Detection Logic with Smoothing (DELOS) algorithm, and an artificial neural network model. All of the algorithms are 're-calibrated' and tested using a common data set.

The problem of increasing congestion on freeways is a growing concern. There are two types of freeway congestion: recurring and non-recurring. The first type occurs on a daily basis as a result of reduced capacity at some freeway sections. Non-recurring congestion is caused by random, but not infrequent, events, such as accidents, spilled loads, broken down vehicles, maintenance works and special events. Incidents on freeways cannot be prevented entirely. However, the implementation of an effective incident detection and management system can mitigate the impacts of non-recurring congestion problems. The benefits include:

- decreased delay due to the reduction in the duration and impact of incidents;
- improved safety and a reduction in the number of incidents due to less stressful driving and better anticipation of traffic conditions ahead; and
- improved travel information and notification of unusual traffic conditions and appropriate alternative routes, which increase the operating efficiency and mobility of the freeway.

Incident detection algorithms

Freeway incident management systems often rely on algorithms to detect incidents using data collected from vehicle sensors installed on freeways. Since the 1970s a variety of freeway incident detection algorithms have been developed based on traffic flow theory, pattern recognition and statistical techniques.

Algorithm performance

The performance of an incident detection algorithm is characterised by:

- *Detection rate (DR)*

  The number of detected incidents to the recorded number of incident in the data set (expressed as a percentage)

- *False alarm rate (FAR)*

  The false alarm rate is the ratio of incorrect detection intervals to the total number of intervals over which the algorithm was applied (usually given as percentage per section).

  False alarm rate can be expressed in two forms: FAR_{on} and FAR_{off}. FAR_{on} is an indication of on-line performance, where FAR is the percentage of **total** number of intervals that are false. The latter (FAR_{off}) is an off-line indicator based on the proportion of **incident-free** intervals that are false. This paper refers to on-line FAR performance.

- *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.

The 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 yet tend to generate a large number of false alarms. Whereas less sensitive algorithms detect less incidents and produce fewer false alarms.

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

Typical performance requirements specified by road operators are in the order of: DR > 90%, FAR < 0.1% and MTTD < 3 minutes.

Performance Index

The calibration of 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, FAR and 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 typical performance curve of an incident detection algorithm is shown in Fig. 1. 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 (see Fig. 1). 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 in searching 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. The aim is to have a minimum value of PI.

$$\mathrm{PI} = \left[\frac{100 - \mathrm{DR}}{100}\right]^{m} \mathrm{FAR}^{n}\ \mathrm{MTTD}^{p}$$

for DR < 100%, FAR > 0% and MTTD > 0, where m>0, n>0 and p>0.

The PI equation also considers MTTD, a performance indicator not reflected on the FAR versus DR performance curve (see Fig. 1). Other constraints such as maximum acceptable MTTD and FAR can be added to the PI equation to ensure that performance outside the constraints would not be accepted.

The coefficients *m, n* and *p* in the PI equation are used to emphasise the importance of DR, FAR and MTTD respectively. Typical values for the coefficients are m=1, n=1 and p=1. Larger values denote a greater importance of the particular performance indicator.

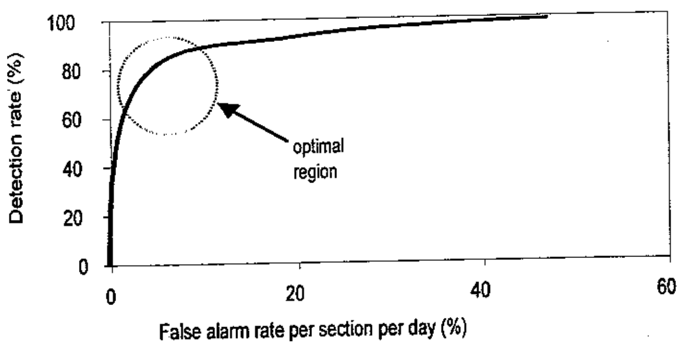

Fig. 1. Typical performance curve of an incident detection algorithm

AID Algorithms

This study deals with four Freeway Incident Detection algorithms: the California algorithm, the ARRB-VicRoads algorithm, Detection Logic with Smoothing (DELOS) algorithm, and an artificial neural network model. Brief descriptions have been provided in the following section. The data requirements for each algorithm are provided in summary form at the end of the section.

California Algorithm

The California algorithm, that was developed in the late 1960s for use in the 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 difference in occupancy between the upstream and downstream detectors;

$$O_u(t) - O_d(t) \geq T_1$$

(ii) the difference in the occupancy between the upstream and downstream detectors relative to the upstream occupancy;

$$\frac{O_u(t) - O_d(t)}{O_u(t)} \geq T_3$$

(iii) the rate of change in the downstream occupancy at a given time interval

$$\frac{O_d(t-\Delta) - O_d(t)}{O_d(t-\Delta)} \geq T_2$$

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, 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. Algorithm 8 is the version currently used in California. This algorithm has an element, which is additional to those in the variations of the classic California algorithm (algorithm 1 to 7), that detects the compression wave at the downstream station.

The structure of algorithm 8 can be broadly divided into two branches. One branch is for cases where compression waves are detected and the other is for cases where there are no incidents or 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 $O_d(t-\Delta)-O_d(t)/O_d(t-\Delta) < T_2$ After the detection of compression waves at the downstream station, the incident detection element of the algorithm is suppressed for 5 intervals. 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 all of the conditions are satisfied. If condition (iii) persists, the status of the incident is upgraded from tentative to confirmed or from confirmed to continuing.

ARRB-VicRoads

ARRB and VicRoads developed an AID algorithm based on speed, occupancy and flow measurements in 20 second time slices (Luk 1989). The traffic parameters are measured by a dual inductive loop system, with stations located 500 m apart. The speed and occupancy values for each detector pair are smoothed with different weighting factors (w_1, w_2, w_3) for the three 20 second time slices j, j-1 and j-2 within each minute as follows:

$$\overline{V} = \frac{w_1 v_j + w_2 v_{j-1} + w_3 v_{j-2}}{w_1 + w_2 + w_3}$$

$$\overline{O} = \frac{w_1 o_j + w_2 o_{j-1} + w_3 o_{j-2}}{w_1 + w_2 + w_3}$$

The traffic flow is smoothed over a time period of 5 minutes and is calculated as a running average value (ie. each 5 minute vehicle count is updated by including the latest 20 second count and discarding the earliest 20 second count).

This algorithm uses four sets of conditions in identifying an incident:

(i) conservation of flow - the upstream and downstream traffic flows are compared to specified values in order to conserve flow;

$$q_u/q_d > k_1 \quad \text{and} \quad q_u > q_0$$
$$q_d = 0 \quad \text{and} \quad q_u > q_0$$

where:

q_u is the upstream 5 minute moving average flow rate,

q_d is the downstream 5 minute moving average flow rate,

q_0 = 360 veh/lane/hr, and

$k_1 = 1.4$.

(ii) adjacent lane comparison - the comparison of a smoothed traffic parameter (flow) from adjacent lanes of the same detector station;

$$q_{kerb}/q_{centre} > k_2 r_n \quad \text{and} \quad q_{kerb} > q_0$$

where:

q_{kerb} and q_{centre} are 5 minute moving average flow rates,

q_0 = 360 veh/lane/hr,

$k_2 = 1.4$, and

$r_n = 0.9$.

(iii) adjacent station comparison - the smoothed traffic parameter of speed from adjacent detector stations is compared;

$$\frac{\overline{V}_u - \overline{V}_d}{\overline{V}_u} < k_3$$

where:

$k_3 = -0.5$,

$\overline{v}_u$ and $\overline{v}_d$ are the upstream and downstream speed respectively, and

$\overline{v}$ is the weighted average over three intervals where w_1=0.5, w_2=0.3 and w_3=0.2.

$$\overline{v} = \frac{w_1 v_j + w_2 v_{j-1} + w_3 v_{j-2}}{w_1 + w_2 + w_3}$$

(iv) time series differencing - this part of the algorithm calculates the differences between a traffic parameter at time slice j with earlier time slice j - Δ at each upstream detector pair

$$\frac{\overline{V}_{j-\Delta} - \overline{V}_j}{\overline{V}_{j-\Delta}} < k_4$$

where $\Delta = 3$ and k4 = -0.5.

An alarm is raised when the calculated difference of one of the four conditions exceed a pre-determined threshold for that condition. An incident alarm is declared when only four consecutive alarms for one of the four conditions has been raised.

Detection Logic with Smoothing (DELOS) Algorithm

The Detection Logic with Smoothing (DELOS) Algorithm is designed to distinguish incidents from other disturbances using upstream and downstream occupancy data (Chassiakos and Stephanedes 1993). To eliminate short-duration disturbances, the raw data is smoothed over large time windows *(n,k)*, which incorporates the present $(t+k)$ and the past $(t-n)$. Three different smoothing techniques can be applied to both upstream and downstream occupancies:

(i) moving average - the occupancy at time t and detector station i is smoothed over the time window k and n. This version of the DELOS algorithm is often referred to as the Minnesota Algorithm (Stephanedes and Chassiakos 1993);

$$OCC_i(t) = \frac{1}{L}\sum_{a=0}^{L-1} O_i(t-a)$$

where:

$OCC_i(t)$ is the smoothed occupancy at time t and detector station i,

O_i is the occupancy measurement at time t and detector station i, and

$L = k$ occupancy values after t

$= n$ occupancy values before t.

(ii) median - the occupancy at time t and detector station i is smoothed over the time window k and n;

$$OCC_i(t) = \text{median}\left[O_i(t), O_i(t-1), \ldots, O_i(t-L)\right]$$

(iii) exponential smoothing - the occupancy at time t and detector station i is smoothed according to a smoothing factor α:

$$OCC_i(t) = \alpha O_i(t) + (1-\alpha)OCC_i(t-1)$$

where:

$OCC_i(t-1)$ is the smoothed occupancy at time $t-1$ and detector station i, and

$O_i(t-1)$ is the occupancy measurement at time $t-1$ and detector station i, and

α = smoothing factor.

This algorithm uses two sets of conditions to identify an incident:

(i) congestion test - to detect when congestion occurs upstream and flow downstream is reduced; that is, the spatial occupancy difference $\Delta OCC(t+k)$ for the present period $(t+k)$ is normalised by the highest value between upstream i and downstream $(i+1)$ smoothed occupancies and then compared to a threshold T_c;

$$\frac{\Delta OCC_i(t+k)}{\max OCC(t)} \geq T_c$$

where:

$$\Delta OCC_i(t+k) = OCC_i(t+k) - OCC_{i+1}(t+k)$$
$$maxOCC(t) = max[OCC_i(t), OCC_{i+1}(t)]$$

$OCC_i(t+k)$ is the smoothed occupancy at time $t+k$ and detector station i, and

T_c is the congestion threshold.

(ii) incident test - to distinguish between bottleneck conditions and incidents; that is, the spatial occupancy difference $\Delta OCC(t+k)$ for the present period is compared to the spatial occupancy difference $\Delta OCC(t)$ for the past period and then normalised by the maximum smoothed occupancy and compared to a threshold T_i;

$$\frac{\Delta OCCi(t+k) - \Delta OCCi(t)}{maxOCC(t)} \geq T_i$$

where:

$$\Delta OCC_i(t+k) = OCC_i(t+k) - OCC_{i+1}(t+k)$$
$$\Delta OCC_i(t) = OCC_i(t) - OCC_{i+1}(t)$$
$$maxOCC(t) = max[OCC_i(t), OCC_{i+1}(t)]$$

$OCC_{i+1}(t+k)$ is the smoothed occupancy at time $t+k$ and detector station $i+1$, and

T_i is the incident threshold.

Once an incident is detected only the incident test is applied to determine whether or not the incident is continuing.

The algorithm is coded as DELOS$x.y(z,w)$ where x and y are the smoothing techniques applied (given by 1 for moving average, 2 for median and 3 for exponential smoothing). For the moving average and median smoothers, the values of z and w are the respective past n and current k window sizes. For exponential smoothing, z represents the smoothing factor α and w is the time present period k.

Artificial Neural Network (ANN)

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) with densely parallel interconnections. A single PE can receive inputs (weighted by the strength of associated connection values) from many other PEs, and then rapidly communicate its outputs to 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 external sources and only interacts with the input and output layers of the network.

Various ANN architectures are suitable for incident detection. The multi-layer, feed forward (MLF) structure (see Fig. 2) has been found to exhibit better performance than the self-organising feature map (SOFM) and the adaptive resonance theory (ART) (Cheu and Ritchie 1995). 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.

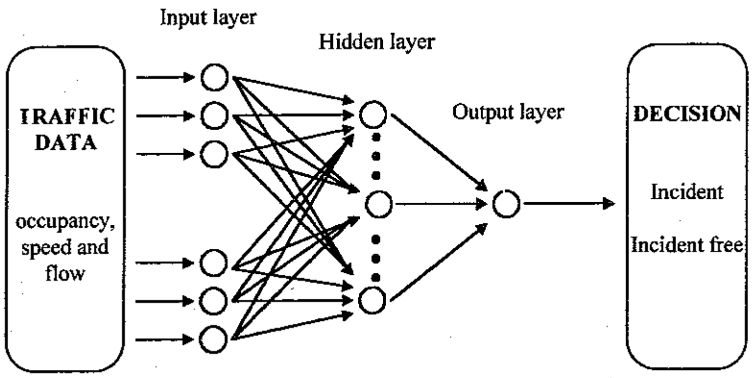

Fig. 2. Artificial neural network modelling framework

Data Requirements

Table 1 provides the data requirements of each algorithm described in the previous section.

Table 1 Data requirements for aid algorithms

Algorithm	Occupancy	Volume	Speed
California	✓		
ARRB-VicRoads		✓	✓
DELOS	✓		
Artificial Neural Network	✓	✓	✓

Calibration and evaluation of incident detection algorithms

Optimisation Software

Software, FRIO, was developed to optimise rule-based freeway incident detection algorithms, such as ARRB-VicRoads, California and DELOS algorithms. An example of the FRIO input screen for the California algorithm is shown in Fig. 3. The optimisation routine used in FRIO is a systematic procedure for generating and testing candidate solutions with a performance index equation *PI* of the form described below. The following statements represent the control variables (using the California algorithm as an example) to determine its performance index *PI*.

$$minimise\ \mathrm{PI} = \left[\frac{100-\mathrm{DR}}{100}\right]^m \mathrm{FAR}^n\ \mathrm{MTTD}^p$$

Subject to:

$$\mathrm{DR}\ \_\ \mathrm{DR}_{min}$$
$$\mathrm{FAR}\ \_\ \mathrm{FAR}_{max}$$
$$\mathrm{MTTD}\ \_\ \mathrm{MTTD}_{max}$$
$$0 < T_1,\ T_2,\ T_3,\ T_4,\ T_5 < 1$$

where:

$\mathrm{DR} < 100\%$,
$\mathrm{FAR} > 0\%$,
$\mathrm{MTTD} > 0$,
$m>0$, $n>0$, $p>0$, and
T_1, T_2, T_3, T_4 and T_5 are control variables.

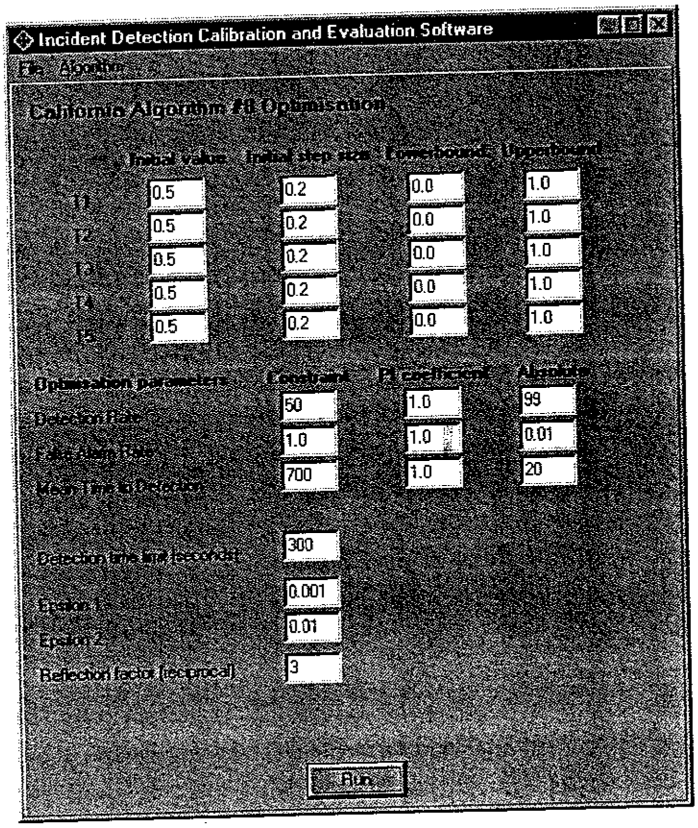

Fig. 3. FRIO input menu

The optimisation routine begins with some initial trials. The number of initial trials is equal to three times the number of control variables. For example control variable T_1 will have three initial values of T_1–_T_1, T_1 and T_1+_ T_1, where _ T_1 is the initial step size. These initial trials form the first solution set.

The most favourable response value in the current solution set replaces the previous solution thus moving the routine to a different point of the solution space. A new set of control variable values and their respective neighbourhood values (ie. __) are then calculated. This new trial replaces the previous trial in the solution set. At each iteration the optimisation routine moves steadily towards more favourable conditions.

Calculated control variable values outside the effective boundaries of the control variables are reflected away from the boundary. The degree of reflection is one of the input parameters. A reflection factor of $\frac{1}{3}$ is used in this study.

The optimisation routine can also adjust the step size depending on the response in each iteration. The routine expands the step size when the solution is stuck outside the optimum region (eg. $DR < DR_{min}$) and contracts when the solution converges to a minimum solution. The procedures for expansion and contraction enable the routine both to bounce out of the unfavourable conditions and to home in on the optimum conditions. Therefore, the routine will reach the optimum region quicker.

Study Site

VicRoads incident data has been used for calibrating and validating the incident detection algorithms in this study. Inductive loop detectors are installed at approximately 500 m spacing on the freeways to collect speed, flow and occupancy data for all lanes at 20 second cycles. A total of 100 incidents were collected from the South Eastern and Tullamarine freeways in Melbourne. The data set is divided into training and testing data sets. These data sets are the same data sets used by Dia (1996) for the development of Dia's neural network freeway incident detection model. This is to ensure that the performance of the algorithms calibrated for this study can be compared with Dia's neural network model.

The calibration-training data set consists of 60 incidents on the Tullamarine Freeway. The validation-test data set of 40 incidents (independent from the training data) comprises 25 and 15 incidents from the Tullamarine Freeway and South Eastern Freeway respectively. The ratio of 20 second incident-free to incident intervals is 22512:40240 (56%:44%).

Calibration and validation results

The calibration data set and FRIO were used for calibrating the ARRB-VicRoads, California, and DELOS algorithms. The m, n and p coefficients of the PI equation were set to 1. A larger coefficient value of the particular performance indicator could be used to emphasise the importance, eg. m=1.2 for detection rate.

Controls have been introduced to ensure that a "divided by zero" error will not occur when a perfect detection rate of 100% is realised and PI=0 will not occur when FAR or MTTD equals 0. Absolute values of DR=99%, FAR=0.01% and MTTD=20 seconds have been used as defaults for the optimisation routine. That is, control variable values that achieve DR=100% will be set to 99%, FAR=0% will be set to 0.01% and so forth

Other constraints such as DR_{min}=50%, FAR_{max}=1% and $MTTD_{max}$=700 seconds have been specified to ensure that performance outside the constraints is not accepted.

FRIO also calculates the performance of algorithms with and without restrictions on the time to detect (TTD) incidents. The optimisation routine in FRIO only uses a PI with unrestricted time to detect incidents. In this study a TTD restriction of 5 minutes is used ie. incidents detected more than 5 minutes after the incidents occurred are considered undetected. The calibration results of the four algorithms are presented in Table 2.

Table 2 Calibrated results based on training data set of 60 incidents

Algorithm	Without TTD restriction				With TTD=5 minutes restriction			
	DR (%)	FAR (%)	MTTD (sec)	PI	DR (%)	FAR (%)	MTTD (sec)	PI
ARRB-VicRoads	61.7	0.004	464	0.710	43.3	0.004	166	0.377
California	71.7	0.004	344	0.389	50.0	0.004	183	0.367
DELOS 3.3	76.7	0.047	253	2.765	63.3	0.047	173	2.976

The performance results show that the DELOS model has the highest detection rate under restricted and unrestricted conditions. On the other hand the DELOS model also has the highest false alarm rate. A false alarm rate of 0.1% is equivalent to 4.3 alarms per section per day. The false alarm rate does not necessarily translate into the algorithm's 'real world' on-line false alarm rate. The reason for this is that the training data set contains incident free data for a short period before and after each incident. Consequently, the algorithms may generate additional false alarms over the remainder of the incident free period during the day.

The mean detection time for unrestricted condition ranges from 253 to 580 seconds where the DELOS algorithm has the shortest mean detection time. The MTTD for restricted conditions has a much smaller range than the unrestricted condition (only166 to 184 seconds). The ARRB-VicRoads algorithm has the shortest MTTD of 166 seconds for the restricted condition.

Based on PI values alone, the California algorithm has the best performance for both conditions. (Remembering that low PI values are the objective.) The low PI values for the California algorithm are attributed to their relatively high detection rates and low false alarm rates.

The results of the calibration process using m, n and p coefficients of 1 for the optimisation routine produced low FAR. If a higher DR or a quicker MTTD is desirable, the coefficients m and p respectively could be adjusted to a larger value to emphasise the importance of the performance indicators.

The control variable values obtained from the calibration were validated with the test data set This data set contains 40 incidents from the Tullamarine and South Eastern freeways. The performances of the four calibrated algorithms showed that DELOS algorithm has the lowest PI for restricted and unrestricted conditions (see Table 3) The ARRB-VicRoads algorithm has a higher FAR and lower DR, relative to the other two algorithms resulting in a high PI value

When the calibrated algorithms are evaluated using the total data sets of 100 incidents, again the PI values of the California and DELOS algorithms for unrestricted and restricted conditions were the better than the ARRB-VicRoads algorithm (see Table 4).

Table 3 Validation results based on test data set of 40 incidents

Algorithm	Without TTD restriction				With TTD=5 minutes restriction			
	DR (%)	FAR (%)	MTTD (sec)	PI	DR (%)	FAR (%)	MTTD (sec)	PI
ARRB-VicRoads	47.5	0.106	847	47 144	20 0	0.106	180	15 264
California	70.0	0 010	824	2 472	22.5	0 010	200	1 550
DELOS 3.3	67 5	0.000	462	1 502†	47 5	0.000	205	1.076†

† *A minimum FAR=0 01% is used for calculating PI.*

Table 4 Results Based on Total Data Set of 100 Incidents

Algorithm	Without TTD restriction				With TTD=5 minutes restriction			
	DR (%)	FAR (%)	MTTD (sec)	PI	DR (%)	FAR (%)	MTTD (sec)	PI
ARRB-VicRoads	56 0	0 041	594	10.711	34 0	0.041	169	4 583
California	71.0	0 005	533	0.773	39.0	0.005	187	0.571
DELOS 3.3	73 0	0 030	330	2.673	57 0	0.030	184	2 367

The ANN model used in this study is based on the ANN model, MLF8-1, from the work of Dia and Rose (1997) This ANN model meets the criteria of FAR_{off}=0 1% while maximising the detection rate with a detection threshold of 0.64 and a persistence test of 2 intervals. The ANN model results for the training, test and total data sets are shown in Table 5.

Since the optimisation criteria used for the ANN model is different from those used for the three rule-based algorithms, it is not appropriate to directly compare the ANN model with the other algorithms. Performance envelopes (DR versus FAR) of the three rule-based algorithms, obtained during the calibration process, together with the ANN model calibration results have been plotted. The objective is to determine whether the performance of the rule-based algorithms are comparable to the ANN model, and to determine the equivalent control variable values for each algorithm (see Fig 4 - Fig. 6).

Table 5 ANN Model Results Based on Dia and Rose (1997) Study

Data Set	Without TTD restriction				With TTD=5 minutes restriction			
	DR (%)	FAR (%)	MTTD (sec)	PI	DR (%)	FAR (%)	MTTD (sec)	PI
Training (60 incidents)	96.7	0.260	295	2.555	83.3	0.260	170	7.381
Test (40 incidents)	97.5	0.034	331	0.281	82.5	0.034	204	1.211
Total (100 incidents)	97.0	0.176	309	1.636	83.0	0.176	184	5.503

From Fig. 4 to Fig. 6 it was clear that the ARRB-VicRoads does not perform as well as the ANN model. However, the California and DELOS algorithms are comparable in performance and, in some cases, are better than the ANN model. As a result, only the performance of the California and DELOS algorithms are compared with the ANN model. Note that the algorithms' control variable values for the restricted and unrestricted conditions are different (see Table 6).

Using the control variable values shown in Table 6, the California and DELOS algorithms were tested with test and total data sets. The evaluation results of three algorithms are shown in Table 7. There are two sets of results for the California and DELOS algorithms denoted by superscript 1 and 2. The first and second sets of results for the algorithms are based on the control variable values for unrestricted and restricted conditions respectively listed in Table 6.

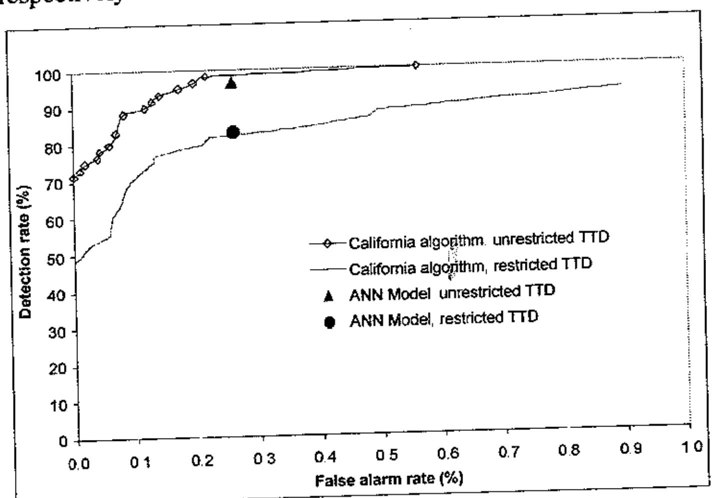

Fig. 4. Performance envelope curve of California algorithm based on training data set

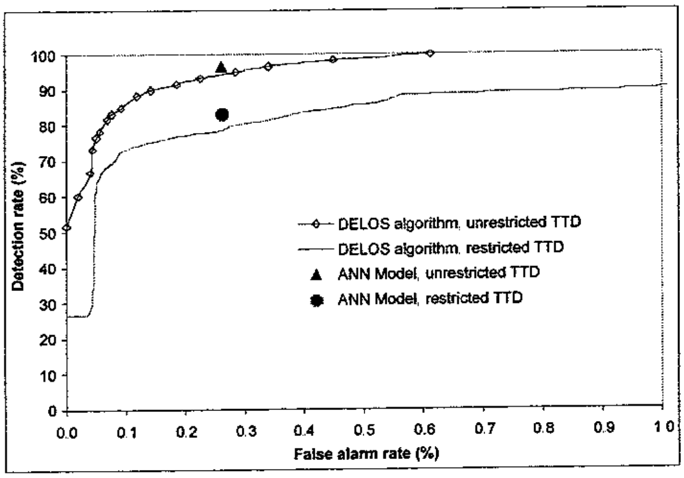

Fig. 5. Performance envelope curve of DELOS algorithm based on training data set

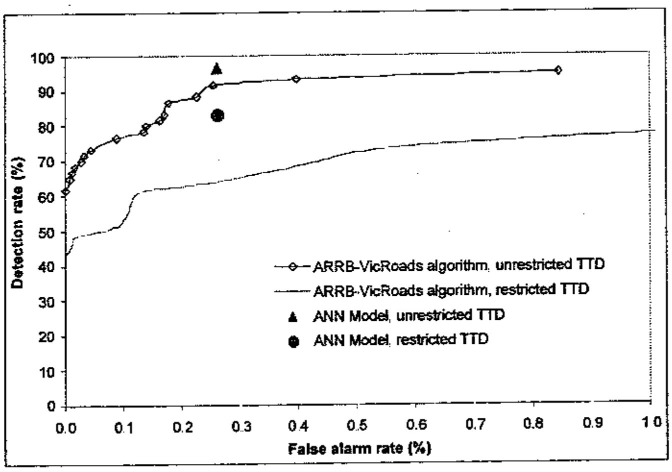

Fig. 6. Performance envelope curve of ARRB-VicRoads algorithm based on training data set

Table 6 Control variable values of California and DELOS algorithms

California[1] (Unrestricted condition)	California[2] (Restricted condition)	DELOS[1] 3.3 (Unrestricted condition)	DELOS[2] 1.1 (Restricted condition)
$T_1 = 0.11$	$T_1 = 0.11$	$T_c = 0.40$	$T_c = 0.40$
$T_2 = 0.10$	$T_2 = 0.10$	$T_i = 0.30$	$T_i = 0.60$
$T_3 = 0.50$	$T_3 = 0.40$	$\alpha_1 = 0.16$	Past period size = 6
$T_4 = 0.18$	$T_4 = 0.18$	$\alpha_2 = 0.20$	Present period size = 7
$T_5 = 0.55$	$T_5 = 0.65$	Present period size = 3	

Although the California algorithm performance is better than the ANN model for the training data set, the algorithm's results for the test and total data sets are not as good as the ANN model. Similarly for the DELOS algorithm, the results for the training data set were comparable to the ANN model but the algorithms did not perform as well with the test and total data sets. It should be noted that results from model calibrations are related to the calibration data set that was used and thus, indicate the fit of a model to a specific calibration data set. That is, a model may be developed to fit the calibration set extremely well but may perform poorly when applied to another data set.

From the calibration and validation study using 100 real incident data collected on two freeways, the following conclusion can be drawn:

- California and DELOS algorithms are the two best rule-based algorithms, and
- the performance of the ANN model is better than the California and DELOS algorithms.

Table 7 Performance of ANN model and California and DELOS algorithms

Algorithm/ Model	Data Set	Without TTD restriction				With TTD=5 minutes restriction			
		DR (%)	FAR (%)	MTTD (sec)	PI	DR (%)	FAR (%)	MTTD (sec)	PI
ANN Model	Train	96.7	0.26	295	2.53	83.3	0.26	170	7.38
	Test	97.5	0.03	331	0.28	82.5	0.03	204	1.21
	Total	97.0	0.18	309	1.64	83.0	0.18	184	5.50
California[1]	Train	96.7	0.20	289	1.90	75.0	0.20	129	6.38
	Test	90.0	0.41	381	15.61	75.0	0.41	175	17.95
	Total	94.0	0.27	324	5.32	75.0	0.27	148	10.10
California[2]	Train	96.7	0.33	242	2.64	83.3	0.33	131	7.14
	Test	92.5	0.55	403	16.67	80.0	0.55	169	18.66
	Total	95.0	0.41	305	6.21	82.0	0.41	146	10.70
DELOS[1] 3.3	Train	96.7	0.34	333	3.76	80.0	0.34	143	9.70
	Test	90.0	0.33	357	11.86	72.5	0.33	196	17.95
	Total	94.0	0.34	342	6.92	77.0	0.34	163	12.63
DELOS[2] 1.1	Train	88.3	0.39	165	7.54	83.3	0.39	148	9.67
	Test	95.0	0.29	399	5.78	77.5	0.29	189	12.32
	Total	91.0	0.35	263	8.39	81.0	0.35	164	11.04

[1] *Performance based on unrestricted control variable values listed in Table 6*
[2] *Performance based on restricted control variable values listed in Table 6*

Conclusion

The comparative study of freeway incident detection algorithms undertaken in this study found that the ANN model has a better performance than the rule-based algorithms (eg. ARRB-VicRoads, California, and DELOS algorithms). The California and DELOS algorithms performed the best out of the three rule-based algorithms that were evaluated.

When implementing incident detection algorithms consideration should be given to other practical matters in addition to the calibration and validation results. It is important to note that training an ANN model is far more complex than calibrating a rule-based algorithm. The ratio of incident to non-incident data in training data sets can be critical to the success of the ANN model. On the other hand, the calibration of a rule-based algorithm is more straight forward. In order to maximise the performance of rule-based algorithms, an optimisation software FRIO has been developed to select the optimum algorithm parameter values during the calibration process.

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