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INCIDENT DETECTION BY FRACTAL DIMENSION ANALYSIS OF LOOP DETECTOR DATA.

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ABSTRACT

This paper describes a research project which aimed to demonstrate the feasibility of using Fractal Dimension analysis of speed, occupancy and flow data for automatic incident detection (AID).

Non-recurrent congestion resulting from accidents, breakdowns and other incidents accounts for about 60% of the delays on freeways (Dia and Rose, 1997). Therefore, the sooner an appropriate incident response is implemented, the less impact the incident will have on road user safety, congestion and the environment.

Various models have been developed for AID from a variety of theoretical backgrounds and data sources. However, most of these models have limitations, namely high false alarm rates or difficulties with portability and configuration. Artificial neural networks have had the most success, with low false alarm rates and relatively easy configuration.

The use of fractal dimension analysis is becoming widespread. Experts in fields as diverse as Medicine (Hara *et al*, 1995), Physics (Mouradian and Soruescaut, 1991), Seismology (Tosi *et al*, 1999), Economics (Richards, 2000), Meteorology (Suresh *et al*, 1999) and Ecology (Wigley *et al*, 1999) are using fractal dimension analysis to quantify various phenomena. Fractal analysis has been used to model traffic flow (Torok and Kertesz, 1996), but does not appear to have been used for incident detection.

Two fractal models were developed and tested on a data set of 100 incidents collected by VicRoads for the development of artificial neural network incident detection models (Dia and Rose, 1997). A similar methodology to that presented by Dia and Rose (1997) was used in this project so that the results of the fractal models could be compared with those of the ARRB/VicRoads and the Artificial Neural Network Models.

1 INTRODUCTION

The number of vehicles making use of metropolitan freeway facilities is increasing every year. Associated with this are increasing social and economic costs from congestion, with resulting decreased productivity, accidents and pollution. To alleviate these problems, road agencies seek to improve the efficiency and capacity of their networks using Advanced Traffic Management Systems (ATMS).

Traffic congestion can be divided into two categories:

- *Recurrent congestion* which may result from lack of road capacity (e.g. during peak periods); and
- *Non-recurrent congestion* which may be due to incidents such as accidents; vehicle breakdowns; obstacles on the road or weather conditions.

Non-recurrent congestion is responsible for about 60% of delays on freeways (Dia and Rose, 1997). Further, for every minute of incident duration, it takes four minutes for the traffic to recover (Saka, 2000). For this reason, automatic incident detection has become an important part of ATMS. Figure 1 illustrates some of the main ATMS applications and shows the main components of incident management systems.

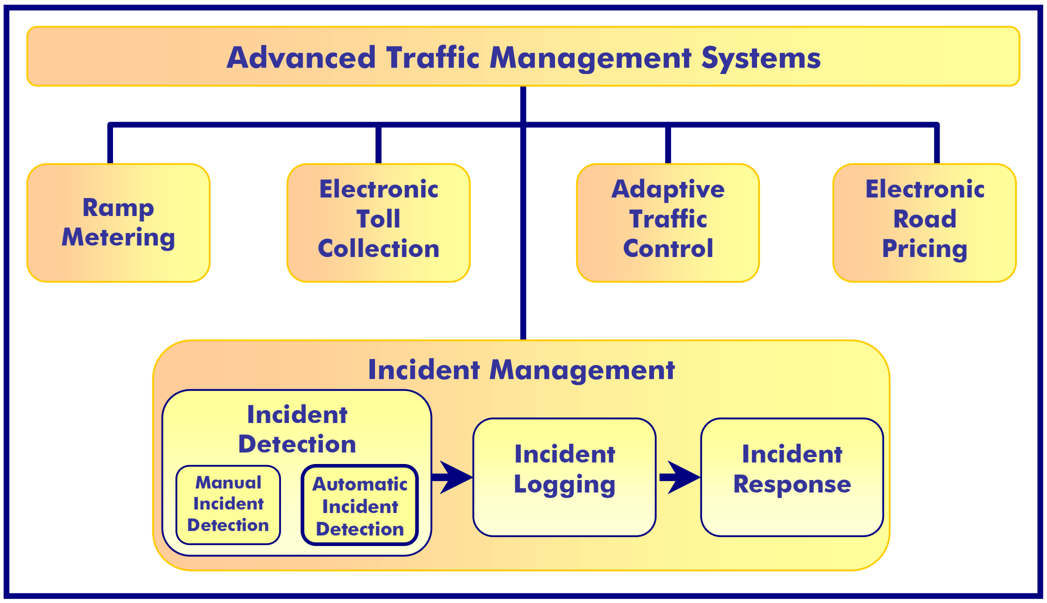


Figure 1. Advanced Traffic Management Systems

This paper will first present the research objectives of this project. The section which follows provides a summary of the various automatic incident detection models and describes the evaluation criteria used for comparison of model performance. This is followed by a brief introduction to Chaos Theory and Fractals. The model used to calculate the fractal dimension of the loop detector data is then described in detail. The paper then describes the research methodology and the development of the two fractal models. The results produced by the Fractal Threshold model are discussed, and compared with the models discussed in Dia and Rose (1997). Some conclusions are presented, and directions for future research are proposed.

2 OBJECTIVES

This project aims to demonstrate the feasibility of using fractal dimension analysis for freeway incident detection based on field data obtained from inductive loop detectors. The data set used for evaluation is a set of 100 incidents collected by VicRoads for the development of an Artificial Neural Network (ANN) model (Dia and Rose, 1997). The same data set will be used to compare the performance of the fractal models with the artificial neural network and the ARRB/VicRoads models.

3 Background

3.1 Automatic Incident Detection Models

Automatic Incident Detection (AID) models can be collected into five main groups (Stephanedes and Chassiakos, 1993, Dia and Rose, 1997, Teng, 2000). These are described in Table 1. While the literature abounds with papers on these models, there are very few performance comparisons which make use of standardised parameters (Dougherty, 1995). This makes assessment of their relative merits difficult.

Table 1 Automatic Incident Detection Models

Model Groups	Performance and Limitations
Comparative Models Traffic measurements obtained from downstream and upstream detectors are compared. Measured traffic parameters are compared to pre-established thresholds.	• Reported detection rates (Dia and Rose, 1997) are quite low for false alarm rates less than 1%. • These simple algorithms are fairly easy to implement. • Assume that traffic flow is continuous (Lee and Taylor, 1999), hence cannot be used on signalised streets, where flow discontinuities occur. • Work better when there are substantial capacity reductions on the road (Ivan *et al*, 1994); hence have trouble detecting incidents that occur during low flow periods. • Some of these models rely on comparisons with collected historical data, which may be unreliable. • Thresholds depend on road geometry and other factors, which decreases the portability if the model, and its responsiveness to changing conditions.
Time Series Models These models use statistical or time series models to estimate the current traffic trend based on past observations. The estimates are compared with actual measurements or threshold values.	• Many models use the observations from a single station. This can be an advantage in an arterial environment where downstream stations are not available. • Limited by the use of previous data, which may be unreliable. • Models typically make use of fixed smoothing factors (Lee and Taylor, 1999) with equal weightings. The parameters cannot adapt to the changing environment.
McMaster Model Developed based on the Catastrophe theory, where congestion results in an abrupt change in speed, while flow and occupancy change continuously.	• Reported false alarms rates are very low (Ivan *et al*, 1994), but detection rates are not that high at 68%. These results were for detection of serious lane-blocking incidents. • Calibration of the model is labour intensive, and is site-dependent.

Model Groups	Performance and Limitations
Neural Network Models Neural network models are used to recognise the traffic patterns that occur in incident conditions.	• Artificial neural networks have produced high detection rates with low corresponding false alarm rates (Dia and Rose, 1997). • Neural networks are quicker to build than a statistical analysis (Dougherty, 1995), and do not require the analyst to have a full understanding of the situation. • Large data sets are needed for training. This has been a major problem, and most training has been done with simulation data.
Fuzzy Logic Models Fuzzy Logic Models incorporate inexact reasoning and uncertainty into the incident detection logic.	• Designed to make decisions based on imprecise or missing data, and calculate the likelihood of an event. • Produced promising results but have the disadvantage of taking a larger amount of computation time (Lee and Taylor, 1999) • Fuzzy logic has been combined with artificial neural networks (Teng, 2000).
Macroscopic Models Macroscopic measurements such as traffic density, mean space speed, and mean travel time are used.	• These models have been used in special situations such as tunnels where lane changing is prohibited (Yagoda and Buchanan, 1991).

3.1.1 Evaluation Criteria

The following parameters are used to quantify the performance of an incident detection model.

Table 2 Evaluation Criteria

Criterion	Description
Detection Rate (DR)	The Detection Rate is defined as the number of detected incidents divided by the total number of incidents known to have occurred.
False Alarm Rate (FAR)	The False Alarm Rate is defined as the number of incident free intervals which gave false alarms, divided by the total number of incident free intervals. This is a more strict definition than dividing by the total number of time intervals, which is also used in the literature.
Time to Detect (TTD)	The Time to Detect is defined as the difference between the time of occurrence of the incident, and the time at which the incident was detected. If the model takes longer than 5 minutes to detect an incident, the incident is marked as undetected.
Mean Time to Detect (MTTD)	The Mean Time to Detect is the average time to detect for the collection of incidents.

The detection rate and false alarm rate are positively correlated. For example, if model thresholds are relaxed, the DR will increase, but so will the FAR. Setting thresholds and model parameters is a process of optimisation for highest possible DR, and lowest possible FAR.

The detection rate and false alarm rate are optimised using a Performance Envelope Curve, where detection rate is plotted as a function of false alarm rate. The area under the curve gives a measure of the performance of the model. An area of 10000 corresponds to an ideal performance. The ellipse shows the optimal DR/FAR combination.

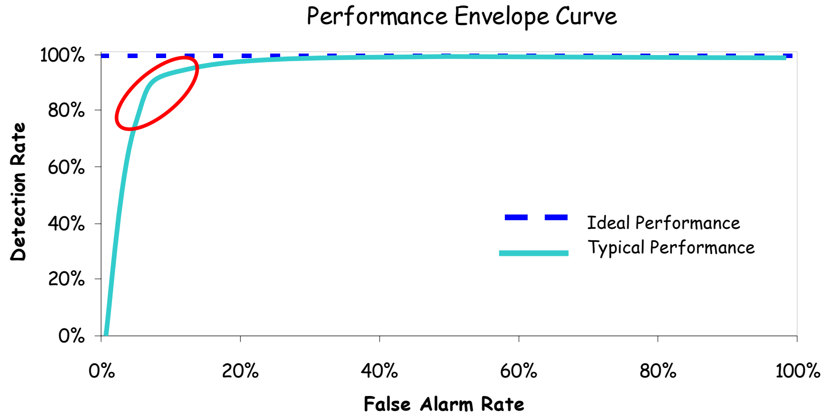


Figure 2. A Performance Envelope Curve.

3.2 Chaos Theory and Fractal Geometry

Prior to the development of Chaos theory, the general belief was that the world behaved deterministically, like a huge clockwork mechanism. Science was the process of deciphering the laws of nature. It was believed that once all the laws were understood, everything would fall into place, and it would be possible to predict the behaviour of any system. Unfortunately, in real systems, order (or predictability) always breaks down eventually, resulting in an increase in entropy, and chaotic behavior.

This makes accurate modelling of real systems somewhat challenging. A classic example of this is modelling the weather. The smallest error in measurement of an input parameter is amplified with each time step, until the error is so huge that the model outputs become unreliable. The term ‘butterfly effect’ describes this: the perturbation caused by butterfly flapping its wings over Brazil may result in a tornado in Texas (Gleick, 1987). Ironically, within all the disorder of a chaotic system, regular behavior can be found – order within chaos.

The term fractal was invented by Mandelbrot in his 1983 magnum opus ‘*The Fractal Geometry of Nature*’ and is from the Latin *frangere*, ‘to break’. A fractal is an object that has fine detail at all scales. Typically, no matter how much you magnify a fractal, the basic structures you see are the same. Self-similarity and the final shape of a fractal result from the natural processes that an object undergoes as it develops. Hence, plants, snowflakes, blood vessels and coastlines share similar fractal characteristics.

3.2.1 Limitations of Euclidean Geometry

The following two figures are fractal in nature. The Koch snowflake is constructed from an equilateral triangle. A new triangle is added to the middle of each side, and the process is repeated. The Koch snowflake has a boundary of infinite length, but has a finite area. The Koch snowflake is a simple model of a coastline.

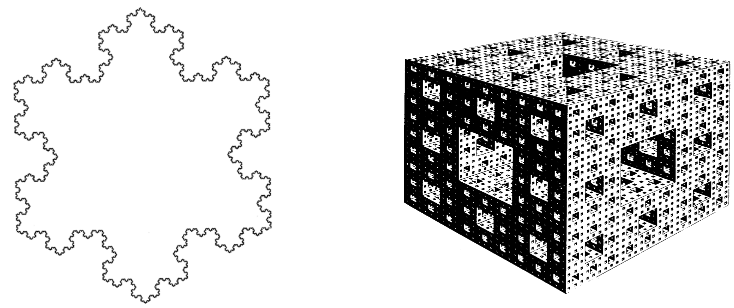


Figure 3. The Koch snowflake and Menger sponge (Source: Gleick, 1987)

Similarly, the Menger sponge is created by taking away a cube 1/9th the size of the original cube, from the centre of each surface, and iterating. The Menger sponge has infinite surface area but zero volume. These objects demonstrate how ill equipped Euclidean geometry is to deal with fractal shapes. Fractal Geometry was developed to better quantify these shapes.

While Euclidean geometry is successful with objects which exist in integer dimensions, fractal geometry deals with objects which have non-integer dimensions. The next two figures show a series of randomly generated points between 0 and 1 plotted linearly, and as a surface.

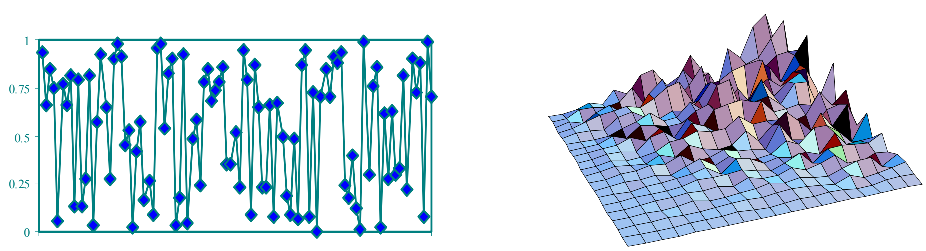


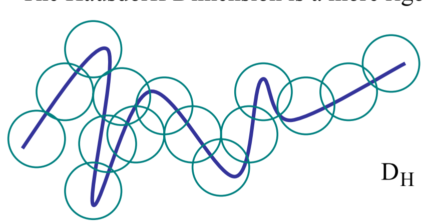
Figure 4. Fractal Objects

While a straight line has a dimension of exactly one, the line above is more complex and tends to cover an area. Similarly, the surface above fills more space than a simple square or circle. To quantify this difference, the fractal dimension is calculated. The more a line fills up a plane, the closer its fractal (non-integer) dimension is to 2. Similarly, the fractal dimension of a surface will tend towards 3 as the surface becomes more complex. The fractal dimension gives a measure of how much area or space an object fills, or the complexity (irregularity) of an object.

There are a variety of methods for calculating fractal dimension, including the self-similarity dimension, the box dimension and the Hausdorff dimension (Peitgen *et al*, 1992, Bourke, 1993).

3.2.2 The Hausdorff Dimension

The Hausdorff Dimension is a more rigorous expression for the fractal dimension:



$$D_H = \lim_{\varepsilon \to 0} -\frac{\mathrm{Ln}\,N(\varepsilon)}{\mathrm{Ln}(\varepsilon)}$$

Equation 1

where $N(\varepsilon)$ is the number of circles of radius ε needed to completely cover a linear set of length L. In most situations, this value is difficult to calculate.

3.2.3 Calculation of the Fractal Dimension of Speed, Flow or Occupancy Data

Sevcik (1998) proposed the following approximation for the Hausdorff Dimension:

$$D_H = \lim_{\varepsilon \to 0}\left(1 - \frac{\mathrm{Ln}(L)}{\mathrm{Ln}(\varepsilon)}\right) \cong 1 + \frac{\mathrm{Ln}(L)}{\mathrm{Ln}(2N')} \qquad \textbf{Equation 2}$$

where L is divided into $N(\varepsilon) = L/2\varepsilon$ segments, each of length 2ε. N' is set to $1/2\varepsilon$.

Analysis is performed on a set of N data points (N > 2). The data may be occupancy, speed of flow.

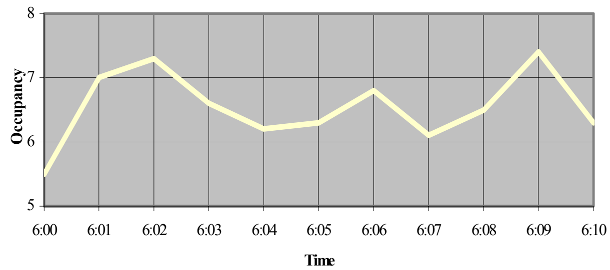


Figure 5. Set of N Occupancy Data Points

Each occupancy value O_t at time t is normalised. The choice of normalization factor is fairly significant, as too high a constant reduces the features too much, resulting in very small differences between the incident conditions and normal flow. The 90th percentile (the number that is greater than or equal to 90% of the data set) was used initially. The normalization constant became a significant parameter for calibrating the model (See 4.2.3).

The time gap is also normalised. For N data points, the time gap is normalised to 1, hence each time step is of length 1/(N-1). The Length Element, that is the length of the line between two data points, is calculated (by Pythagoras) as:

$$LE_i = \sqrt{\left(\overline{O}_i - \overline{O}_{i-1}\right)^2 + \left(\frac{1}{N-1}\right)^2}\,, \qquad \textbf{Equation 3}$$

where $\overline{O}_i = O_i/O_{MAX}$ is the normalised occupancy at time i. The total length of the set of N points is then calculated, and is attributed to a time j in the middle of the interval of N data points:

$$L_j = \sum_{i=j-\mathrm{TRUNC}(N/2)}^{j+\mathrm{TRUNC}(N/2)} LE_i\,, \qquad \textbf{Equation 4}$$

where TRUNC is truncation e.g. TRUNC(5.662) = 5, TRUNC(1.2) = 1. The fractal dimension of the interval j is then approximated as:

$$D_j \cong 1 + \frac{\mathrm{Log}(L_j)}{\mathrm{Log}(2 \times (N-1))} \qquad \textbf{Equation 5}$$

3.2.4 Incident Detection using Fractal Dimension Analysis

Incident detection using fractal dimension analysis is based on the following assumptions.

- The traffic upstream of an incident arrives at random times, and has correspondingly irregular speed, occupancy and flow values; hence this data should have a high fractal dimension.

- Downstream of an incident, the traffic behaviour is more regular, as the vehicles are typically accelerating to a similar speed following the obstruction, and less traffic is able to get through due to the reduction in capacity of the road during an incident.

Hence, it should be possible to compare the fractal dimensions of the upstream and downstream speed, occupancy and flow time series. During an incident, the upstream fractal dimension should be greater than the downstream fractal dimension.

4 METHODOLOGY

4.1 Data Collection

The data used in this study was collected from VicRoads' Traffic Control Centre for developing the neural network incident detection models reported in Dia and Rose (1997). This data set is believed to comprise the largest set of field incidents in the world and has been thoroughly pre-processed in a format suitable for incident detection algorithm development.

The data set was provided as lane-by-lane values or averaged per detector site in 20-second cycles. In order to be consistent with the methodology used by Dia and Rose (1997), the averaged data was used.

4.2 Model Development

4.2.1 Fractal Model

The Fractal Model was developed to compare the upstream and downstream fractal dimensions of the averaged speed, flow and occupancy data. It rapidly became clear that the flow showed no suitable trends, so the tests were performed on the speed and occupancy data only.

First, the speed was tested. If the upstream fractal dimension was greater than the downstream fractal dimension, then a possible incident was declared. The occupancy was tested in the same way. If both tests were passed, then Probable Incident was declared. If this occurred for the required number of time steps (called the persistence interval *PI*), an alarm was triggered. This process is illustrated in Figure 6.

Once all the incident files have been evaluated, the detection rate, false alarm rate and mean time to detect were calculated for the set of incident files.

The resulting performance was dependent on a number of parameters used in the calculation. Table 3 describes the effects of each parameter.

Table 3 Parameter Descriptions for the Fractal Model

Parameter		Description
N		This is the number of data points used for the fractal calculation (See 3.2.3).
	Effect:	Increasing N decreases the false alarm rate, but also decreases the detection rate.
PI		This is the persistence interval, or the number of time steps that a possible incident must be declared before a Probable Incident is declared.
	Effect:	Increasing the PI has the effect of decreasing the number of Probable Incident declarations.

Parameter	Description
S_{MAX}, O_{MAX}	These are the normalization constants for the speed and occupancy data.
Effect:	Increasing the normalization constants has the effect of damping the data variations. This is desirable to an extent, but if the values are too high then the characteristic behaviour of the upstream and downstream detectors is masked.

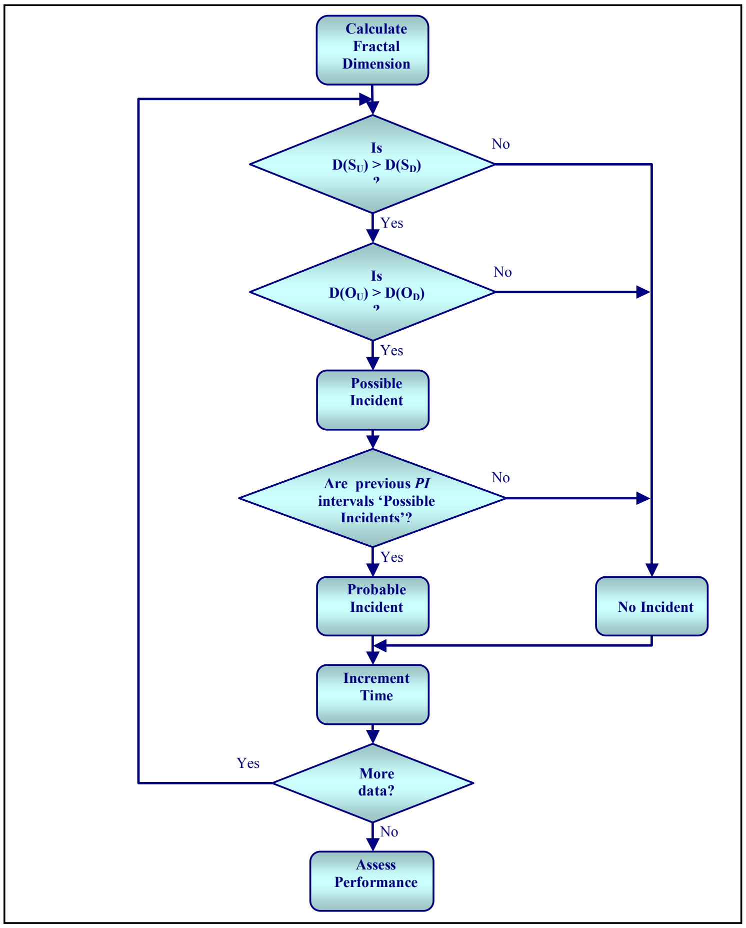


Figure 6. Flowchart for Fractal Model

The performance of the Fractal Model was very poor, with very large false alarm rates for a wide range of parameter values. The tests used on the speed data were not contributing to the performance of the model, as the speed fractal dimension did not exhibit the same trends as the occupancy data. Figure 7 shows typical trends for speed, occupancy and flow fractal dimensions. The upstream speed fractal dimension shows sudden peaks at the start and end of an incident. This would indicate sudden irregularities in the data, corresponding to sudden variations in the measured speeds.

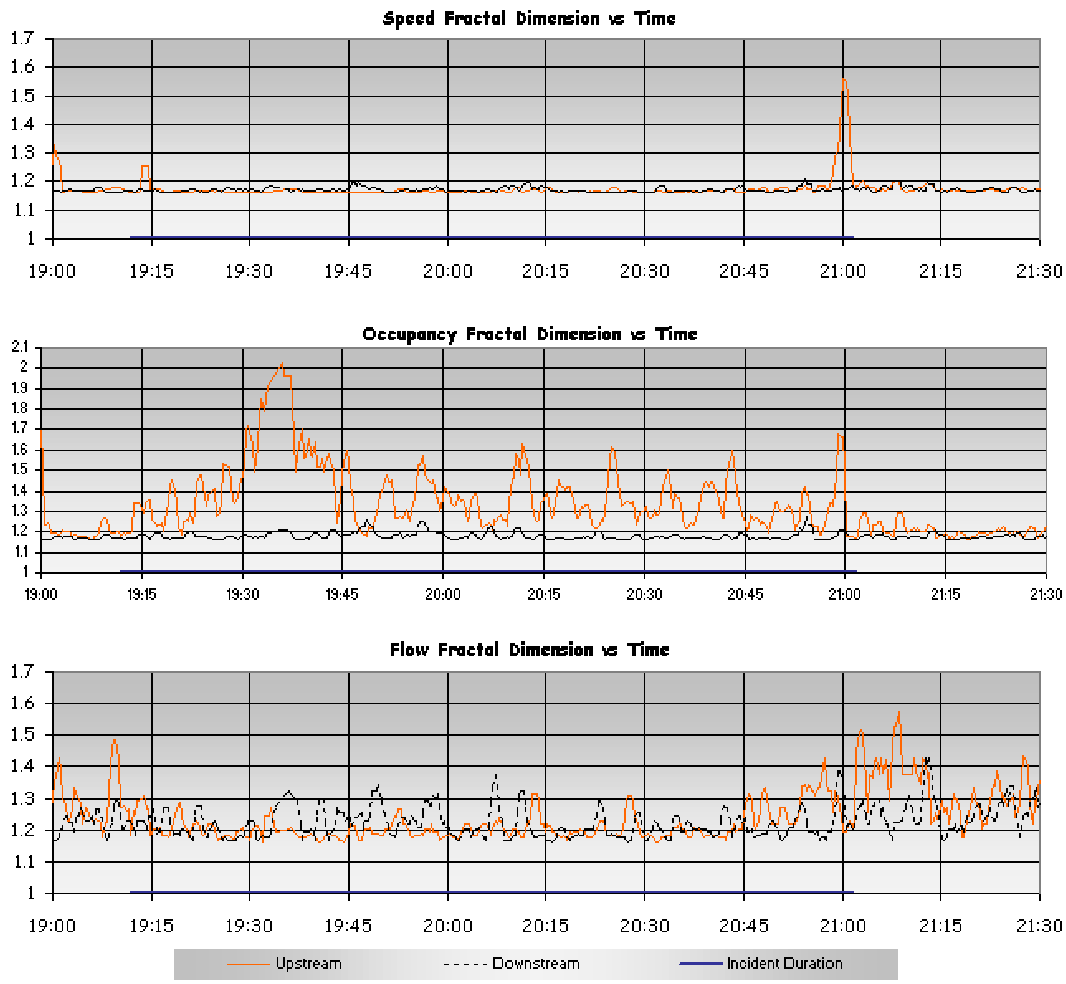


Figure 7. Typical Speed, Flow and Occupancy Fractal Dimension trends.

4.2.2 Fractal Threshold Model

The Fractal Threshold Model (FTM) was developed to perform two tests on the occupancy data:

Test 1 Compare upstream fractal dimension with downstream fractal dimension of the occupancy data.

Test 2 Check whether the upstream occupancy fractal dimension is greater than a threshold value.

If both conditions were met, then a probable incident was declared. If this occurred for the required persistence interval, an alarm was triggered. The flow chart is similar to that in Figure 6. As outlined previously, the detection rate, false alarm rate and mean time to detect were also calculated for the incident data set.

The resulting performance was dependent on the values set for N, PI, the normalization constant O_{MAX} (described in 4.2.1) and a threshold value set for the upstream occupancy:

Table 4 Parameter Description for Fractal Threshold Model

Parameter		Description
O_T		This is a limit value for the upstream occupancy fractal dimension. Physically, this indicates that the upstream traffic is becoming increasingly irregular due to congestion.
	Effect:	Increasing O_T has the effect of reducing the number of possible incident declarations.

4.2.3 Calibration of the Fractal Threshold Model

This study implemented a similar approach to that described by Dia and Rose (1997). The set of 100 incidents was divided into two sets:

- A training set of 60 incidents and
- A validation set of 40 incidents.

The parameters N, the number of intervals; PI, the persistence interval; O_{MAX}, the normalization constant; and O_T the occupancy threshold value were optimised on the Training data set. The optimisation process tested each parameter for its DR / FAR dependence, with the aim of obtaining a FAR of less than 0.9% to be comparable with the ANN and ARRB/VicRoads Model results.

Selection of the number of intervals, N

Firstly, the value of N was optimised. While the DR was 98% for N=3, the FAR was a huge 32%. (See Figure 8: Detection Rate is plotted with respect to the left axis, while False Alarm Rate is plotted with respect to the right axis.)

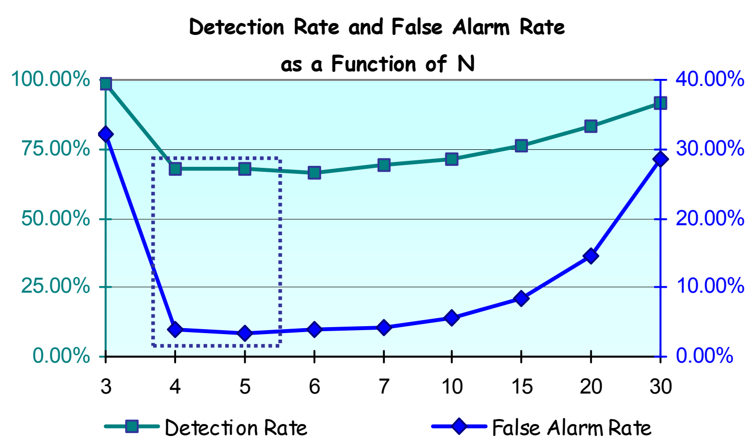


Figure 8. Detection Rate and False Alarm Rate as a function of N

Two possible values for N were selected: 4 and 5, as these corresponded to the lowest false alarm rates. All MTTD values were reasonable, ranging from 2 min 50 s to 4 min 40 s.

Selection of the persistence interval, PI

Persistence intervals in the range 2 – 10 were tested for N values of 4 and 5. A persistence interval of 6 yielded the best combination of DR and FAR for both N values. As expected, both the FAR and DR decreased for greater PIs.

Selection of occupancy threshold, O_T

Suitable values for this parameter ranged between 1.1 and 1.4. The optimal value was found to be 1.31. With this setting, the N value of 4 gave the best results. Lower values resulted in higher DR and FAR, while higher values decreased the DR without significantly improving the FAR.

Selection of the Occupancy Normalisation factor, O_{MAX}

The model showed great sensitivity to this parameter. A wide range of values were tested (20 – 90), and the optimal value was found to be 55. Again, lower values resulted in higher DR and FAR, while higher values decreased the DR without significantly improving the FAR.

The parameter values N = 4, PI = 6, O_T = 1.31 and O_{MAX} =55 yielded the best results for this model, with a DR of 28% and a FAR of 0.54% for the training data set. These parameters were applied to the Validation data set of 40 incidents. Results are discussed in the next section.

5 RESULTS

5.1 Performance of Fractal Threshold Model

The validation data was tested with the parameter values derived in Section 4.2.3.

The data was tested for dependence on the occupancy normalization constant O_{MAX} and the occupancy threshold value O_T. Table 5 lists the outputs of the model, for various values of the occupancy normalization constant, while Table 6 lists outputs for various occupancy thresholds.

Table 5 Incident Detection Performance with variation of Occupancy Normalization Constant.

Occupancy Normalisation Constant (O_{MAX})	Incident Detection Performance		
	Detection Rate (DR)	False Alarm Rate (FAR)	Mean Time to Detect (MTTD)
20	47.50%	0.94%	0:03:01
25	37.50%	0.42%	0:02:51
30	32.50%	0.14%	0:03:08
35	30.00%	0.05%	0:03:07
40	27.50%	0.05%	0:03:02
45	25.00%	0.05%	0:03:00
50	20.00%	0.05%	0:02:50
55	20.00%	0.05%	0:03:15
70	5.00%	0.03%	0:04:20
85	5.00%	0.01%	0:04:40
90	5.00%	0.01%	0:04:40

Table 6 Incident Detection Performance with variation of Occupancy Threshold.

Occupancy Threshold (O_T)	Incident Detection Performance		
	Detection Rate (DR)	False Alarm Rate (FAR)	Mean Time to Detect (MTTD)
1.1	75.00%	9.86%	0:02:08
1.15	75.00%	9.86%	0:02:08
1.2	37.50%	0.43%	0:02:51
1.25	27.50%	0.05%	0:03:02
1.3	20.00%	0.05%	0:03:00
1.4	5.00%	0.01%	0:04:40

The results are very similar, and are plotted in Figure 9. The performance of the Fractal Threshold Model shows the same trend regardless of the parameter varied, although the performance envelope curve resulting from varying the normalization constant is marginally better. The graph is plotted on a 0 to 1% scale in order to show the small differences between the two performance envelope curves.

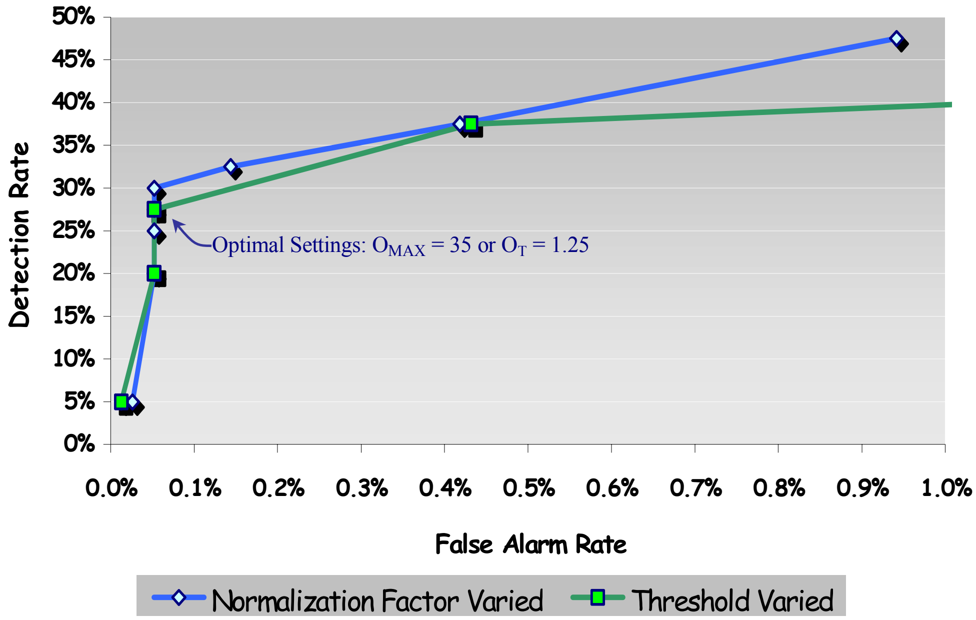


Figure 9. Performance Envelope Curves for the Fractal Threshold Model.

The validation data set consists of a wide range of incident types. The incidents could be characterised by the severity or number of lanes blocked (1, 2 or 3); the time of day (Peak or Off-peak) or the flow (Low, Medium or High). The validation data was divided into these groups, and was tested using O_{MAX} = 35, and all other parameters having their calibration values.

The FTM performed better for off-peak incidents, compared to incidents that occurred during peak periods. This may not be significant, as the flows during both peak and off-peak periods ranged from low to high. The model performed best with low flow rates, although the data set consisted of only 4 incidents. The test's performance was better for Medium flow than for High Flow. The model was also better at detecting catastrophic 3-lane blocking incidents.

The data set used for this work has been used to test two other models (Dia and Rose, 1997), the artificial neural network model presented in the paper, and the ARRB/VicRoads Model. The performance of the FTM was compared with the performance of the other models.

5.2 Comparison with Other Models

The Detection and False alarm rates reported in Dia and Rose (1997) are used with the Fractal Threshold Model data from Table 5 to generate Figure 10.

Clearly, the Fractal Threshold Model performs poorly when compared to the neural network, and is roughly equivalent to the ARRB/ VicRoads Model. For the range of acceptable false alarm rates (<0.1%), the Fractal Threshold Model outperforms the ARRB/ VicRoads Model.

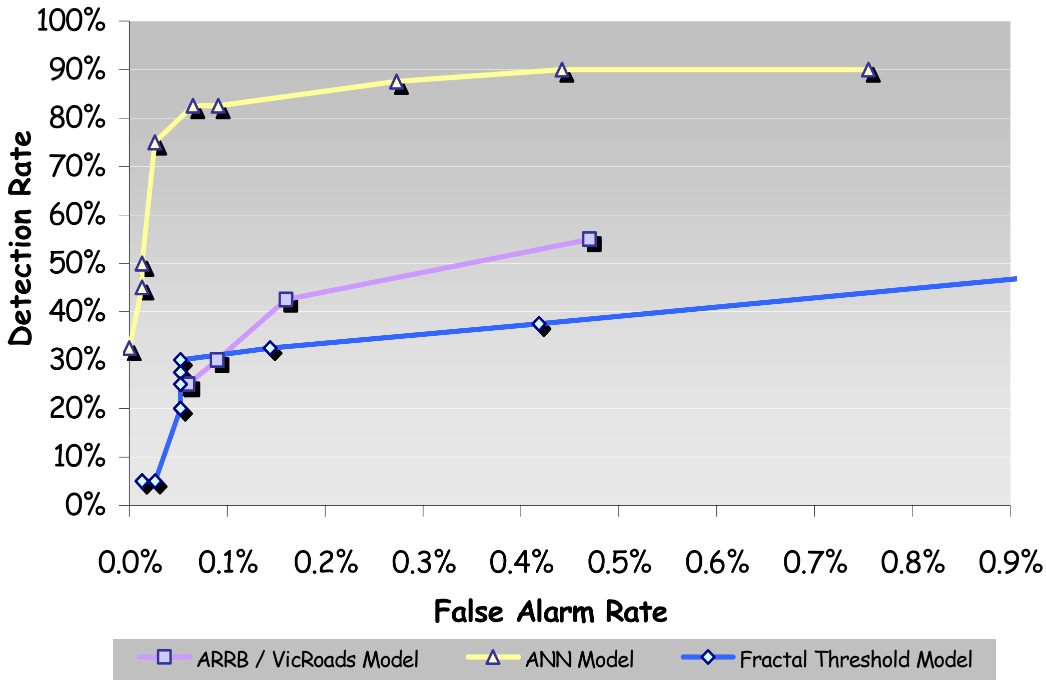


Figure 10. Comparison of Fractal Threshold Model with ARRB/ VicRoads Model and ANN Model.

Calculation of the area under the performance envelope curves provides a quantitative assessment of the relative performance of the models. Over the whole range of FAR values, the ARRB/VicRoads model outperforms the FTM, and is outperformed by the ANN model.

Table 7 Performance Envelope Curve Areas for the Three Models

Model	Performance Envelope Curve Area (PECA)
Artificial Neural Network Model	9963
ARRB/VicRoads Model	7732*
Fractal Threshold Model	7340*

*Data was extrapolated to the (100%, 100%) point to calculate these values.

6 CONCLUSIONS

This project aimed to demonstrate the feasibility of fractal dimension analysis of speed, occupancy and flow data for the purpose of incident detection. The project involved the development of two models: the Fractal Model and the more successful Fractal Threshold Model for testing on a data set of 100 incidents collected by VicRoads.

Two other models had been tested with the same data set: the ARRB/VicRoads Model, which makes use of a comparative model, and an Artificial Neural Network Model developed by Dia and Rose (1997). The Fractal Threshold Model was compared with these models.

Fractal analysis and neural network pattern identification share the property that they are able to function well in non-linear environments. This is evidenced by the ability of the Fractal Threshold Model to outperform the ARRB/ Vicroads Model at false alarm rates in the acceptable range of 0 – 0.1%. Based on the results from the Validation data set of 40 incidents, the Fractal Threshold Model performed well in detecting catastrophic lane-blocking incidents, and worked better in a low flow or off-peak environment. This performance is based on two simple tests on the occupancy data. There is scope in future research projects to explore the addition of suitable tests on the speed and flow profiles in order to improve the performance of the model.

There's also some scope in future research efforts to explore some of the following research directions:

- testing the model with flow-weighted average speed and occupancy;
- adding a threshold test for the downstream occupancy fractal dimension;
- detection of the upstream speed fractal dimension peaks before and after an incident;
- some success has been obtained in the literature with analysing the flow to occupancy ratio (Ivan *et al*, 1994, Sethi *et al*, 1994). The fractal dimension of this ratio should be tested.

Possibly the most interesting option would be to providing the fractal dimension of speed or occupancy data as an input to an ANN model. This may further improve the ANN model's performance.

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