Proceedings of the 12th International Conference "Reliability and Statistics in Transportation and Communication" (RelStat'12), 17–20 October 2012, Riga, Latvia, p. 274–284. ISBN 978-9984-818-49-8
Transport and Telecommunication Institute, Lomonosova 1, LV-1019, Riga, Latvia

OVERVIEW TO SOME INCIDENT DETECTION ALGORITHMS: A COMPARATIVE EVALUATION WITH ISTANBUL FREEWAY DATA

Onur Deniz, Hilmi Berk Celikoglu, Gurkan Emre Gurcanli

Department of Civil Engineering, Technical University of Istanbul
Ayazaga Campus, Maslak, 34469, Istanbul, Turkey
E-mail: gurcanlig@itu.edu.tr

Delay and congestion are both important problems in traffic engineering studies. Causes of these problems are broadly studied by many scientists. However, congestion and delay can exist due to different reasons; approximately 25% of them are caused by incident like crashes, stalled cars, spilled debris, etc. Incident management systems deal with detecting and removing incidents as quick as possible. Incidents may be detected by video surveillance or detection algorithms, which use data obtained by detectors. Whatever the method of detection is, it should be quick enough to detect the incident and reduce the duration of congestion or possibility of secondary crashes caused by incidents. This also reduces the amount of fuel consumed. Automatic Incident Detection (AID) approach is the fastest among the incident detection methods. There are numerous algorithms for this purpose all of which have different advantages and disadvantages. Data needed for detection may differ from one algorithm to another. It is important to fairly compare these algorithms and define their pros and cons carefully because the performance of an incident management system is directly related to the performance of the incident detection algorithm used.
In this paper, firstly, incident management systems are briefly defined. Then, the logic behind incident detection algorithms is defined to classify incident detection algorithms. Processing of widely used algorithms is introduced in terms of flowcharts. The selected algorithms are then coded in C# programming language and tested within simulation that is calibrated with flow measures obtained from a stretch over Istanbul freeway network. Their performances are compared in terms of statistical performance measures, i.e., false alarm rate, detection rate and mean-time to detect, by explicitly referring to their weak and strong points. Finally, an overall evaluation on the results obtained is provided.

Keywords: Incident Management; Incident Detection Algorithms; Traffic Congestion

1. Introduction

Traffic congestion is a chronic issue in many cities and increase in usage of motorized vehicles in road traffic network worsens this problem. In urban areas traffic congestion may exist during within a day morning and/or evening peak periods because of the oversaturated traffic flow. Sometimes a road section may suffer traffic congestion at off-peak periods. An event that blocks one or more traffic lanes may cause this type of congestion. One type of congestion that may exist within a day is related to the general demand/ capacity ratio of the road section. It is easy to forecast this type of congestion while demand and capacity of the road are more or less the same in general. It is almost not possible to forecast a second type of congestion, which occurs because of rapid capacity drop, due to unexpected reasons. The reason of the second type of congestion may be an accident, stopped car, spilled cargo, etc., all of which is called an incident. Therefore it is possible to conclude that there are two different types of congestion. The first type of congestion is categorized as recurring congestion and the second type of congestion is non-recurring congestion. Whatever the reason is, congestion increases fuel consumption and emission due to increasing speed differentiation in addition to decreased travel speed and increased travel time. It is not easy to reduce these negative effects in recurring congestions however it is highly possible in non-recurring congestions.

Traffic Incident Management (TIM) systems aim to reduce the negative effects of non-recurring congestion. Numerous TIM systems are deployed around the world, which yield to decrease in fuel consumption, duration of the incident and possibility of secondary crashes. The most important phase of a TIM system is incident detection, which directly influences the performance of an incident management system. Incidents may be detected by cellular phones or Automatic Incident Detection (AID) methods. In case of information dissemination by cellular phones, a witness calls the responsible road authority and gives information about incident. AID may be performed by different methods, incorporating image processing and detector/sensor based incident detection algorithms. While image processing is based on detection of incidents by video processing software, which evaluates the video recordings captured by

traffic surveillance cameras, incident detection algorithms use different traffic variables which are collected by detectors/sensors.

The present paper concentrates on the incident detection phase of AID methods. In the second section of the paper, incident management systems are briefly defined and incident detection algorithms are categorized. The processing of incident management systems are explained in terms of flow-charts in this section. Section 3 presents a broad summary of different incident detection algorithms, data needed and flowcharts of selected algorithms. A comparative evaluation of selected algorithms coded in C# programming language and tested with selected data set, is provided in Section 4. Finally results are evaluated in the last section.

2. Incident Detection and Management: Basic Definitions

Developments in information technologies (IT) have provided many innovations in our life. Most of the problems of education, health systems, and industry are solved with the developments in IT. In traffic engineering, incidents are major problems which may cause congestion and safety related problems. However incidents cause increases in travel time, fuel consumption, air pollution, and decrease in road efficiency, TIM systems, thanks to IT developments, offer possible solutions to decrease negative effect of incidents.

2.1. Overview to Traffic Incident Management Systems

TIM system contains detection and verification, information dissemination, response and clearance steps which can be achieved by using different technologies such as, global positioning system (GPS), Dedicated Short-Range Communications (DSRC), Wireless Networks, mobile phone technology, radio wave or infrared beacons, roadside camera recognition and inductive loop detectors (Ezell S. 2010). This paper mainly focuses on detection phase of a TIM. First step of a TIM system is detection and verification, which covers getting information about existing of an incident and properties of the mentioned incidents such as type, severity and exact location. Incident detection can be achieved either manually or automatically. Phone calls from road users from incident location and detection of incidents by service patrols are examples of manual incident detections. Incidents may be detected automatically by using closed circuit television (CCTV) cameras or loop detectors. CCTV system provides video images as a data which can be processed manually by an operator or an image processing algorithm. CCTVs are beneficial as they allow visual data on incident provide proper information about incident severity and exact location and provide speed, volume, occupancy and headway data (Ozbay K. et al. 2001).

Loop detectors may provide speed (with two detectors), volume, vehicle class, occupancy, and headway data. Mathematical models and algorithms can be used to detect incidents with data obtained by loop detectors.

Second step of a TIM system is information dissemination which aims to inform motorists about the existence of an incident. Information dissemination may be achieved by variable message signs, radio broadcasts, telephone information systems, internet services, etc. Informing motorist about existence of an incident, allows motorist to choose alternate routes which reduces congestion and possibility of secondary crashes.

Response is the third step of a TIM system which covers activating responsible agencies or authorities and employing correct personnel and equipment. Last step of a TIM system is clearance, which covers removal of materials or cars which disrupt traffic flow. Figure 1 shows the general flowchart of a TIM system.

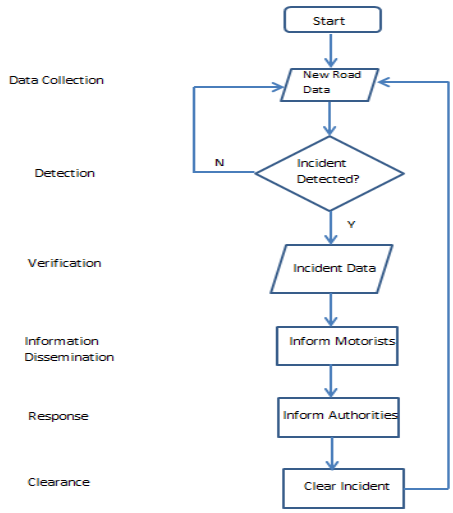

Figure 1. Basic flow chart of a TIM system

2.2. Automatic Incident Detection Methods Overview

However different AID methods may use different traffic data to detect incidents, all of them have data collection and data analysing phases. Data collection phase contains obtaining real traffic conditions by different data collectors such as Remote Traffic Microwave Sensors (RTMS), Inductive Loop Detectors (ILD), etc. Performance of a TIM system is directly related to the performance of incident detection phase. A general AID method takes traffic data as an input and processes data to reach road condition data (whether there is an incident or not).

Response is the third step of a TIM system that covers activating responsible agencies or authorities and employing correct personnel and equipment. Last step of a TIM system is clearance, which covers removal of materials or cars that disrupt traffic flow.

3. Overview to Incident Detection Algorithms

There are many studies on incident algorithm comparison or performance evaluation. In 1991, Subramaniam compared statistical, pattern recognition, Catastrophe Theory, neural networks and video processing algorithms with ILD and video surveillance data according to their performance measures [5]. In 1992 Stephanedes et al. compared macroscopic traffic analysis, comparative logic and statistical forecasting algorithms using data set which is obtained from Minneapolis, Minnesota and concluded that for more appropriate detection, traffic noise should be filtered out from the ILD data and statistical forecasting algorithms are beneficial as they allow filtering. In 1999 Mahmassani et al. divided AID algorithms into five groups and compared comparative, statistical, time-series, theoretical and advanced algorithms' performance measures. In 2001 Martin et al. made a comparative evaluation of AID algorithms by dividing into four groups which are pattern recognition based algorithms, Catastrophe Theory, statistical algorithms and Artificial Neural Networks (ANN) algorithms and concluded that video imaging systems are more beneficial than algorithms which use ILD data.

As mentioned in Section 2.2, most of the AID methods take traffic data as input; process the input with an algorithm and outputs road condition information such as existence of incident as output. Data needed for an AID method may differ according to selected incident detection algorithm. Table 1 shows some AID algorithms and relevant data.

Table 1. Data needed to process some incident detection algorithms

Algorithm	Occupancy	Volume	Speed
California Algorithm (Basic)	+	-	-
California Algorithm #7	+	-	-
California Algorithm #8	+	-	-
All Purpose Incident Detection(APID)	+	+	-
Pattern Recognition	+	-	-
Standard Normal Deviates (SND)	+	+	-
Bayesian	+	-	-
Time Series	+	+	-
Exponential Smoothing	+	-	-
Neural Networks	+	+	+
Fuzzy Sets	+	+	+
Modified McMaster	+	+	-

In Table 1, required data for an algorithm are signed with "+" and unrequired data is signed as "-". As shown in table 1, 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.

However many researchers used different classification for AID algorithms, it is preferred to classify algorithms in four groups in this paper as Martin et al. did, which are pattern-based algorithms, catastrophe theory, statistical algorithms and artificial intelligence based algorithms [8]. Pattern based algorithms take patterns from road condition by generally ILDs, and they compare these patterns with a preset threshold to identify if there exists any "abnormal" situation on the road section. As they compare existing road

conditions with a certain preset threshold, this type of algorithms are also called as comparative logic algorithms. California Algorithm (and its variations), All Purpose Incident Detection (APID) algorithm, Pattern Recognition (PATREG) algorithm are examples of pattern based algorithms.

Incident detection with Catastrophe Theory approach is introduced by Persaud and Hall in 1989. Catastrophe Theory based on detecting a rapid change in one of the interested variables while others do not change considerably.

Statistical algorithms based on comparison of actual traffic data obtained from a road section with generally ILDs and forecasted traffic variables. If there are relatively considerable differences between actual traffic variables and forecasted variables, this traffic condition is labelled as incident condition. Bayesian and Standard Normal Deviates (SND) algorithms are well-known examples of statistical algorithms.

In this paper, APID, Double Exponential Smoothing (DES) and California Algorithm #7 (TSC 7) are chosen for comparative evaluation.

3.1. California Algorithm #7 (TSC 7)

California Algorithm #7 is a comparative algorithm which uses preset thresholds to classify current road condition (Levin and Krause, 1978). California Algorithm #7 needs only occupancy data from two adjacent detector stations. Algorithm 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;

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

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

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.

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

After comparisons of thresholds and inputs, algorithm decides in what state the road currently is. There are 4 identified states for California Algorithm #7. Road is in state 0 when there are no incidents, in state 1 when there is a possibility of incident but still there aren't any detected incident, in state 2 when the incident is detected and state 3 when incident continues. Logic behind the California Algorithm #7 can be found in Levin and Krause, 1978.

APID algorithm was proposed for COMPASS advanced traffic management system, which is implemented in Toronto Metropolitan Area (Masters et al., 1991). In addition to OCCDF, OCCRDF, DOCCTD, DOCC, APID algorithm needs relative temporal difference in speed, SPDTDF as input. Calculation procedure for SPDTDF of APID is given in Equation 4.

$$SPDTDF(i,t) = (SPD(i,t-2) - SPD(i,t))/SPD(i,t-2). \tag{4}$$

$SPD(i,t)$ is the speed data obtained from upstream detector in time period t. APID algorithm can only be executed when all the data above are derived. APID algorithm uses 4 different states to categorize road conditions which are exactly same with California Algorithm #7. APID algorithm contains 5 major routines, which are general incident detection routine, light traffic incident detection routine, medium traffic incident detection routine, compression wave test routine, persistence test routine (Masters et al., 1991). APID algorithm contains 11 threshold parameters and 6 control parameters, which are briefly explained in Table 2.

3.2. APID Algorithm

Table 2. Parameters and procedures of APID algorithm

Control Parameters	Symbols	Default Value
Compression wave test enabled/disabled	CW_TEST_ENABLED	Disabled
Persistence test enabled/disabled	PST_TEST_ENABLED	Disabled
Medium traffic incident detection enabled/disabled	MED_TRAFFIC_INC_DETECTION_ENABLED	Disabled
Light traffic incident detection enabled/disabled	LIT_TRAFFIC_INC_DETECTION_ENABLED	Disabled
Compression wave test period	CW_TEST_PERIOD	5 minutes
Persistence test period	PST_TEST_PERIOD	5 minutes
Light traffic flow threshold	TH_LIT_TRAF	20
Medium traffic flow threshold	MED_LIT_TRAF	60
Incident clearance threshold	TH_INC_CLR	-0.4
Persistence test threshold	TH_PT	0.1
Compression wave test threshold 1	TH_CW1	-1.3
Compression wave test threshold 2	TH_CW2	-1.5
Incident detection threshold 1	TH_ID1	10.2
Incident detection threshold 2	TH_ID2	0
Incident detection threshold 3	TH_ID3	20.8
Medium traffic incident threshold 1	TH_ME_ID1	Not used
Medium traffic incident threshold 2	TH_ME_ID2	Not used

APID algorithm employs 3 main incident detection check procedures, which are incident check procedure (INC_DETECT_CHECK), low volume incident detection check procedure (LO_VOL_INC_DETECT_CHECK), medium volume incident detection check procedure (MED_VOL_INC_DETECT_CHECK). General structures of these procedures can be found in Min, S.L.C., 2004.

3.3. Double Exponential Smoothing Algorithm

DES algorithm is a time-series based incident detection algorithm, which is proposed by Cook and Cleveland in 1974. DES algorithm basically calculates tracking signals for speed, volume and occupancy and compares them to pre-defined thresholds. Before the execution of algorithm certain initial values have to be determined which are mean absolute deviation smoothing factor, SFM, single smoothing factor, SFS, double smoothing factor, SFD, error in prediction, e, cumulative error in prediction in, E and mean absolute deviation, m. Calculation procedure of DES algorithm by using initial values is given in Equations 5–10.

$$S(x, i, t) = SFS \cdot x(i, t) \cdot (1-SFS) \cdot S(x, i, t-1) \quad (5)$$

$$D(x, i, t) = SFD \cdot S(x, i, t) + (1-SFD) \cdot D(x, i, t-1) \quad (6)$$

$$e(x, i, t) = x(i, t) - D(x, i, t) \quad (7)$$

$$E(x, i, t) = E \cdot (x, i, t-1) + e(x, i, t) \quad (8)$$

$$m(x, i, t) = SFM \cdot |e(x, i, t)| + (1-SFM) \cdot m(x, i, t-1) \quad (9)$$

$$Tracking\ Signal\ (x) = E(x, i, t)/m(x, i, t), \quad (10)$$

where, x is a traffic variable such as volume occupancy and speed, i is the detector station number and t is the time period. Other parameters of DES algorithm are briefly summarized in Table 3.

Table 3. Parameters of DES algorithm

Control Parameters	Definition	Default Value
VOL_TS_ENABLED	Incident Test for Volume	Disabled
OCC_TS_ENABLED	Incident Test for Occupancy	Enabled
SPD_TS_ENABLED	Incident Test Speed	Enabled
T(V,i,t)	Volume Tracking Signal	0
T(O,i,t)	Occupancy Tracking Signal	0
T(S,i,t)	Speed Tracking Signal	0
TH_VOL	Volume Threshold	To be determined
TH_OCC	Occupancy Threshold	To be determined
TH_SPD	Speed Threshold	To be determined
ts	Number of tests	0
tse	Number of test exceeds thresholds	0

4. Comparative Evaluation

In the present study three measures of effectiveness have been used for comparison of incident detection algorithms those are false alarm rate, FAR, detection rate, DR, mean time to detect, MTTD, for comparison of incident detection algorithms. However FAR, DR and MTTD measures used for comparison in most of the previous studies do not have consistent definition. In order to perform a clear comparison on algorithms clearly, these terms are defined. False alarm rate is the percentage of false alarms relative to the number of alarms. Formula of FAR is given in Equation 11.

FAR = (number of false alarms / number of total alarms) x 100. (11)

Detection rate is the ratio of detected incident periods to the total incident periods. Formula of DR is given in Equation 12.

DR = (number of detected incident periods / number of total incident periods) x 100. (12)

Mean-time to detect is the average time an algorithm takes to detect incidents. Formula of MTTD is given in Equation 13.

$$MTTD = \sum_{i=1}^{n} (t_a - t_{inc}) / n, \quad (13)$$

where n is the number of detected incidents, t_a is the time that incident detected and t_{inc} is the time that incident occurred.

4.1. Data Collection and Study Area

Data for incident simulations are generated in VISSIM software. VISSIM does not contain real incident model so all incident model data generated with parking lots which is an incident like condition. 3 incident locations were modelled as 3 different parking lots in a 4-lane homogenous roadway. Wiedemann's (1974) microscopic model was applied with 2 m average standstill distance, 2 m additive part of safety distance, 3 m multiplication part of safety distance, maximum 200 m look ahead, 150 m look back distances values.

A 4-lane homogenous road section is designed for simulation. 2 detector stations are embedded in the road. Both detector stations have 1 loop detector for each lane, where both detector stations have 4 loop detectors in total. The distance between two detector stations is assumed 1500 meters. Incidents are generated in 3 different locations on the second lane between detector stations. First incident location is 50 meters away from the upstream detector station (see Detector Station #1 on Fig. 2). Second incident location is 750 meters away from the upstream detector station and corresponds exactly at the midpoint of

the road section. Third incident location is 1450 meters away from the upstream detector station. Data are obtained for 30 seconds time interval from the detector stations. Figure 2 depicts the simulated study area.

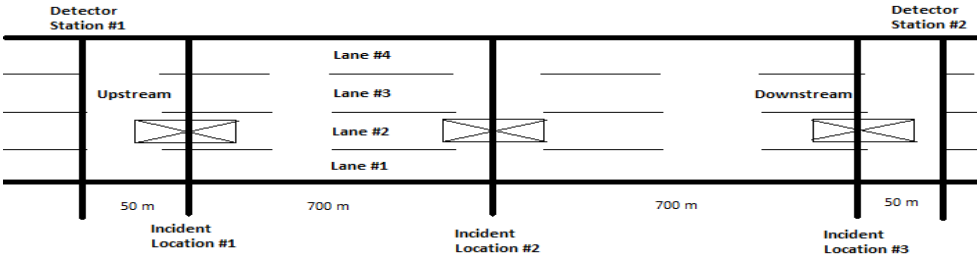

Figure 2. Simulation area and locations of incidents

In order to compare performance of the algorithms in different traffic conditions, road section is loaded with 4 different traffic volume values conditions (which are 2000 vehicles per hour, 3000 vehicles per hour, 4000 vehicles per hour, 9000 vehicles per hour). All algorithms are tested in for 4 different road conditions and 3 different incident locations throughout 12 different scenarios. Road section is loaded for 1 hour for each scenario where incidents have taken place between 27th and 87th time periods. Each time period has 30 seconds.

4.2. Comparison on Performance of Selected Algorithms

In the following, first the performances of the algorithms are analysed according to different traffic conditions and then analysed according to location of the incidents.

4.2.1. Comparison on Performance of Selected Algorithms According to Traffic Conditions

Another important performance indicator of algorithms is the detection of incidents correctly in different traffic conditions. In order to evaluate performances of the algorithms according to this purpose, incident's distance from the upstream detector is fixed for all algorithms and traffic flow values are increased in 4 for different scenarios. Figures 3, 4, 5 show detection performances of selected algorithms with different flow conditions on Incident Location #1.

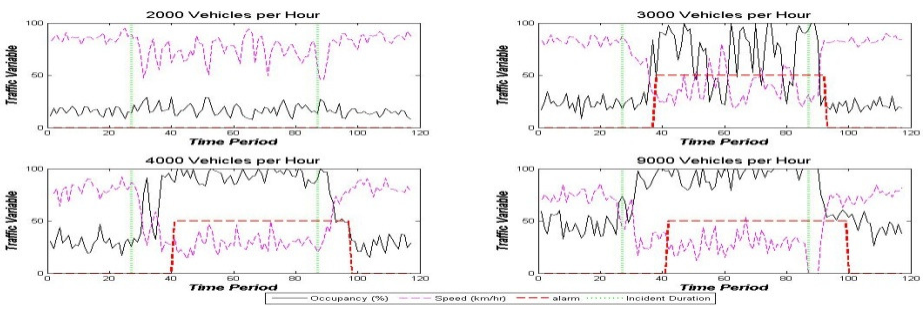

Figure 3. Detection performance of APID algorithm when incident is close to upstream detector

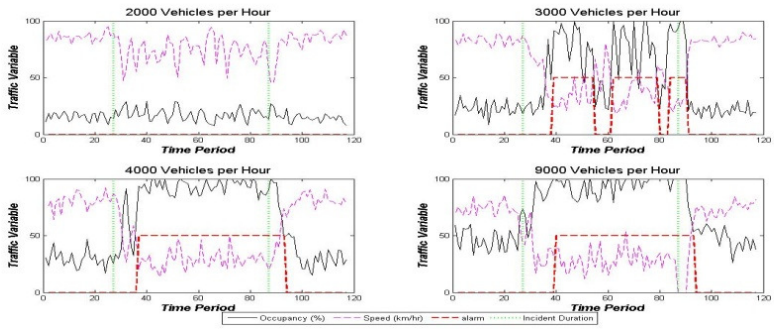

Figure 4. Detection performance of TSC algorithm 7 when incident is close to upstream detector

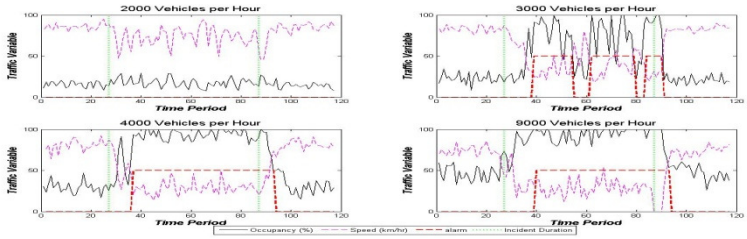

Figure 5. Detection performance of DES algorithm when incident is close to upstream detector

APID and TSC 7 algorithms could not detect any incident when the traffic flow is 2000 vehicles/h. Only DES algorithm is found to detect incident under same traffic conditions. In case of the same incident when the traffic flow value is 3000 vehicles/h, APID algorithm detected approximately the whole incident duration, TSC algorithm 7 detected 3 different incidents and DES algorithm detected 5 different incidents. In the third scenario traffic flow is increased to 4000 vehicles/h. In this case, APID algorithm and TSC algorithm 7 detected 1 incident with approximately correct incident duration but DES algorithm detected 3 different incidents. In the fourth scenario traffic flow is increased to 9000 vehicles/h. APID and TSC algorithm 7 detected 1 incident with approximately correct incident duration and DES algorithm detected 3 different incidents under same traffic conditions.

Distributions of DR, FAR and MTTD values on selected algorithms in different traffic conditions are given on Figures 6, 7, 8, respectively.

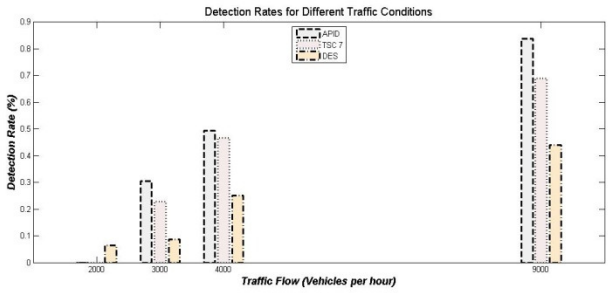

Figure 6. DRs of selected algorithms in different traffic conditions

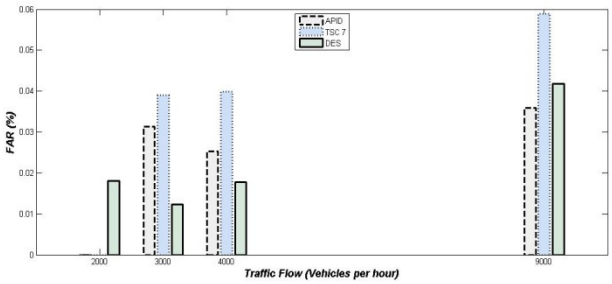

Figure 7. FARs of selected algorithms in different traffic conditions

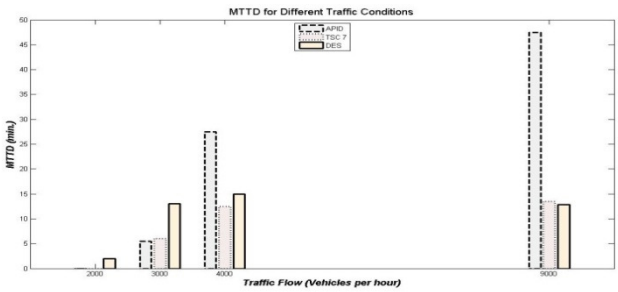

Figure 8. MTTDs of selected algorithms in different traffic conditions

Values of DR, FAR, MTTD measures increase with the increase in traffic flow for all algorithms.

Figures 9, 10 and 11 provide information about the performances of algorithms in same traffic conditions (3000 vehicles/h) for different incident locations.

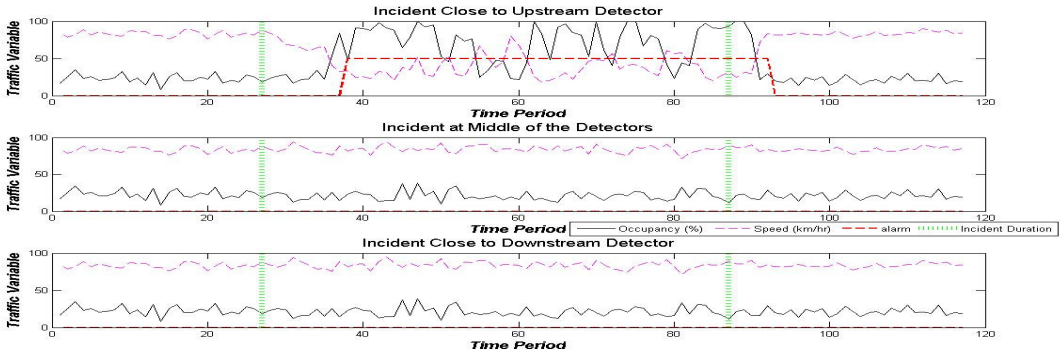

Figure 9. Performance of APID algorithm for different incident locations

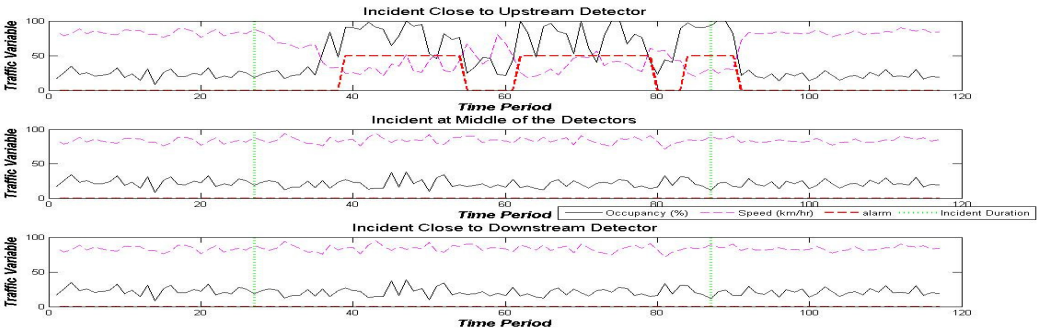

Figure 10. Performance of TSC Algorithm #7 for different incident locations

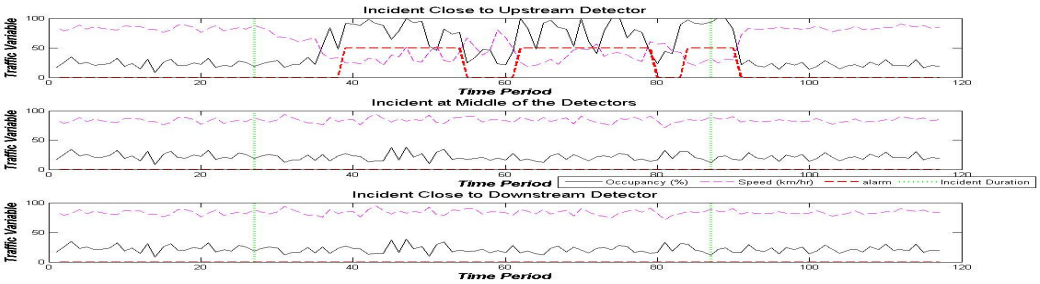

Figure 11. Performance of DES algorithm for different incident locations

As it can be seen on Figures 9, 10 and 11 all of the selected algorithms clearly perform better when the incident location is close to upstream detector. DES algorithm is the only one within the selected algorithms that can detect an incident that occurs close to downstream detector.

Values of DR, FAR and MTTD measures of selected algorithms for different incident location are given on Figures 12, 13, 14, respectively.

Figure 12. DRs for different incident locations

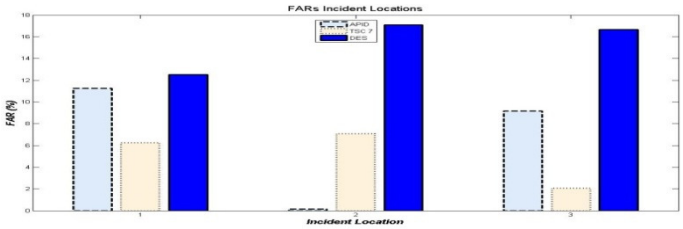

Figure 13. FARs for different incident locations

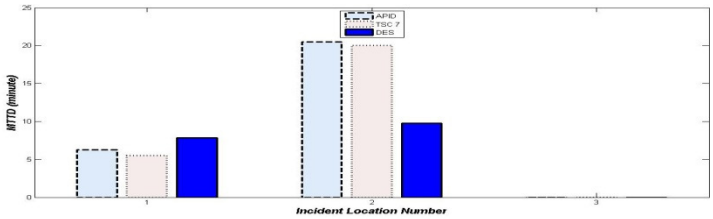

Figure 14. MTTDs for different incident locations

It can be stated considering Figure 12 that DRs of the selected algorithms are related to the distance of the incident from the upstream detector station. As the detection performance of the decreases, FARs of the selected algorithms are increased with the increased incident distance from the upstream detector station. MTTDs seem 0 where incident occurs close to the downstream detector station from Figure 14.

5. Conclusions

There are numerous researches proposing an algorithm for incident detection. In most of these researches, DRs, FARs, MTTDs selected as the main indicators of algorithm's performance. In this 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. Moreover it is seen that, when incident occurs at a point closer to the upstream detector station, MTTDs of the algorithms tend to decrease.

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