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Comparative Performance of Freeway Automated Incident Detection Algorithms

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Abstract:

Common measures of performance of incident detection algorithms are detection rate, false alarm rate and mean time-to-detect. These measures are not independent and it is therefore necessary to determine the underlying performance trade off. In this paper, the performance of the incident detection algorithm currently implemented on Melbourne's freeways is evaluated based on a set of one hundred incidents that occurred on Melbourne's freeways under varying traffic conditions. The results are interpreted in relation to the broader operational experience with the incident detection algorithm.

An improved algorithm, based on artificial neural networks, is also presented. An independent set of forty incidents, not used in the development of either model, was used for comparing the performance of the two algorithms. Evaluation results, in terms of detection rate, false alarm rate and mean time-to-detect are presented using performance envelope curves that show the trade off in performance between the two models. The results clearly demonstrate the substantial improvement in incident detection performance obtained by the ANN model over the ARRB/VicRoads model.

Keywords:

incident detection, detection rate, artificial neural networks, artificial neural networks (ANNs), comparative evaluation traffic data, calibration data set.

INTRODUCTION

1. The high contribution of freeway incidents to urban congestion, pollution and deteriorated safety conditions has prompted road authorities around the world to implement automatic incident detection (AID) systems on urban freeways. A number of AID models with varying structures and data requirements have been developed over the last two decades. Common measures for the evaluation of incident detection algorithms, which are independent of the theoretical foundations of the algorithms, have also been formulated. Few of the developed algorithms, however, have been implemented in practice due to various limitations and varying operational levels in terms of incident detection performance criteria such as detection rate, false alarm rate and time-to-detect. Therefore, the need is pressing for more effective real-time incident detection algorithms that maximise detection rate while only generating an acceptable level of false alarms.

2. In 1989, VicRoads undertook the task of implementing an AID algorithm for the South Eastern Arterial (Sin and Snell, 1992). The Australian Road Research Board (ARRB) and VicRoads jointly developed an AID algorithm based on dual inductive loop detectors that provided speed, flow and occupancy measurements in 20-second cycles (Luk and Sin, 1992). The performance of the algorithm, in terms of the previously discussed incident detection measures, was not reported in the literature. This paper provides the necessary background information on the development of the ARRB/VicRoads model and evaluates its incident detection performance based on a master incident data set of 100 incidents that were collected during the period from January 1992 to April 1995 from both the Tullamarine Freeway and South Eastern Arterial (SEA) in Melbourne.

3. One promising approach for the implementation of AID systems involves the application of Artificial Neural Networks (ANNs). These are also referred to as parallel distributed processing systems or connectionist systems and have been implemented within recent years as a paradigm of computation and knowledge representation. A calibration data set of 60 incidents (a subset of the master incident data set) that were collected from the Tullamarine Freeway were used to develop an AID system based on ANNs (Dia and Rose, 1995). This paper also provides the necessary background information on the development of the ANN model and presents its performance results based on the remaining data set of 40 incidents (the validation-test data set) that were collected from the Tullamarine Freeway and South Eastern Arterial.

4. Comparative evaluation of the two incident detection algorithms can only be meaningful when the two algorithms are calibrated and tested on the same data sets. Due to the fact that 60 of the 100 incidents were used for the development of the ANN model, only the remaining 40 incidents (validation-test set) were used for comparing the performance of the ANN and ARRB/VicRoads models. The comparative performance results for the two AID models are also reported in this paper.

ALGORITHMS DESCRIPTION

5. Before reporting on the performance results of the two models, the theoretical foundations of the ARRB/VicRoads and ANN models are first presented.

ARRB/VICROADS MODEL

6. The basic logic behind the ARRB/VicRoads model (based on dual inductive loop detectors that provide speed, flow and occupancy measurements in 20-second cycles) is to compare the traffic data between adjacent stations and adjacent lanes and declare an incident if the differences exceed pre-determined threshold values. To begin with, the speed and occupancy values for each detector pair are averaged or smoothed with different weighting factors over three time intervals (one minute).

7. In contrast, the traffic flow is smoothed over a time period of five minutes and is calculated as a running average value. At the end of each five minute interval, the vehicle count is updated by including the latest 20-second vehicle count and discarding the earliest 20-second count.

8. In addition to the conservation of flow principle, where the loss of traffic flow is considered a good indicator of an incident, three sets of algorithms are also used for identifying an incident. Each algorithm represents a certain condition that must be met before an alarm is raised (Snell *et al.*, 1992):

   - Adjacent station comparison

     This part of the algorithm compares the smoothed traffic data (speed, flow and occupancy) between adjacent stations, typically separated by 500 meters.

   - Adjacent lane comparison

     For each detector station, the algorithm compares the smoothed traffic data from adjacent lanes.

   - Time series differencing

     The difference between a traffic parameter at any two consecutive time intervals is calculated for each pair of detectors.

9. For each algorithm, the conditions for raising an alarm are only satisfied when the calculated differences for a certain traffic parameter exceed a pre-determined threshold for that parameter. In the ARRB/VicRoads model, an incident alarm is only declared when four consecutive alarms (from any of the algorithms) are raised within any two minutes (six intervals).

10. The algorithms used for comparing the flow between stations and between lanes were reported to be effective for medium to high flow conditions (Sin and Snell, 1992). Similarly, the algorithms used for comparing speeds between lanes and for performing speed differencing were also found to be effective for low to medium traffic conditions. The performance of the algorithm, however, in terms of the previously discussed incident detection performance measures (detection rate, false alarm rate and time-to-detect) was not reported in the literature.

ARTIFICIAL NEURAL NETWORKS (ANNs)

11. Neural Networks, as the name implies, are loosely modelled after the biological structure of the brain. A neural network is constructed from a set of inter-connected simple processing elements (PEs). Each PE performs only a few simple computations such as receiving inputs from other PEs and computing an output value which it sends to other PEs. The processing ability of the network, stored in the connection strengths or weights, is obtained by a process of adaptation to, or learning from, a set of training patterns. Neuro-computing differs from other branches of computing in that the algorithms are "data-driven". Rather than the computer working through lists of instructions written by a programmer, it deduces the strengths of different relationships by being exposed to a set of examples of the behaviour concerned. By absorbing patterns in the data, the network learns to generalise.

12. Ritchie and Cheu (1993), demonstrated the feasibility of using ANNs for incident detection. They tested a multi-layer feed-forward (MLF) ANN on a Los Angeles freeway using simulated traffic detector data. Their results, however, were limited in the sense that they trained the ANN models on simulated traffic detector data and used only volume and occupancy data.

13. ANN models can be visualised as a network. Consider the section of freeway shown in Figure 1(a) which is defined by upstream and downstream detector locations. A corresponding ANN model structure is shown in Figure 1(b). The detector station data form the input to the ANN. The output is a {0,1} variable indicating the absence or presence of an incident in the freeway section, respectively. The basic principle behind the ANN model was the classification of detector data (speed volume and occupancy provided in 20-second cycles) into one of two classes or states: incident and incident-free conditions. An incident alarm is raised when the classified traffic conditions change from incident-free to incident conditions.

14. The main advantage of using ANNs for incident detection is that the network is capable of capturing the essential information needed for performing the required classification by being shown examples of incident and incident-free conditions. In addition, the parameters that govern the relationship between the input parameters and the output traffic states do not need to be specified using a functional form like in other models. ANN models develop these relationships by adjusting the network parameters such that the required classification is performed.

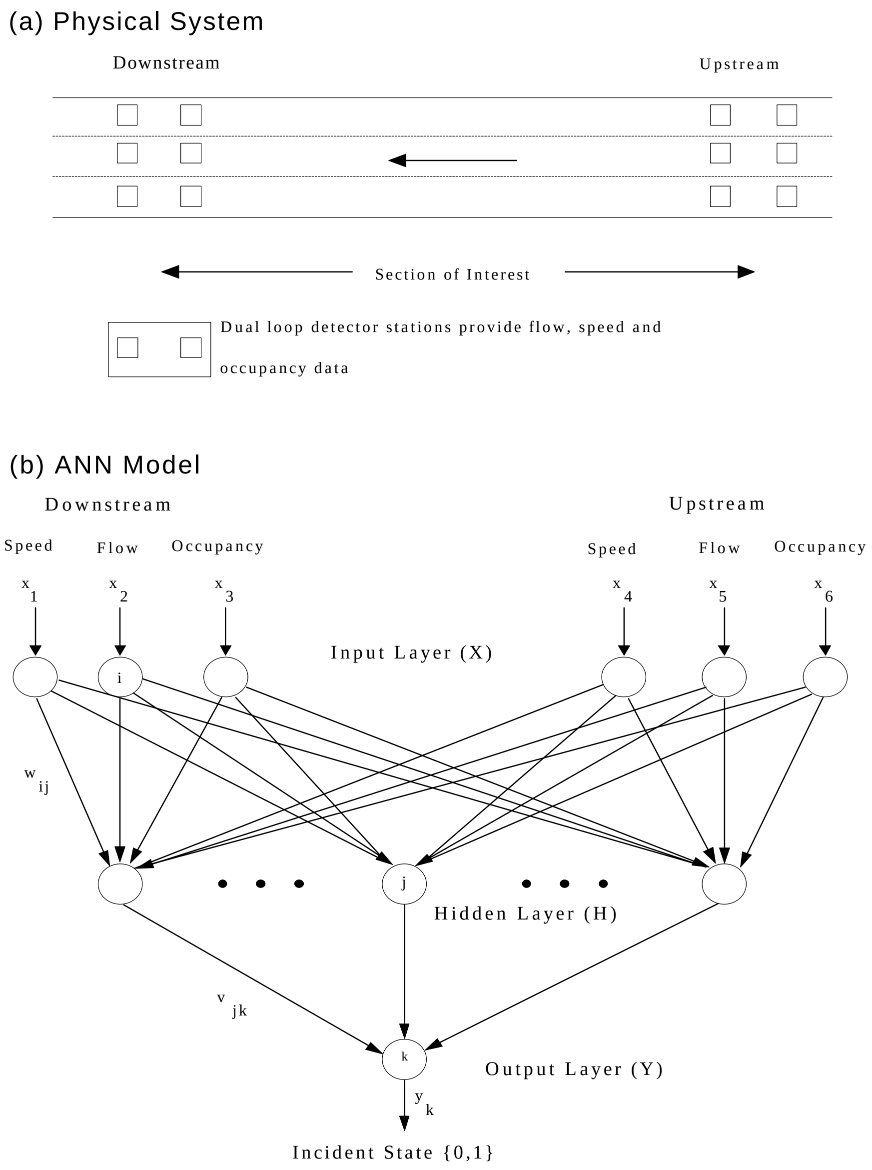

Fig. 1 - ANN modelling framework

15. The parameters of the ANN model are established through a process known as training. In order to train a neural network to perform incident detection, the network must be presented with input detector data and output states for both incident and incident-free conditions. The traffic measurements obtained from each lane are averaged across all lanes and presented to the model. Therefore, the input to the ANN model comprises real-time speed, flow and occupancy measurements provided in 20-second cycles from each of the upstream and downstream stations. The output of the ANN model is the traffic state within the section. Output State 1 {0} represents incident-free conditions and output State 2 {1} represents incident-conditions.

16. One of the well-known and widely used neural network models is the back-propagation or multi-layer feed-forward (MLF) network. The MLF was chosen for implementation

in this study based on its earlier success, especially in real-time pattern recognition problems, and based on its demonstrated superior incident detection performance over the other ANN architectures (Cheu, 1994). In particular, the standard three-layer feed-forward neural network has been chosen for this study. It consists of a set of processing elements (PEs) arranged into three layers as shown in *Figure 1(b)*: a layer of six input PEs is connected to a layer of (14) "hidden" PEs, which is connected to an output layer comprising only one PE.

17. In order for a neural network to perform some actual task, it must undergo a training process during which the weights on inter-connections (w_{ij}, v_{jk}) and the thresholds associated with the PEs (q_j, q_k) are determined. This process begins by assigning random initial values to all the connection weights. Then, each example from the training set is presented to the network and the output vector produced by the network is compared with the desired results. The error between the actual and desired outputs is computed. By applying a learning rule, usually some form of the Generalised Delta Rule, the inter-connection weights and other network parameters are adjusted in such a way that the error between the desired and actual outputs is reduced. This is achieved by implementing a gradient descent on the error curve of the network's output.

DATA DESCRIPTION

18. The results reported in this paper are based on 100 incidents (master incident data set) collected from both the Tullamarine and South Eastern Freeways in Melbourne. These freeways are two of the busiest roads in Melbourne, each carrying at present around 100,000 vehicles per day. A calibration data set comprising 60 incidents from the master data set that were collected from the Tullamarine Freeway was used for training the (ANN) model. The validation-test data set, comprising the remaining 40 incidents that were collected at a later stage from both the Tullamarine Freeway (25 incidents) and South Eastern Arterial (15 incidents), will be used for comparing the performance of the two models. These 40 incidents were not used in the development of the ANN or ARRB/VicRoads models.

19. The 100 incidents reported in this study had varying characteristics that included a representative range of expected incidents on freeways. For example, four incidents resulted in blocking one lane of traffic, 77 in blocking two lanes and 19 in blocking three lanes. Five of the incidents occurred during low flow conditions (below 700 vphpl), 58 during heavy flow conditions (above 1550 vphpl) and 37 during moderate flow conditions. A total of twenty five incidents also occurred during peak-hour traffic conditions. As for the distribution of incident duration, 26 incidents lasted for less than 30 minutes while 12 lasted more than 90 minutes. Out of the 100 incidents, 16 involved a single-vehicle accident, 22 involved a two-vehicle accident, 35 involved a multiple-vehicle accident, 9 involved a vehicle breakdown and 18 involved other types of incidents such as spilled loads, vehicles on fire etc. A more detailed treatment of the incident characteristics is found in Dia and Rose (1995).

20. In addition to the incident data which comprised the characteristics of incidents and their location on the freeway, detector data files comprising speed, flow and occupancy measurements in 20-second cycles were also collected from the VicRoads Traffic Control and Communications Centre. These data files formed the input to both the ANN and ARRB/VicRoads models. The output of the ARRB/VicRoads model for each 20-second interval (ie. alarm or no alarm), which was also provided in the data files, will be used in the evaluation of the model's performance as it was running on-line at the time the incidents occurred.

21. It is appropriate to point out the significance of the master data set that was compiled for this study. This data set is believed to be the largest data base of "real" incidents compiled anywhere in the world for the development of incident detection models. Many months of full time work were involved in compiling the data set. More importantly, this data base has provided the first opportunity to quantify the performance of the existing incident detection algorithms operated by VicRoads as well as providing for the development of improved algorithms based on real-world data. Part of the challenge in developing these algorithms was the ability to deal with the inherent "noisy" character of the loop detector data (Rose and Dia, 1995).

ALGORITHMS EVALUATION

22. Before presenting the performance results of the ARRB/VicRoads and ANN models, the criteria used for evaluating the incident detection models are first presented.

PERFORMANCE MEASURES FOR INCIDENT DETECTION ALGORITHMS

23. The performance of an incident detection algorithm is measured by three criteria: detection rate (DR), false alarm rate (FAR) and time-to-detect (TTD). The DR is defined as the number of incidents detected by the algorithm divided by the total number of incidents known to have occurred during the recorded time. The FAR is defined as the number of incident-free intervals which gave false alarms divided by the total number of incident free intervals. Finally, the TTD is the difference between the time of occurrence of the incident and the time at which the incident was declared or an alarm was raised by the algorithm. When an algorithm is being evaluated, however, it is customary to report the mean time-to-detect (MTTD) a set of (n) incidents. The occurrence time of an incident is usually not known precisely and an estimate has to be deduced from loop detector data or records kept by police, traffic control centres or towing companies.

24. The above definitions clearly show that both the DR and FAR measure the effectiveness of the algorithm while the MTTD reflects its efficiency. The detection rate and false alarm rates are, unfortunately, positively correlated. In order to detect more incidents, the algorithm thresholds are relaxed which causes some incident-free intervals to be interpreted as alarms. Since many false alarms are caused by random fluctuations in traffic flow, a persistence test is usually performed by waiting for alarms to be raised a

number of consecutive intervals before declaring an incident. This method, in conjunction with increased duration of the persistence test, has been shown to reduce the FAR. However, this was also found to reduce the efficiency of the algorithm since it increased the MTTD considerably. Clearly the three performance measures are all inter-related. The relative importance of the measures, however, is typically DR, FAR and MTTD.

EVALUATION OF ARRB/VICROADS MODEL BASED ON 100 INCIDENTS

25. The initial ARRB/VicRoads model was calibrated on a small sample of data collected from the South Eastern Arterial before the implementation of the surveillance system (Luk and Sin, 1992). System enhancement and tuning has taken place since installation. Due to the system's dependency on 'good' data, it ceases to generate alarms if vehicle detectors are deemed to be faulty of if the detector is behaving abnormally. The first step in the evaluation of the current algorithm is therefore to report its on-line performance at the time these incidents occurred. Since the 100 incidents in the master incident data set were not used in the calibration of the algorithm, this part of the evaluation will be based on these 100 incidents. Several versions of this algorithm were evaluated using these data sets to gain further understanding of the sensitivity of various parameters.

26. For each of the 100 incidents in this study, at least 15 minutes of traffic data before and after the occurrence and clearance of the incident were also included. This was necessary to ensure that enough time was given for traffic conditions to stabilise prior to and after incident occurrence and clearance. This incident-free data will be used for the calculation of the FAR. The number of incident and incident-free conditions in the data files are listed in Table I. The 100 incidents comprised a total of 224 hours or about 9 days. Fifteen of these incidents were not detected by the ARRB/VicRoads model due to faulty detectors and/or abnormal data (5 in the calibration data set and 10 in the validation-test data set).

TABLE I
DISTRIBUTION OF INCIDENT AND INCIDENT-FREE INTERVALS IN THE INCIDENT DATA

Data set	Number of 20-second intervals		
	Incident-free intervals	Incident intervals	Total intervals
Calibration data set - 60 incidents	14500	10833	25333
Validation-test set - 40 incidents	8012	6895	14907
Total data set -100 incidents	22512	17728	40240

ARRB/VicRoads Model: Version 1

27. The incident detection results of the original version of the model (Luk and Sin, 1992) are shown in Table II below. In the ARRB/VicRoads model, an incident is declared only when four alarms are raised in any six consecutive intervals. Based on the 100 incidents, this was found to be equivalent to the implementation of a 3-interval persistence test. The detection rate for the original version of the model could be regarded as "reasonable". The detection times, being between two and three minutes are acceptable from an operational perspective. The concern, however, is with the false alarm rate. In a system where a decision regarding the presence or absence of an incident is made every 20 seconds, a 1% FAR would translate into 43 false alarms/day/section (1% $\times$ 3 decisions every minute $\times$ 60 minutes $\times$ 24 hours/day). Such an excessive amount of false alarms on a facility like the Tullamarine Freeway, with more than 14 sections being monitored, is not acceptable from an operational point of view.

TABLE II
SUMMARY OF ARRB/VICROADS MODEL PERFORMANCE (VERSION 1) BASED ON THE MASTER DATA SET OF 100 INCIDENTS

Data Set	Persistence Test	Incident Detection Performance			
		Detection Rate	False Alarms		Time to Detect
		(%)	Number	Rate (%)	(Sec)
100 Incidents	0	65.0	299	1.32	125
	1	58.0	121	0.53	145
	2	47.0	63	0.28	148
	3	39.0	40	0.18	167

ARRB/VicRoads Model: Version 2

28. The results reported in the previous section confirmed the experience of VicRoads staff with Version 1 of the ARRB/VicRoads model. In an effort to reduce the large number of false alarms generated when this Version was implemented, the speed algorithms were disabled. The revised algorithm is referred to as Version 2.

29. The output of the ARRB/VicRoads model for each 20-second interval (ie. alarm or no alarm) was included in the detector data files provided by VicRoads. The evaluation of the Version 2 model is therefore based on these alarms. A computer program was written to read the data files and extract the incident detection performance measures as shown in Table III below. These results were confirmed and reproduced by VicRoads staff. By disabling the speed algorithms, the false alarm rate has been reduced to almost zero. This was, however, at the expense of a reduced detection rate due to the positive correlation between the two performance measures.

TABLE III
SUMMARY OF ARRB/VICROADS MODEL PERFORMANCE (VERSION 2)
BASED ON THE MASTER DATA SET OF 100 INCIDENTS

Data Set	Persistence Test	Incident Detection Performance			
		Detection Rate	False Alarms		Time to Detect
		(%)	Number	Rate (%)	(Sec)
100 incidents	0	23.0	9	0.04	213
	1	22.0	3	0.01	231
	2	18.0	2	0.01	236
	3	15.0	1	0.00	244

30. The false alarm rates reported in Table III also confirmed the operational experience of VicRoads staff. It was expected that the detection rate was higher; however, before the data base was assembled for this study, it had not been possible to quantify the performance of the algorithm using real-world data.

Recalibrated ARRB/VicRoads Model

31. The results reported for the ARRB/VicRoads model have so far been based on the initial calibration of the model using a small set of data (available within the implementation time frame) that was collected from the South Eastern Freeway (Luk and Sin, 1992). Prior to this study the actual performance of the system was based on the results of comparing a small amount of observed incidents with manual detection logs on the system. This confirmed the system as actually “working”, ie. it was detecting incidents, but it didn’t provide incident detection performance measures in terms of detection rate (DR), false alarm rate (FAR) and time-to-detect (TTD). The data collected and matched with known incidents for this research have allowed the model to be recalibrated. As was mentioned earlier, a comparative performance evaluation of any two AID algorithms is only meaningful if both algorithms are calibrated and tested on the same data sets. The ARRB/VicRoads algorithm was therefore recalibrated using the 60 incidents in the calibration data set. This is referred to as the ‘recalibrated’ ARRB/VicRoads model.

32. The recalibration process involved analysing the outputs of the various algorithms to see how they reacted during various conditions. The ARRB/VicRoads algorithms are essentially rule based tests applied to the incoming data. During non-incident periods the output of the calculations should be relatively stable and consistent. When an incident occurs the output typically shifts significantly from this quiescent value. The threshold for raising an alarm is then set by selecting a value that is just beyond the non-incident output value.

33. Using simple averaging techniques, all four ARRB/VicRoads algorithms were analysed to determine their stability over a 24-hour period. The results showed that at least 2 of

the algorithms (adjacent lane flow and adjacent site speed comparison) suffered instability during certain conditions. Both algorithms suffered badly late at night during conditions of low flow. In the case of lane flow comparison, the vehicles tended to vary lane preference considerably. This resulted in high comparison ratios and consequent alarms. In the case of speed comparison, vehicles tended to travel at high speeds in bursts late at night effectively sending a short shockwave through the speed measurement profile. The algorithm sees this as sufficient cause to raise an alarm. Additional rules are being developed to improve the response of these algorithms. The best model performance was obtained by recalibrating the model using only the conservation of flow principle and the speed differencing algorithm, as shown in Table IV below.

TABLE IV
SUMMARY OF RECALIBRATED ARRB/VICROADS MODEL PERFORMANCE BASED ON THE MASTER DATA SET OF 100 INCIDENTS

Data Set	Persistence Test	Incident Detection Performance			
		Detection Rate	False Alarms		Time to Detect
		(%)	Number	Rate (%)	(Sec)
100 Incidents	0	66.0	333	1.47	129
	1	58.0	127	0.56	150
	2	49.0	63	0.28	156
	3	44.0	37	0.16	170

34. Performance envelope curves (PEC) are typically used to demonstrate the trade-off in performance between the detection rate (DR) and false alarm rate (FAR) as shown in Figure 2 below. From this figure, it is clear that the recalibrated model has superior performance to the other two versions of the model.

35. It is important to mention here that when the original ARRB/VicRoads incident detection system was being devised, the subject of error handling was not addressed as part of the algorithm development. The algorithms essentially assumed error free and accurate data in order to detect an incident. When it came to the actual implementation, it was found that system errors or noise in the data were a primary cause of false alarms.

36. External noise comes from various sources and its effects vary depending on which part of system it infiltrates. In the case of loop detectors the external “noise” could manifest itself as invalid pulses or even a total failure to detect a vehicle. Most of these errors can be detected by special algorithms used at the detection site. In the case of the VicRoads system, a status flag is sent with the data from the detectors every 20 seconds to indicate if there is a possibility of the data being corrupt.

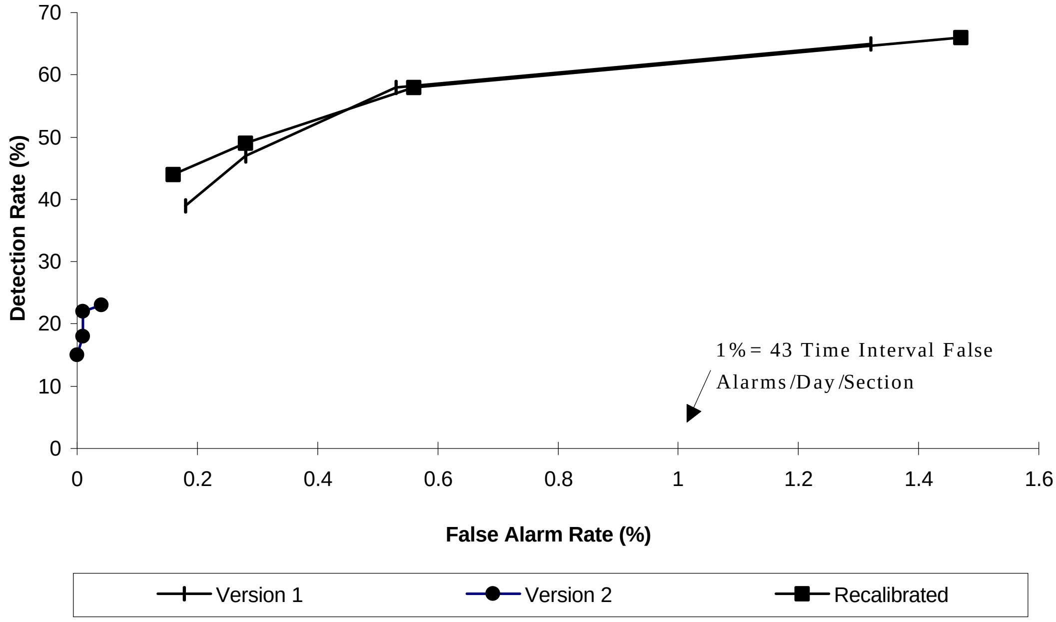

Fig. 2: PEC for VicRoads models based on 100 incidents and persistence tests of zero, 1, 2 and 3 intervals

37. At the point of data collation for algorithm processing, data sets are built based on the incoming data and status flags. Data that is flagged as possibly being in error is not used by the algorithm. The algorithm therefore becomes inoperative for a particular road segment if "bad" data is present. When the data is later flagged as "good", the algorithm allows processing and outputs a result. As the actual data feeding the algorithm is a cumulative data set collected over a period of several minutes, the unstable or "bad" data remains in the system for a short period after the site error has cleared. To avoid false alarms the output of the algorithm is disabled until a settling period has expired. Analysis of the ARRB/VicRoads results revealed that about 15% of the incidents were not detected by the model due to the mechanism of delaying the algorithm's output.

38. From an operational point of view, the results reported for the ARRB/VicRoads model indicate that there is scope to revisit the implementation of the error handling techniques in order to increase the detection rate of the model. A system of data insertion and additional averaging may be required to replace missing or possibly corrupt data. As will be shown in the next section, the performance of the ANN model is not affected by these types of errors because it does not rely on traffic measurements from individual lanes. Instead, the ANN's input is based on average traffic measurements across all lanes. However, and as part of this research program, the impact of systematic and random errors in the average input values on the performance of the ANN model is currently being examined.

COMPARATIVE EVALUATION OF ANN AND ARRB/VICROADS MODEL BASED ON THE VALIDATION-TEST DATA

39. The next step in the evaluation process involved comparing the performance of the ANN and ARRB/VicRoads models based on the independent data set of 40 incidents (the validation-test set) which was not used in the calibration or development of either model. This data set was collected from both the Tullamarine Freeway (25 incidents) and South Eastern Arterial (15 incidents). The performance of the previously discussed versions of the ARRB/VicRoads model on the validation-test set is shown in Table V below.

TABLE V
SUMMARY OF ARRB/VICROADS MODEL PERFORMANCE
(BASED ON THE VALIDATION TEST SET OF 40 INCIDENTS)

Model Version	Persistence Test	Incident Detection Performance				
		Detection		False Alarms		Time to Detect
		Number	Rate (%)	Number	Rate (%)	(Sec)
Version 1	0	23/40	57.5	147	1.83	160
	1	20/40	50.0	70	0.87	189
	2	13/40	32.5	45	0.56	167
	3	09/40	22.5	33	0.41	164
Version 2	0	01/40	2.5	1	0.01	180
	1	01/40	2.5	0	0.00	200
	2	01/40	2.5	0	0.00	220
	3	01/40	2.5	0	0.00	240
Recalibrated	0	22/40	55.0	38	0.47	176
	1	17/40	42.5	13	0.16	202
	2	12/40	30.0	7	0.09	193
	3	10/40	25.0	5	0.06	204

40. Table VI below lists the incident detection performance measures for the ANN model based on the application of a two-interval persistence test and a range of decision thresholds (DT). Typically, a decision threshold of 0.5 is used in ANN models whereby incident conditions are only declared if the ANN's output is greater than 0.5. Increasing the DT above 0.5 has the effect of reducing the number of false alarms (and consequently detected incidents). Decreasing the DT below 0.5 has the opposite effect. The trade off in model performance between the DR and FAR can be illustrated by implementing a range of decision thresholds for the ANN algorithm, as shown in Table VI.

41. The results of the comparative evaluation of the ANN and ARRB/VicRoads models are shown in Figure 3. The PECs clearly demonstrate the trade off in performance using each of the models, based on the validation-test set of 40 incidents. The results also demonstrate the substantial improvement in incident detection performance obtained by the ANN model over the ARRB/VicRoads model for the data set used in this study. The ANN model achieves higher detection rates and lower false alarm rates than the ARRB/VicRoads model. In addition, the MTTD for the ANN model is comparable or better than the ARRB/VicRoads model.

TABLE VI
SUMMARY OF ANN MODEL INCIDENT DETECTION PERFORMANCE (VALIDATION-TEST SET OF 40 INCIDENTS)

Data Set	Decision Threshold	Incident Detection Performance				
		Detection		False Alarms		Time to Detect
		Number	Rate (%)	Number	Rate (%)	(Sec)
Test Set (40 incidents)	0.300	36/40	90.0	60	0.75	156
	0.400	36/40	90.0	35	0.44	170
	0.500	35/40	87.5	22	0.27	181
	0.640	33/40	82.5	06	0.07	203
	0.650	30/40	75.0	02	0.03	205
	0.695	20/40	50.0	01	0.01	216

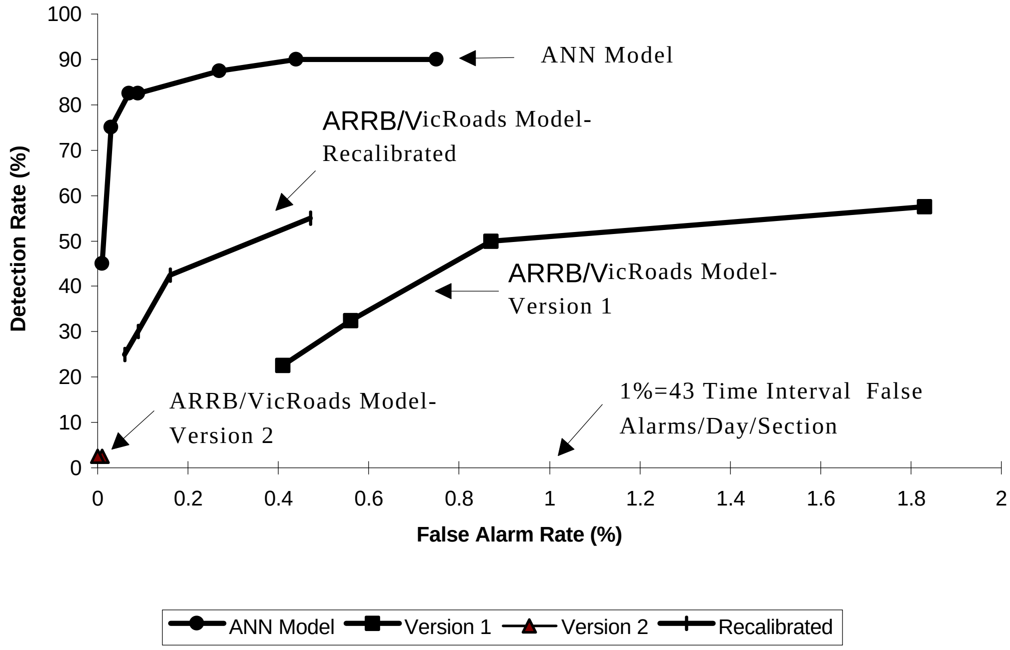

Fig. 3: PEC for the ANN and ARRB/VicRoads models based on the validation-test set of 40 incidents

CONCLUSIONS

42. This paper considered two freeway incident detection systems: the ARRB/VicRoads and ANN models. Performance of the ARRB/VicRoads model was evaluated off-line using a set of 100 incidents collected from the Tullamarine Freeway and South Eastern Arterial in Melbourne. The ANN model was developed using a set of 60 incidents with varying characteristics. An independent data set of 40 incidents, not used in the development of either model, was then used to compare the incident detection performance of the two algorithms. Performance envelope curves were also used to demonstrate the trade off in performance between the two models. Different versions of the ARRB/VicRoads model that were developed in an effort to improve the operational performance of the model were evaluated. There is scope for further analysis across the 100 incident data files since a high number of false alarms may have been associated with one or two particular data files. However, the reported results clearly demonstrated the substantial improvement in incident detection performance obtained by the ANN model over the ARRB/VicRoads model.

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