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Traffic volume responsive incident detection

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Abstract

Incident detection is one of the major concerns of freeway operators, as incidents account for more than 60% of the travel delays faced by motorists, especially under recurrent traffic congestion. Algorithms detecting incidents are categorized based on the intelligence they use to analyse the measurements taken by traffic monitoring (volume, occupancy, speed). As roadway geometry and traffic conditions affect the algorithms' accuracy, the objectives of this paper is to take them into account when specifying the threshold values, and to assess the effect on the algorithms' performance on the network operations.
The main steps of the methodology are the calibration of available incident detection algorithms (California #7 και DELOS) to a set of traffic and incident data and the validation of the threshold values. Further adaptation of these values is attempted to the changing traffic volumes. When the threshold values were being calibrated on the prevailing traffic conditions, an improvement was observed on all three performance indices (detection rate increase by 20%, false alarm rate decrease by 25% and time to detect at the same levels).

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Keywords: incident detection; detection algorithms; calibration and verification; threshold values

1. Introduction

Road congestion is one of the main problems and challenges, transportation research domain has to address. According to the latest report on urban congestion by TTI (2015), congestion caused urban Americans to travel in 2014 an extra 6.9 billion hours and purchase an extra 3.1 billion gallons of fuel for a congestion cost of US$160 billion. In order to reliably arrive on time for important freeway trips, travelers had to allow 48 minutes to make a trip that takes 20 minutes in light traffic (TTI, 2015). Similarly, the congestion cost in Europe is estimated to be more than 110 billion euros, on a yearly basis (EC, 2011).

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Road congestion is the inability of the network to service traffic demand, when it is higher than the roadway capacity. It may be recurrent and non-recurrent. While the first type is observed regularly in time and space, the second one may appear in random time and location, owing to incidents, which reduce the facility's capacity, such as vehicle crash, vehicle breakdown, flat tire, overturned vehicle, or other special event (Nathanail, 1996). Traffic incidents are a significant cause of congestion delays that motorists encounter every day and according to the Federal Highway Administration (FHWA), 60% of the delays in urban motorways are due to incidents (FHWA, 2003; FHWA, 2010a).

In addition to delays, congestion also affects fuel consumption and air pollution. For example, a stochastic model by Salimol and Jacko (2007) estimates the average emission of CO, VOC, NOX, and PM2.5, and traffic delays due to incidents. The study indicates that a 5% reduction in traffic via rerouting or other demand management can reduce emissions up to 30%.

One of the most important actions to relief non-recurrent congestion owing to incidents is to reduce incident duration. Incident duration is composed of incident detection and verification, allocation and routing of emergency response units and on-scene servicing. Minimizing either one time component results in the reduction of the overall incident duration, thus it reduces impacts, such as delays, secondary accidents, energy consumption and environmental deterioration (Nathanail & Zografos, 1995).

This paper focuses on incident detection and aims at optimizing performance of incident detection algorithms, thus detection rate and time to detect. The methodology concerns identification of threshold values used by the algorithms to detect an incident and is applied on two well-known algorithms, California #7 and DELOS, which are calibrated to actual data of the Attica Tollway, an urban freeway in Athens, Greece, and their performance is estimated and compared.

2. Incident Management

2.1. Incident management systems

Incident Management (IM) is one of the main activities of Traffic Management Centers (TMCs). Effective IM reduces the duration and the impacts of traffic incidents and improves the safety of motorists, crash victims and emergency responders (FHWA, 2010b). Functions of IM include incident detection and verification, information dissemination, fleet allocation and operations coordination and incident response and clearance and traffic management, so that for traffic flow to recover as safely and quickly as possible (Mustafa & Nathanail, 1998; FHWA, 2008).

In freeways, an essential component of IM, is Patrol or Intervention Teams which are small trucks or vans patrolling along the freeway and are usually dispatched by Traffic Control Center operators to intervene to an incident. Studies in the USA indicated that the percentage of covered motorways by Patrol Services in 2008 was 46% of the total motorway network (FHWA, 2008).

TransGuide is an advanced Intelligent Transportation System (ITS) in San Antonio, USA, which initiated its operation in 1995, and covers 100 miles of freeway (San Antonio Area Freeway System web site). It employs fiber optic cables network, 2500 detectors, radars and video cameras at 220 sites for traffic monitoring and incident detection. Data are collected every 20 seconds, and its capability reaches 2 incidents detected per 2 minutes. Benefits of the system implementation have been estimated to 20% reduction of incident response time, with respective decrease in fuel consumption and costs

Caltrans (California Department of Transportation) implements Advanced Traffic Management Systems (ATMS), among other, for fast detection, based on loop, video and microwave detectors, which measure traffic flow, speed and occupancy (CALTRANS, 2009), which is followed by other modes of traffic management, in order to alleviate problems owing to the incidents and provide reliable and efficient incident restoration.

2.2. Detection algorithms – a review

Several studies (Martin et al, 2001; Parkany and Xie, 2005; Mahmassani et al, 1999; Prevedouros et al, 2006) provide a synoptic review of incident detection algorithms categories. Comparative Algorithms were initially introduced in the 1960s. They rely on recognizing and differentiating unusual patterns of traffic from normal conditions. The basic principle for detecting incidents is to compare upstream and downstream traffic parameters and issue an alarm when the difference exceeds a threshold. The drawback of the comparative algorithms is that they are sensitive to fluctuating traffic demands because alarms are triggered based on constant thresholds. A well-known set of comparative algorithms are the California Algorithms (Payne and Knobel, 1976), which were initiated with an FHWA study in 1973 and improved as a set of ten algorithms with TSC-7 often used as the benchmark for testing other algorithms. Other comparative algorithms include the Pattern Recognition (PATREG) Algorithm and All Purpose Incident Detection (APID) Algorithm. Statistical Algorithms calculate the difference between observed traffic data and forecasted values. Then they compare the differences with sets of thresholds, and use this to issue alarms. Standard Normal Deviates (SND) and Bayesian methods form the two basic statistical algorithms. SND algorithms use the last three to five minutes of the data to calculate the mean and standard deviation of occupancy. Bayesian statistical techniques are used to compute the probability of an incident, which is derived with historical traffic data of occupancy and volume under incident and non-incident conditions. Time Series Algorithms are a variant of statistical algorithms. They analyze the recent history of occupancy and speed. Short-term traffic forecasts are made and an incident is detected when significant deviations between observed and forecasted traffic parameters are observed. Several time series algorithms were developed including the High Occupancy Algorithm (HIOCC), a double exponential smoothing algorithm, and ARIMA-based algorithms. Theoretical Algorithms pertain mostly to the (Canadian) McMaster Algorithm, which is used widely for incident detection. The algorithm is based on a 2-dimensional analysis of traffic flow with pre-defined incident and non-incident regions (Persaud and Fred, 1989). Prevailing conditions are described with (x,y) coordinates and if they correspond in an incident region of the 2-dimensional chart, then a alarm is triggered. Advanced Algorithms often employ more modern mathematical theory for incident detection such fuzzy sets, artificial neural networks (ANN) or Logit models. Fuzzy set algorithms incorporate inexact reasoning and uncertainty into the incident detection logic. ANN-based algorithms may learn to recognize certain traffic patterns, after training with previous incident and non-incident conditions. Logit-based algorithms recognize incident traffic patterns using an incident index, estimated by multinomial Logit, which represents the probability of an incident occurring

Regarding the advantages and disadvantages of each algorithm, a nationwide Web-based survey was conducted at 29 transportation management centers (TMCs) and transportation operations centers (TOCs) in the summer of 2001 in the USA (Parkany and Xie, 2005). Some interesting results referred to the actual usage of algorithms in daily operations instead of non-automatic detection sources like CCTV and witness reports, which were the principal means of incident detection/verification. In the same study differences among known algorithms in false alarm, detection rates, time to detect and other performance measures are presented. The conclusion of this comparison is that the design of each algorithm determines its own application environment, as the performance of the same algorithm can differ considerably in different environments. Environmental factors include geometric characteristics, sensor type, sensor configuration, data type, data aggregation period, as well as traffic disturbance factors.

Required data and comparisons of algorithms are presented in several studies. Deniz et al (2012) showed that all of the algorithms use occupancy, APID, SND, Time Series, Neural Networks, Fuzzy Sets and Modified McMaster algorithms use both occupancy and volume data. Algorithms with fuzzy sets or neural network approach use occupancy, volume and speed data. In the same study APID, TSC 7 and DES automatic incident detection algorithms are compared with different road condition and incident location scenarios. It is shown in this study that, performance of the algorithms is strongly related location of the incident and the road condition in terms of traffic volume. Algorithms tend to have more false alarm rates in higher traffic volume conditions (Deniz and Celokoglu, 2011).

3. California #7 and DELOS Algorithms

California Algorithm #7 algorithm (Levin and Krause, 1978; Deniz and Celokoglu, 2011; ITS Decision web site) calculates spatial difference in occupancy, OCCDF, and the relative spatial difference of occupancies, OCCRDF. In addition to these two data, algorithm uses occupancy values of obtained from downstream detectors. Calculation process of OCCDF and OCCRDF are given in equations 1 and 2:

$$\mathbf{OCCDF(i,t) = OCC\ (i,t) - OCC(i+1,t)} \qquad \mathbf{(1)}$$

$$\mathbf{OCCRDF(i,t) = (OCC\ (i,t) - OCC(i+1,t))/\ OCC\ (i,t)} \qquad \mathbf{(2)}$$

Where, i denotes the detector station number and t denotes the time period. OCC(i+1,t) is the occupancy value which is obtained from detector station (i+1) in time period t. Downstream occupancy value, OCC(i+1,t), can also be represented as DOCC. California Algorithm #7 basically calculates OCCDF and OCCRDF values and obtains DOCC value from detector stations and compares these inputs with 3 preset thresholds, T1, T2 and T3. T1 is the maximum value of the OCCDF under normal conditions, T2 is the maximum value of the temporal difference in downstream occupancy (DOCCTD) under normal conditions, T3 is the maximum value of the OCCRDF under normal conditions. DOCCTD can be calculated with the equation 3.

$$\mathbf{DOCCTD = OCC(i+1,t) - OCC(i+1,t+1)} \qquad \mathbf{(3)}$$

There are 4 identified states: State 0 – no incident, State 1 – there is an incident but there is no detection, State 2 – the incident has been detected and State3 –incidents continues.

DELOS (Detection Logic with Smoothing) algorithm was developed by Chassiakos and Stephanedes (1993). They used a smoothing technique (moving average, median, exp smoothing) of raw data as the first part before the algorithm calculations. There are four threshold values that need to be estimated: m,n,ψ1,ψ2. The integer m and n are calculated based on the assumption of m*DT=5min and n*DT=3min, where DT is the time elapsed between successive measurements. The other two values ψ1,ψ2 are the upper bounds of the following two functions (functions 4 and 5):

$$\boldsymbol{U_i(t) == \frac{\frac{1}{n} * \sum_{j=o}^{n-1} DOCC(i,t+j)}{K_i(t)}} \qquad \mathbf{(4)}$$

$$\boldsymbol{W_i(t) = \frac{\frac{1}{n} * \sum_{j=o}^{n-1} DOCC(i,t+j) - \frac{1}{m} * \sum_{j=1}^{m} DOCC(i,t-j)}{K_i(t)}} \qquad \mathbf{(5)}$$

where DOCC is the occupancy rate of the upstream detector and Ki(t) is estimated in equation 6:

$$\mathbf{Ki(t) = max}(\boldsymbol{\frac{1}{m} * \sum_{j=1}^{m} OCC(i,t-j), \frac{1}{m} * \sum_{j=1}^{m} OCC(i+1,t-j)}) \qquad \mathbf{(6)}$$

The algorithm itself detects incidents through a high spatial occupancy difference between adjacent stations. The difference between this and standard pattern-based algorithms is that DELOS uses a three-minute average of the spatial occupancy instead of one-time interval. Also, the occupancies for the previous five minutes are stored. Large differences between the two values indicate an incident (Martin et al, 2001).

4. Case study

Attica Tollway (AT) is an urban freeway of about 70 km which constitutes the ring road of the greater Athens (Greece) metropolitan area. The freeway has two separated directional carriageways, each consisting of 373.6 lane-km, of which 71.8% is on 3-lane sections, t 24.5% is in 2-lane sections and 3.7% is in 4-lane sections. The 15.4 km spur of AT leading to the center of Athens through mountainous terrain has 56 tunnels and cut and-cover sections, which comprise 12% of its length. The freeway's operator (Attikes Diadromes S.A.) focuses on providing rapid detection and clearance of incidents, toll collection, and planning and monitoring of routine and major maintenance projects. In-field ITS equipment includes color CCTV cameras, closely spaced emergency roadside telephones, variable message signs (VMS), lane control signals, and variable speed limit signs. The Attica Tollway Patrol Service (ATPS) consists of 50 employees and a fleet of 20 small trucks fully equipped with road signs, cones, traffic lights and other emergency equipment. Patrols are supervised and constantly supervised by the freeway's Traffic Management Centre (TMC). The 10 km central urban section of AT exhibits the worst traffic conditions along the freeway, with an annual average daily traffic (AADT) of 52,000 vehicles/direction in 2014. Peak hour volume of a typical working day in 2014, was approximately 5,300 veh/hr/dir. An average of 20,000 to 25,000 incidents are recorded by TMC per year including accidents, debris, flat tires, mechanical problems etc. (Prevedouros et al., 2008; Attica Tollway website).

The Traffic Management System (TMS) is comprised of a number of subsystems that provide detection, confirmation and response capabilities. A number of sources are used as inputs to the detection subsystem of Attica Tollway TMS. Alarms, relating to traffic problems are confirmed by the operators through the CCTV subsystem and a response is generated (Kopelias et al, 2008). Vehicle Detection System (VDS) provide values of traffic volume, speed and occupancy every 20 seconds. VDS loops are installed every 500 m in open motorway and every 60 m in the tunnels.

For the analysis raw data were used from loops and incidents/accidents, which caused significant length of queues. Table 1 shows 12 selected cases in the central section of the motorway with time stamp and queue length as recorded by TMC operators.

Table 1. Incidents and queue characteristics

ID	Position	Lane blocked	Incident Start time	Queue start time	Incident End time	Queue End time	Max queue length (m)
1	A 28,5	Left Lane	12:35	12:38	13:19	13:12	2600
2	A 25,5	Right Lane	13:47	13:50	14:40	15:00	3100
3	E 28,6	Left Lane	8:48	8:51	9:27	10:45	7000
5	E 24,1	Right Lane	8:11	8:11	9:08	10:45	9100
6	E 28,9	Left Lane	10:53	10:55	11:24	11:10	1600
9	A 25	Left Lane	9:03	9:03	9:26	9:45	2000
11	E 26,3	Right Shoulder	8:03	8:07	8:25	9:50	4000
12	A 24,8	Left Lane	11:11	11:11	12:13	12:32	2500
13	A 29,5	Right Shoulder	16:53	17:00	17:32	17:52	5000
16	A 30,2	Middle Lane	8:44	8:44	9:19	10:31	7800
17	E 26,6	Left Lane	9:32	9:33	9:58	10:17	4200
18	A 28,1	Middle Lane	8:05	8:05	8:36	9:55	6400

Note: A and E: direction of the freeway.

5. Methodology and implementation

The main steps of the methodology are the calibration of available incident detection algorithms (e.g. California #7 και DELOS) to a set of traffic and incident data, the validation of the threshold values, the adaptation of these values to the changing traffic volumes, the examination of the algorithm performance when increasing or decreasing the detectors. Firstly, the incident starting time was set, through cross-analyzing volume, occupancy and speed profiles and was compared to the reported incident time, which was obtained from observations from the traffic control center. Then, for each algorithm, alternative threshold value sets were applied to the sensors' measurements and the performance measures of effectiveness were estimated. The threshold values sets were automatically generated, assuming a prespecified step for each parameter used by the algorithms, and the top five sets were used for validation on a subset of the database.

For each reported incident, measurements were collected for a time window of 20 minutes before the incident reporting period and 20 minutes after the queue dissipation. These measurements are those recorded by the upstream and downstream detectors of the incident site.

An example of the data of detector 3555 is shown in figure 1, where vehicle, occupancy and speed measurements were recorded every 20 seconds.

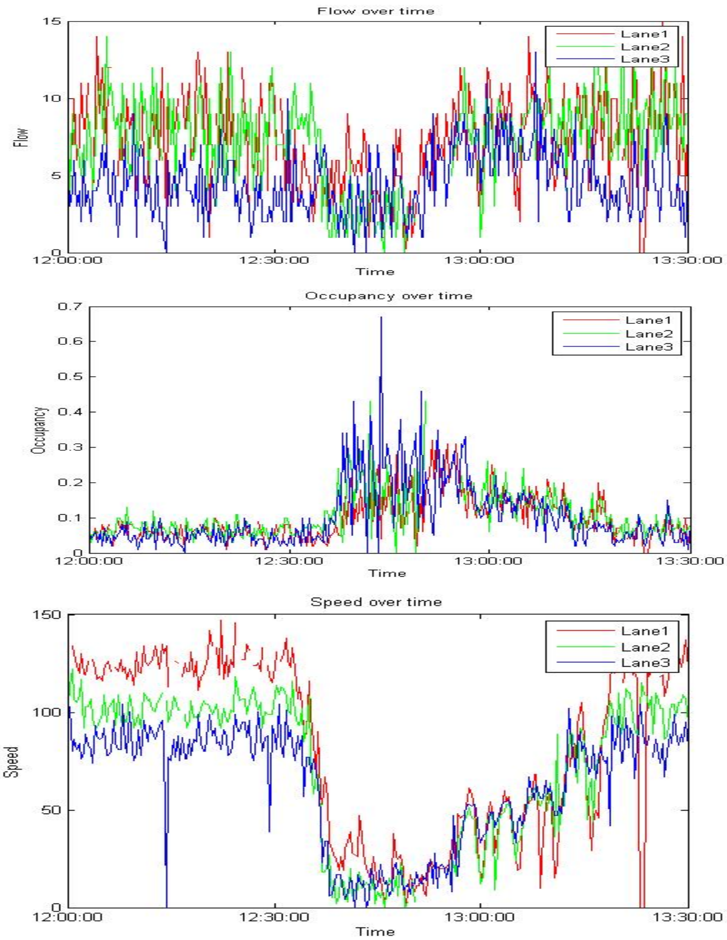


Figure 1. Traffic measurements around the incident reported time.

MatLab was used to emulate incident detection algorithms. Alarms were distributed to correct and false.

5.1. California#7 calibration

For each incident, a plot was produced based on the functions of OCCDF(i,t), OCCRDF(i,t) και DOCCTD (figure 2). Taking the reported incident time as a true incident, alarms occurring on the upstream detector within 10 minutes time after this time were considered as true.

Threshold values were determined for incidents detected on one direction of travel and were validated on the rest of the incidents. For California#7, OCCDF values varied from 0.01 to 0.17 with a step of 0.01, for OCCRDF values between 0.2 and 0.7 were tested with a step of 0.1 and DOCCTD's range was selected from 0.01 to 0.07 with a step of 0.01. All tests summed up to 637.

Based on detection rate (DR(%)) and time to detect (TTD(min)) a best-fit curve was developed (figure 2). As stated in literature, as the detection rate increases, the time to detect also increases.

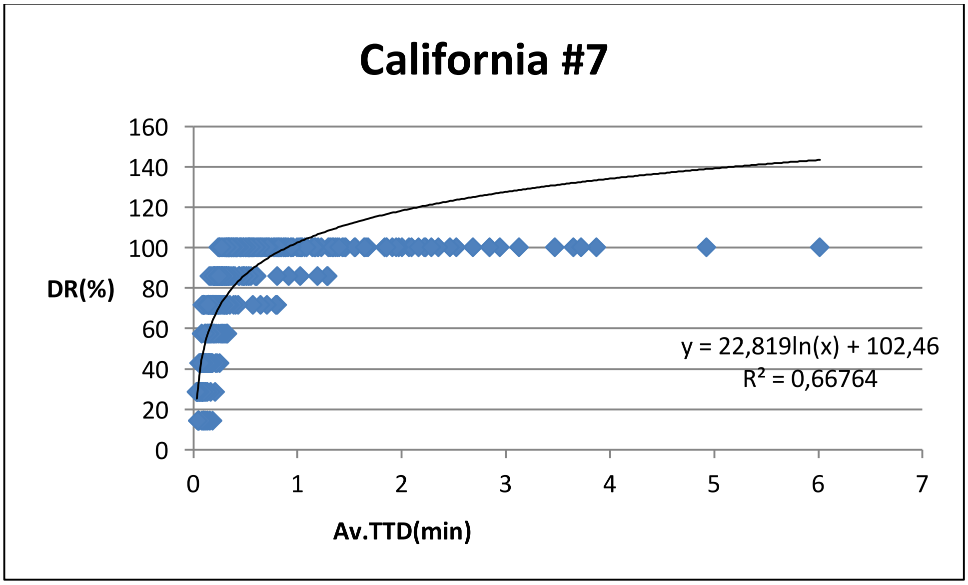
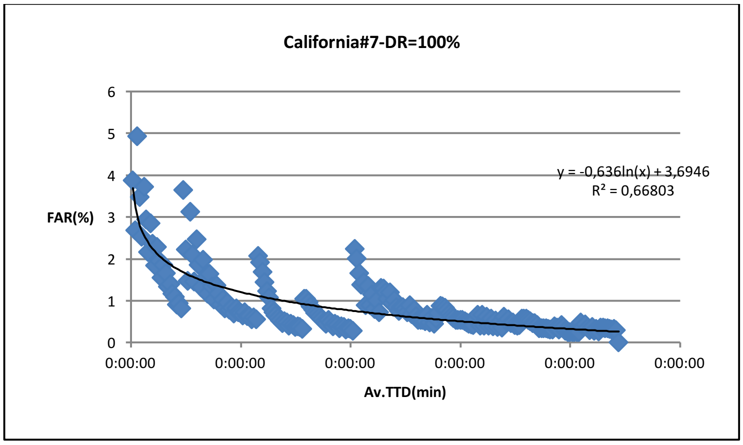


Figure 2: DR versus TTD for California#7 algorithm.

Similarly, a false alarm rate (FAR(%)) and time to detect (TTD(min)) equation was also constructed (figure 3) for different values of DR. The lowest acceptable rate that was used for DR was 71.4%.



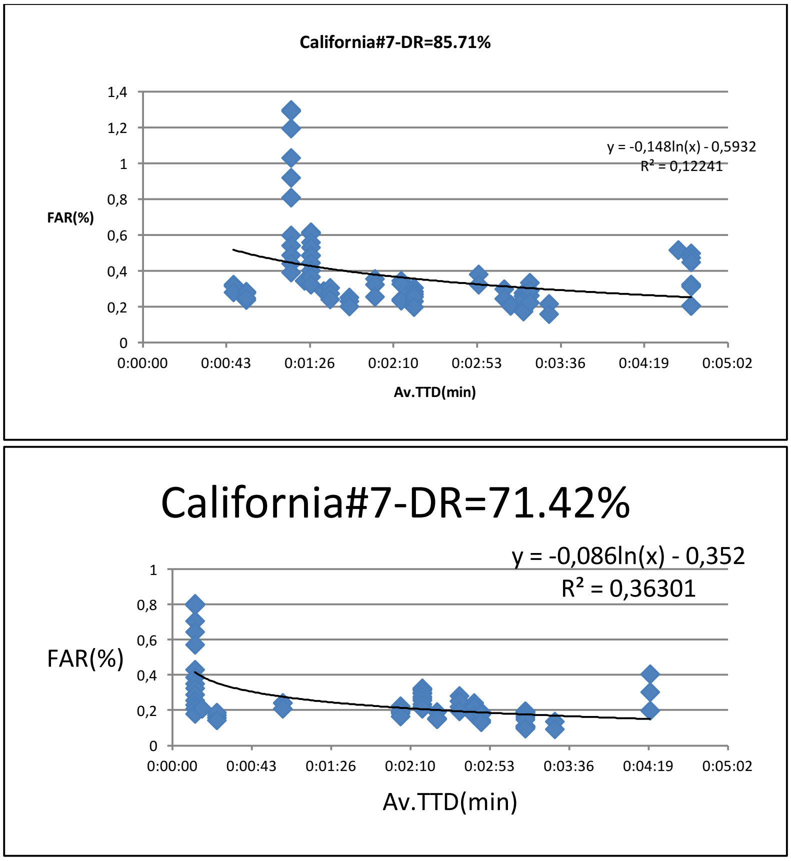


Figure 3: FAR versus TTD for California#7 algorithm.

For the data set used for the estimation of the threshold values, three sets of them led to a local optimum (table 2).

Table 2: Threshold values optimizing performance of California#7 algorithm.

OCCDF	OCCRDF	DOCCTD	FAR(%)	DR(%)	TTD(min)
0.06	*0.4*	*0.06*	0.243131	100	0:02:49
0.12	*0.5*	*0.05*	0.157366	85.71429	0:03:30
0.12	*0.6*	*0.05*	0.091272	71.42857	0:03:28

Testing the calibrated algorithm on the validation incident set, DR ranged between 40 and 60%, FAR between 0.048% and 0.094% and TTD between 3 minutes and 4 minutes and 10 seconds.

Further on, threshold values were estimated as a function of the traffic flow (figure 4). Examined values included those resulting in a FAR of up to 0.3% FAR and TTD less than 5 minutes.

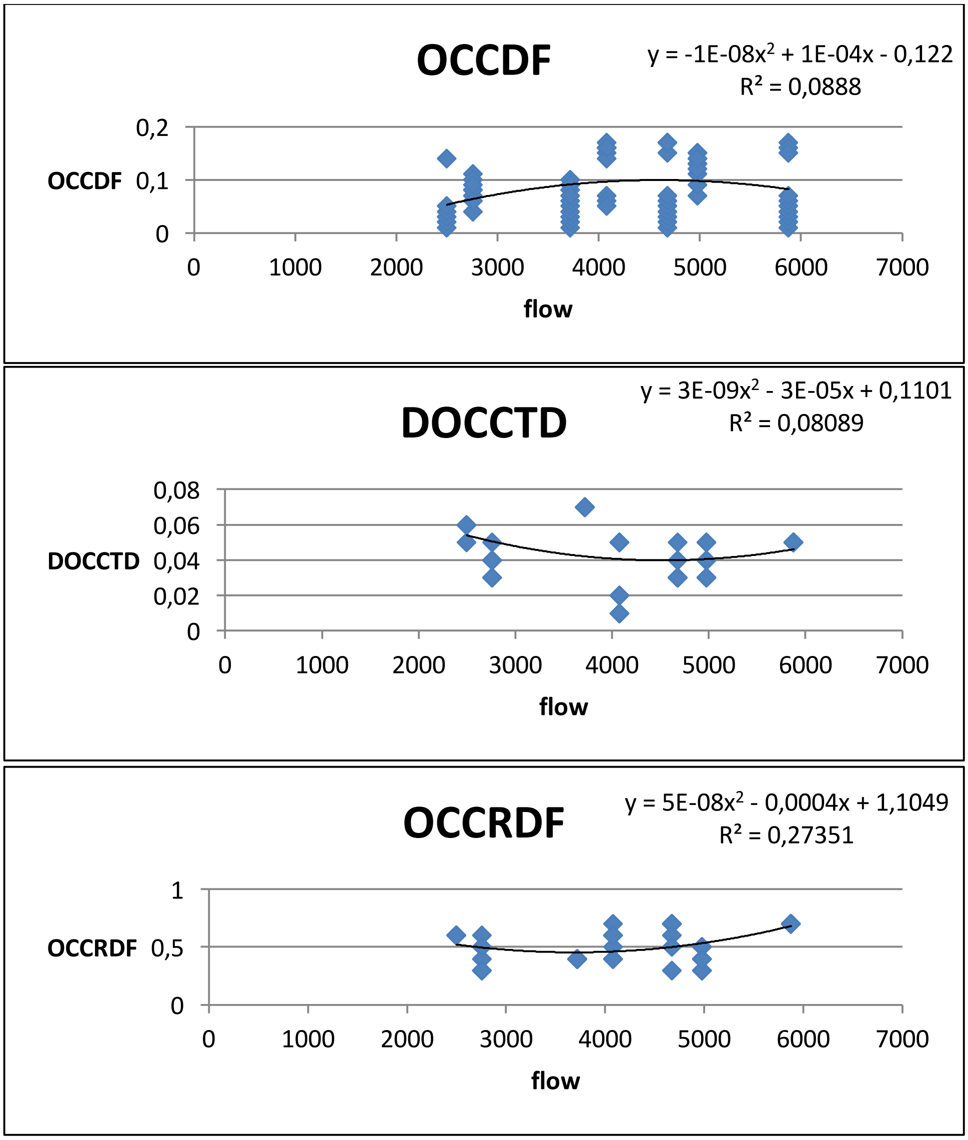


Figure 4: Threshold values of California#7 based on traffic volumes.

When threshold values varied based on the traffic flow, DR increased at 80%, FAR was 0.075% and TTD 3 minutes and 45 seconds.

5.2. DELOS calibration

Similarly, for DELOS' parameters $U_i(t)$, $W_i(t)$, values between 0,1 and 6 were tested, creating 3600 combinations. The interrelation of DR-FAR and FAR and TTD for different levels of DR is depicted in figures 5 and 6, respectively.

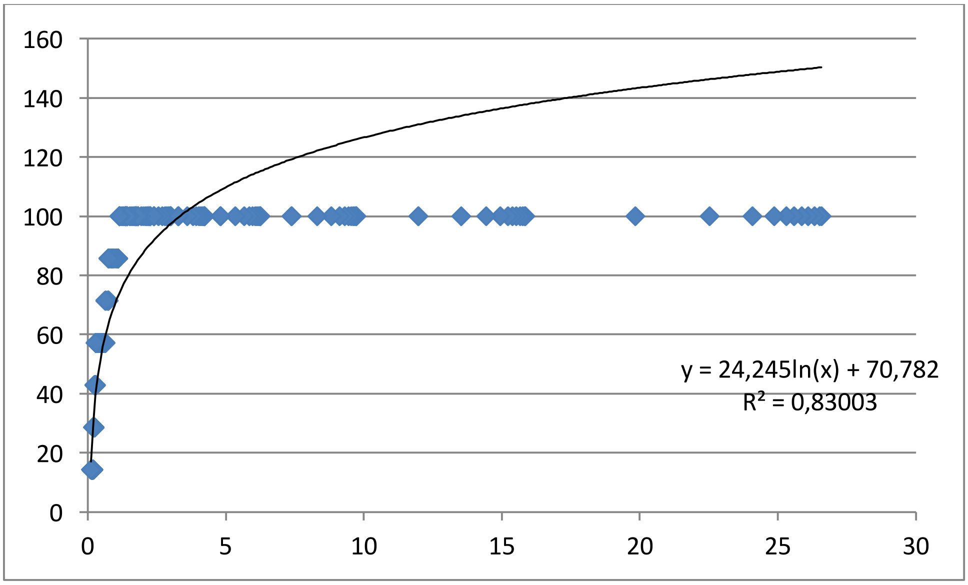
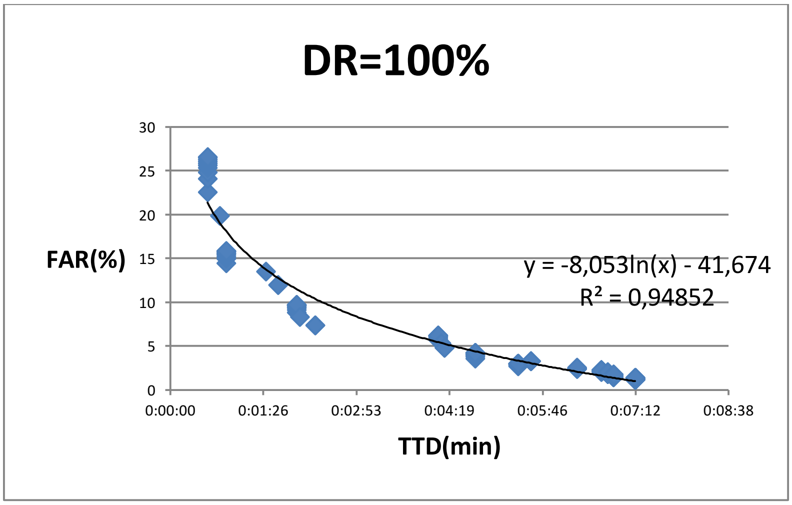


Figure 5: DR versus TTD for DELOS algorithm.



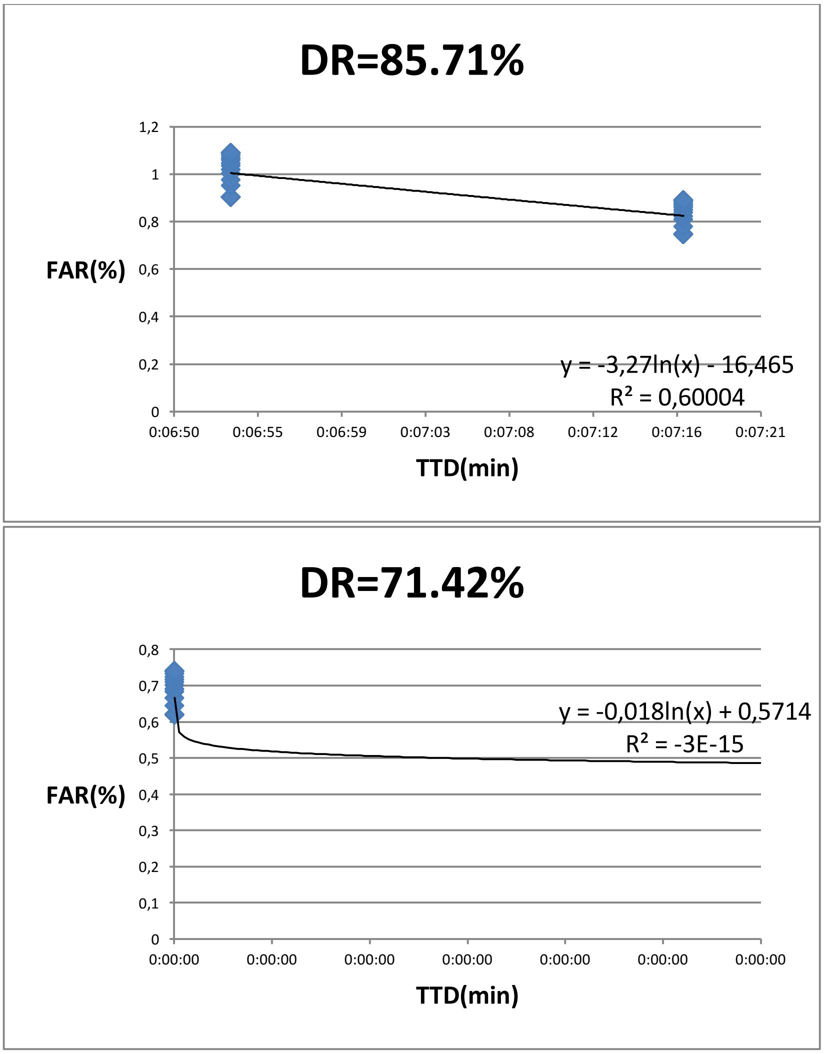


Figure 6: FAR versus TTD for DELOS algorithm.

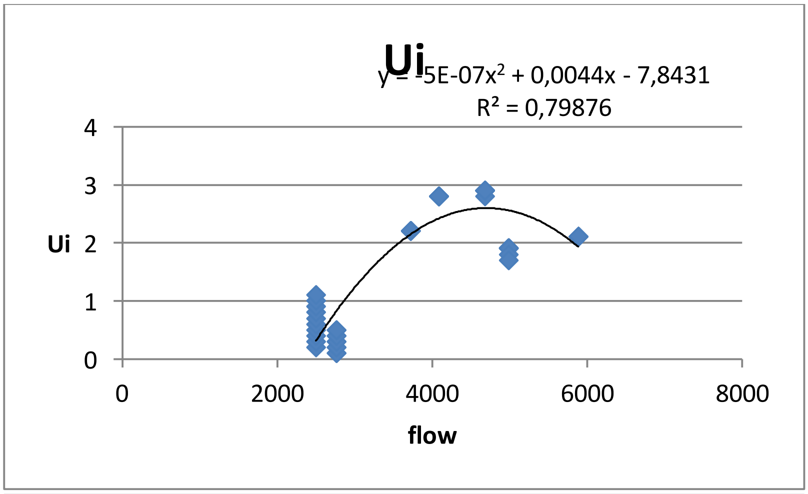
The threshold values sets which give local optimum in the three performance parameters are shown in table 3.

Table 3: Threshold values optimizing performance of DELOS algorithm.

U_i	W_i	DR(%)	FAR(%)	TTD(min)
1.9	*0.9*	100	1.126962	0:07:11
2.1	*1.1*	85.71429	0.745332	0:07:17
2.2	*1.2*	71.42857	0.619846	0:07:00

Despite the results of the calibration process, when testing the calibrated DELOS algorithm on the validation data set, lower performance was indicated. Specifically, DR was 20%, FAR ranged between 6.11% to 9.95% and TTD from 6 minutes and 40 seconds to 7 minutes and 40 seconds.

As in the case of the previous algorithms, threshold values for DELOS were estimated based on traffic volumes (figure 7).



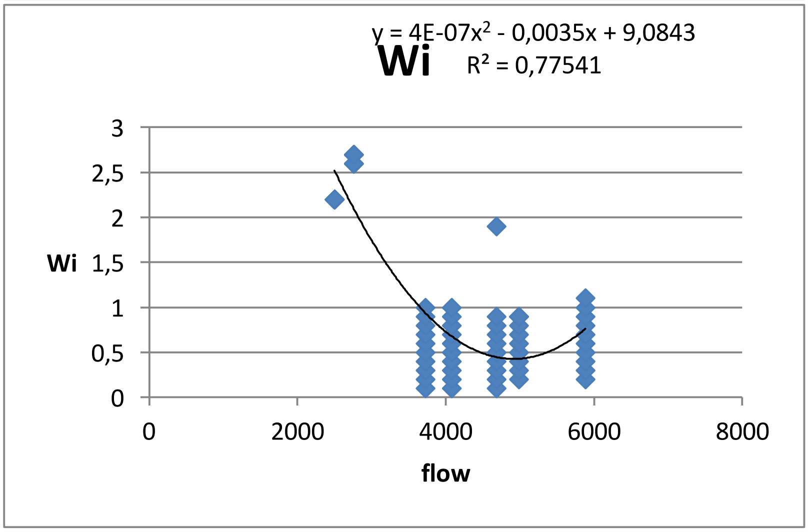


Figure 7: Threshold values of DELOS based on traffic volumes.

With the traffic activated threshold values, DT remained 20%, FAR 4.98% and TTD 8 minutes and 25 seconds.

6. Conclusions

A methodology has been developed for calibrating incident detection algorithms. Threshold values for California#7 and DELOS were estimated and validated on traffic and incident data collected on Attica Motorways. The algorithms' performance was assessed.

Based on the findings, California#7 resulted in incident average detection rate of 60%, false alarm rate 0.071% and average time to detect 3 minutes and 35 seconds (in the validation set). These results justify findings in other sources (Stefanides and Hassiakos, 1993) where the respective indicators are 67%, 0.134% and 2.91 minutes. The threshold values which optimise the algorithm's performance (DR=100%) are OCCDF=0.06 OCCRDF=0.4 DOCCTD=0.06.

Similarly, for the DELOS algorithm, optimum performance (DR=100%) was achieved when threshold values were set to ui=1.9 and wi=0.9. However, all indicators are lesser than those of the California#7 algorithm and average detection rate was estimated to 20%, the false alarm rate 7.91% and average time to detect 7 minutes and 10 seconds (in the validation set).

A significant improvement on the detection rate of California#7 was observed when threshold values were changed, based on traffic volumes, with a value of 80%. The other performance indicators remained the same as in the case of static threshold values. No improvement was observed in the case of DELOS when threshold values varied depending on traffic volumes.

Applying the above methodology for optimizing incident detection performance by identifying the proper threshold values based on the traffic prevailing conditions, may prove to be a useful tool for highway operators, as TMC can collect traffic data in real time and adjust accordingly the algorithms for achieving more reliable detection. In addition, this methodology can be applied for estimating the impact of different detectors' spacing, versus costs, thus optimizing highway assets, and controlling frequency of data flow versus processing speed.

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