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Incident Detection Algorithms: A Literature Review

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Abstract

Traffic congestion in urban areas is a frequently encountered problem in many countries. This problem can be divided into two groups: recurrent and non-recurrent. The first one occurs routinely and is not triggered by a temporary event. However, the latter is generated in response to temporary events, such as bad weather conditions, work zones, traffic incidents or other non-recurring events. Studies have shown that more vehicle hours of delay result from unexpectedly occurring traffic disturbances rather than recurrent network overload during peak hours. Some of the temporary events, such as accidents, breakdowns or any type of obstacles that can cause induced traffic congestions are called the term incident in the traffic. Incident detection can be seen as a significant component of the overall incident management process. In this study, a literature review is presented on various incident detection algorithms and their real-time and simulation based implementations. An integration of flow and crash modelling that might be useful for developing incident detection algorithms is also discussed.

Keywords: Incident, traffic congestion, delay, detection algorithm, modelling.

1. INTRODUCTION

The current efforts for modelling and solution of traffic problems, such as the congestion and congestion propagation, are to represent the problem, and consequently the solution, in a time-varying, or dynamic, way. Realistic solutions to such problems can now be performed only if a certain amount of input data is obtained in real-time or in a time-varying fashion. Solution to traffic problems at various scales necessitates both the realistic modelling and the real-time processing of traffic flow.
Deterministic and/or stochastic traffic flow models, that have a wide range of application domains, may be simply evolved to account for the issues, such as within-day dynamics and peak-hour flow variation. A more complex problem of interest is to quickly specify and model the effect of non-recurrent events in traffic flow, such as an accident, and consequently to maintain the stability of flow. In order to detect the 'incident', noted as the main cause of the non-recurrent congestion in the relevant literature, and manage the overall traffic flow propagation a number of approaches and methods are utilised.

With the motivation of dynamically detecting and predicting variation on traffic flow conditions, including incident and accident based propagations, the present study aims to develop incident detection algorithms, by making use of varying traffic flow theories that represent realistically the spatio-temporal variation of traffic flow, and evaluate their performances within a holistic approach where flow modelling and crash modelling frames will be integrated by coupling specific simulation platforms.

2. LITERATUR REVIEW

Because of conducting model that contain area of traffic flow and crash dynamic in existing incident and accident, the literatur is presented two main subtitle.

Congestion is a major transportation issue causing safety problems and huge economic losess while affecting almost every individual every day. According to Federal Highway Administration (FHWA) 25% of road congestion is attributed to traffic incidents, such as crashes, disabled vehicles and spilled loads (FHWA, 2005) Due to different reasons congestion can be classified into recuuring and non-reccuring. Recurring congestion results from demand exceeding supply over a certain time or space. Non- recurring congestion usually caused by occasional events, e.g, incidents, work zones and special events.

Many measures have been used to mitigate recurrent congestion for years, such as ramp metering and hard shoulder running. However, only a few previous studies systematically evaluated and compared the effectiveness of such strategies in combating non-recurrent congestion. Incident detection can be seen as a significant component of the overall incident management process. Majority of the type of this algorithm which catch the irregularity of traffic flow is the function of variation of capacity and occupancy.

Incident detection algorithm depends on highway management conditions, geometric design of road, environmental conditions, variation of vehicle classification in flow, distance between sensors, time and severity.

R.Weil , J.Wootton and A.Garcia Ortiz discussed the development of a new novel time indexed anomaly detection algorithm. They establish norms as a time dependent function for each station by integrating past “normal” traffic patterns for a given time period.

Asim Karim and Hojjat Adeli present a new two-stage single-station freeway incident detection model based on advanced wavelet analysis and pattern recognition techniques. Wavelet analysis is used to denoise, cluster, and enhance the raw traffic data, which is then classified by a radial basis function neural network. An energy representation of the traffic pattern in the wavelet domain is found to best characterize incident and nonincident traffic conditions. False alarm during recurrent congestion and compression waves is eliminated by normalization of a sufficiently long time-series pattern. The model is tested under several traffic flow scenarios including compression wave conditions. It produced excellent detection and false alarms characteristics.

Michael Taylor and Kun Zhang have studied a new automated incident detection framework for both freeways and urban arterial roads. A common modular architecture that includes a special data processing module to handle site specialties is applied to the freeway algorithm (TSC_fr) and the arterial road algorithm (TSC_ar). Bayesian networks are constructed to store general expert traffic knowledge and perform universal incident detection. The TSC_fr algorithm is evaluated using a large number of field incident data sets, and the TSC_ar algorithm is tested using simulation data. The testing results are very encouraging. It is found that both detection rate (DR) and false alarm rate (FAR) are not sensitive to incident decision thresholds. When the decision threshold is above the certain level, both DR and FAR reaches a very stable region. This is the unique feature of the TSC algorithms. The results also demonstrate algorithm transferability is achievable under the new incident detection framework.

Dia and Rose (1997) proposed a multi-layer feedforward (MLF) neural network incident detection model. The result of the comparative performance evaluation clearly demonstrate the substantial in incident detection performance obtained by the neural network model and also show how improvements in model performance can be achieved using variable decision threshold.

Srinivasan et. al. (2000) developed a hybrid artifical intelligence technique, with fuzzy- logic and genetic- algorithm technique, for automatically detecting incidents on a traffic network.

Ivan (1997) developed a new technique based on data fusion methods using multiple data sources; induptive loop detectors, and travel times collected from probe vehicle travelling through the street network.

Peter Martin and Joseph Perrin examine a range of incident detection technologies to determine a recommended combination of approaches for use in the Utah Department of Transportationís (UDOT) Advanced Traffic Management System (ATMS). The technologies that were examined are computer-based automatic Incident Detection (AID), Video Image Processing (VIP), and detection by cellular telephone call-ins.

Manoel Mendonca developed a self-learning, transferable algorithm that requires no calibration. The dynamic thresholds of the proposed algorithm are based on historical data of traffic, thus accounting for variations of traffic throughout the day. Therefore, the novel approach is able to recognize recurrent congestion, thus greatly reducing the incidence of false alarms. In addition, the proposed method requires no human-intervention, which certainly encourages its implementation.

3. METHODOLOGY

In this study, incident detection, inspection and detection process will be modelled by bringing in method that provide detection of sudden and severe differentiation. Before this model, flow modelling and crash modelling will be integrated by integration of related software. According to literatur review various methods was decided since it is widely accepted, frequently used and adviced one which could be comparated with other methods. At the subtitles below presents respectively various approach for incident detection which containing the main modelling approach summarized by referring the related data, some methods for comparing proposed methods and crash simulation.

3.1. Various Approach for Incident Detection

3.1.1. Sample – Based Method

The medhod generally uses the capacity and occupancy data taken by induction detector. In this algorithm, threshold that has normal flow condition is determined in advance and the rest of the values are identified as out of the normal. Determining the threshold is hard and to take lots of time.

1. California Algorithm TSC 2

2. California Algorithm TSC 7

3. California Algorithm TSC 8

4. APID (All Purose Incident Detection) Algorithm

5. PATREG (Pattern Recognition) Algorithms

3.1.2. Catastrophe Theory –Based Method

Catastrophe Theory takes its name from the sudden discrete changes that occur in one variable of interest while other related variables are exhibiting smooth and continuous change (Persaud and Hall 1989). These variables are speed, flow, and occupancy. When speed drops dramatically without a corresponding increase in occupancy and flow, the alarm sounds. In this regard, Catastrophe Theory based algorithms are able to differentiate between incidents and recurring congestion. Congestion builds up slowly, while incidents cause a sudden queue to develop and drastic changes in speed to occur. The algorithms exploit this phenomenon. The difference between Catastrophe-based and pattern-based algorithms is that pattern-based methods rely on individual variable and pre-set thresholds, while the catastrophe method uses multiple variables and compares them to previous trends in data for recurrent congestion. The only type of algorithm that fits into this classification is the McMaster algorithm (Persaud and Hall 1989).

3.1.3. Statistical Methods

Statistical methods generally enable real time data to compare the predicted data. When occuring any variation of traffic flow values in accordance with predicted one, occuring the incident/accident situation can be said.

1. HIOCC (High Occupancy) Methods
2. Stochastic Medhods
3. SND (Standard Normal Deviation) Algorithms
4. DES (Double Exponential Smoothing) Methods
5. Filtrasion Medhods
6. Bayesian Based Medhods
7. SSID (Single Station Incident Detection) Algorithms

3.1.4. Artificial Intelligence – Based Method

Artificial Intelligence (AI) is a recent development of AID algorithms. These algorithms detect incidents by either a rule-based algorithm or an algorithm that has .learned. to recognize incident patterns. Neural Network (Stephanedes 1995) and Fuzzy Set Logic (Chang 1994) are the main AI applications that have been applied to AID.

3.2. Some Methods For Comparing Proposed Methods

3.2.1. 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 below;

OCCDF(i,t) = OCC (i,t) – OCC(i+1,t),

OCCRDF(i,t) = (OCC (i,t) – OCC(i+1,t))/ OCC (i,t)

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 below.

DOCCTD = OCC(i+1, t) – OCC(i+1, t+1)

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.

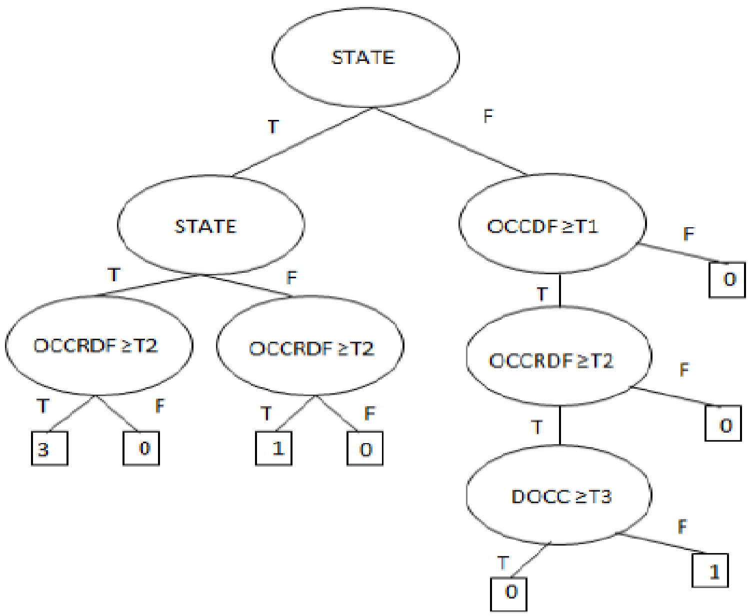

Fig.3.1. California Algorithm #7

3.2.2. APID Algorithm

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 below.

SPDTDF(i,t)= (SPD(i,t–2) – SPD(i,t))/SPD(i,t–2)

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 below.

Table 2. Parameters and procedures of APID algorithm

Control Paramcters	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.

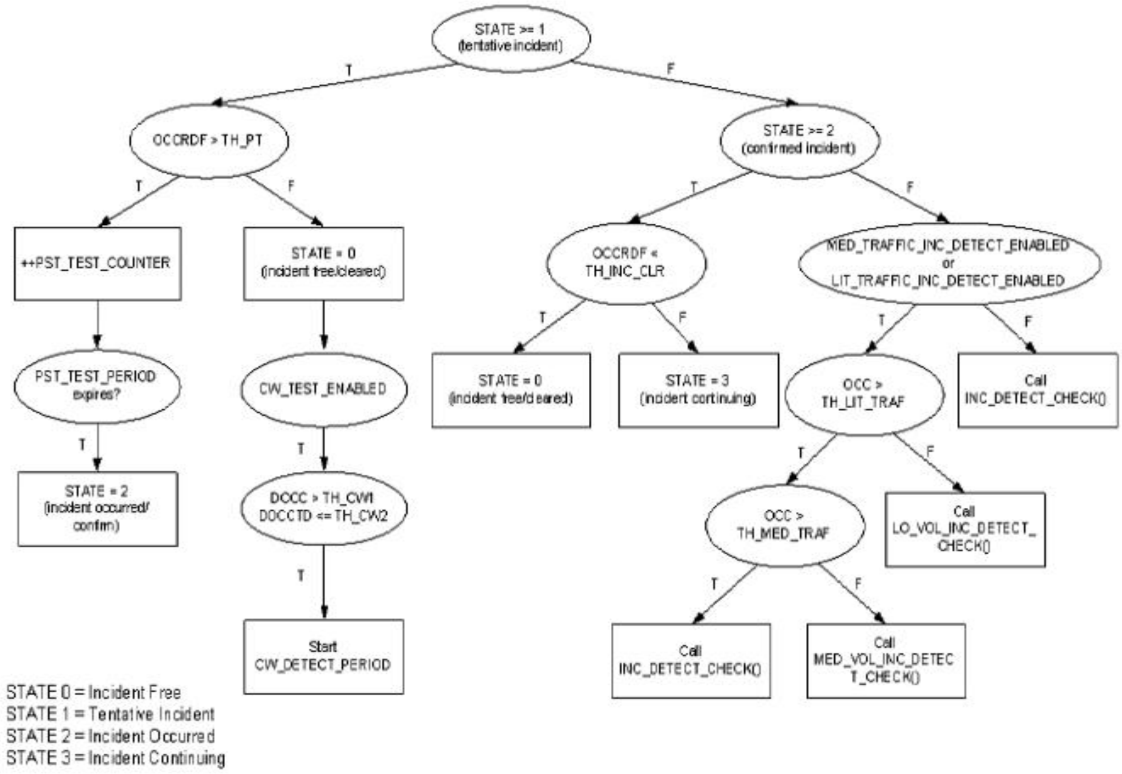

Fig.3.2. APID Algorithm Procedure

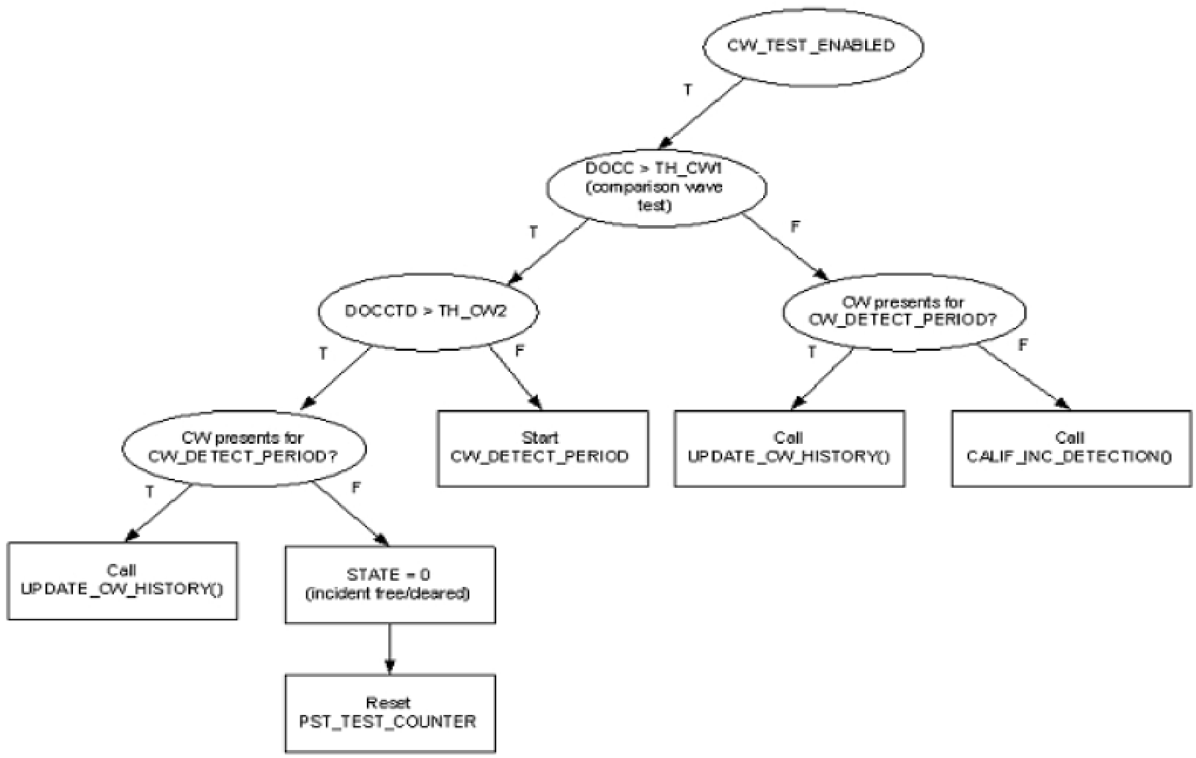

Fig.3.3. APID Algorithm 'INC_DETECT_CHECK' Procedure

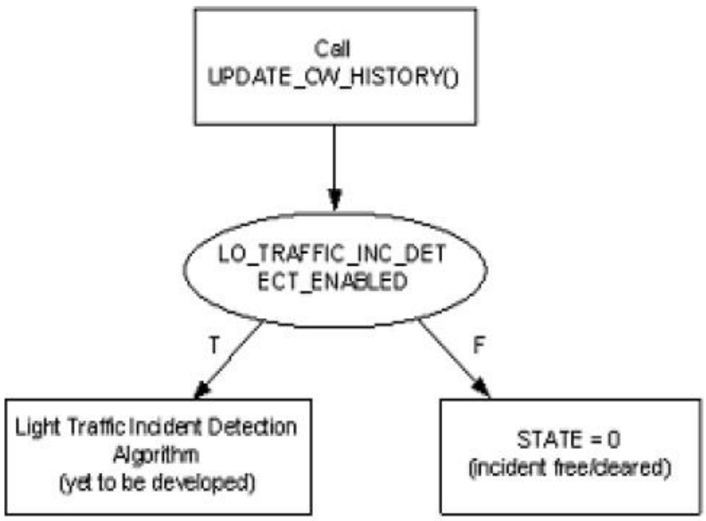

Fig.3.4. APID Algorithm 'LO_VOL_INC_DETECT_CHECK' Procedure

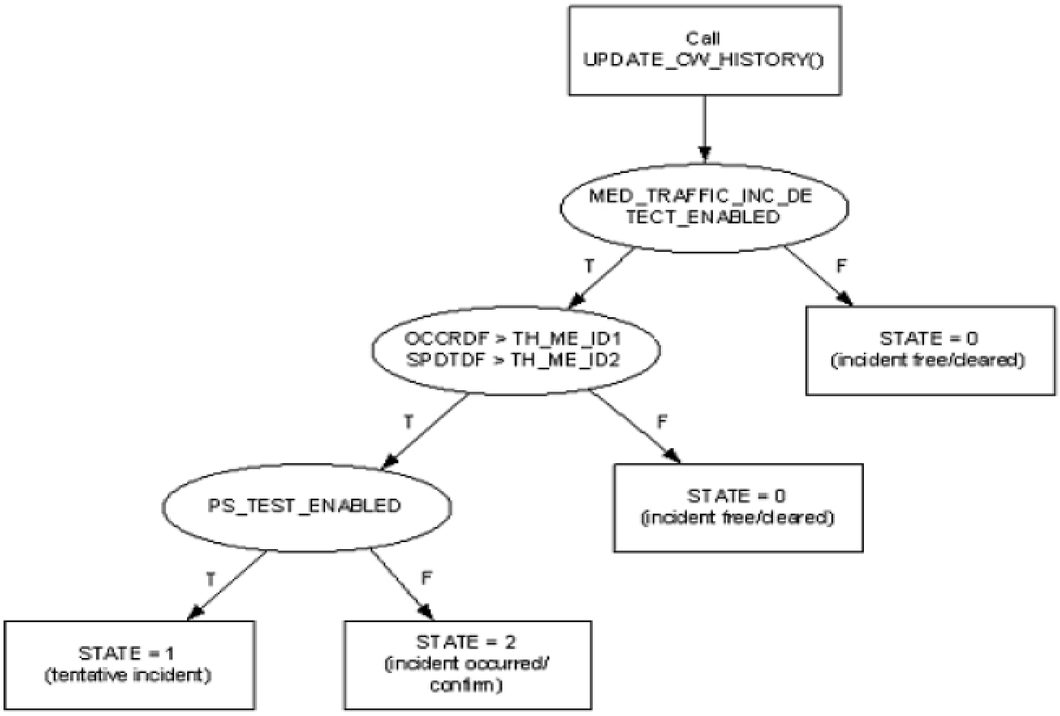

Fig.3.5. APID Algorithm 'MED_VOL_INC_DETECT_CHECK' CHECK' Procedure

3.2.3. DES 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 below.

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

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

$$e(x, i, t) = x(i, t)-D(x, i, t)$$

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

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

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

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 below,

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

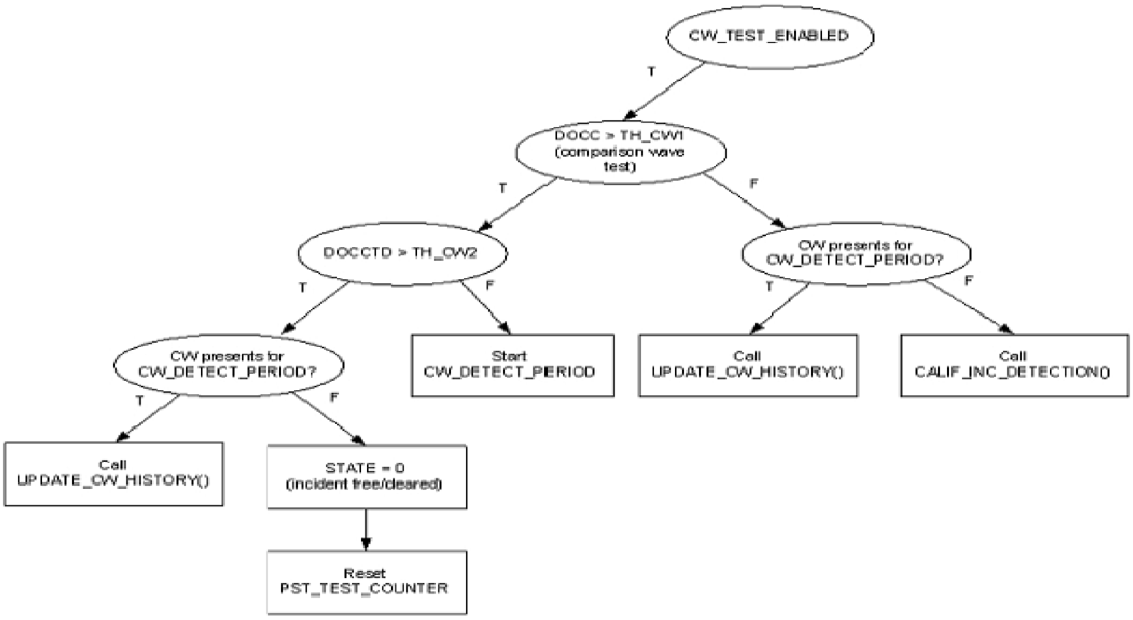

Fig.3.6. Incident Detection with DES Algorithm

3.3. Crash Simulation

In this study, it is aimed that, finit element method which calibreted based on vehicle dynamic crash simulation, as a fast and real timing method, flow simulation models were integrated, is indicated Figure 5.7 Suggested study need to be cross disciplines, such as chrash, vehicle dynamics, traffic flow simulation and programming all those it depends on the eligible researchers work together as a team. It is not come accross those kind of researches in the literature might be explained with those difficulties. Intelligent transportation system, problems faced in the practice, lack of detector, calibration, appriotlessness of distance of detectors, or unpredictable traffic follow perceptions are attached importance as a solution towards management and simulation in order to calculate using multi vehicle and even fleet behavior.

3.4. Proposed Incident Detection Algorithm and Structure of Integrated Model

According to both methods that mentioned above and literatur review, one of the most effective approaches for determining incident or the effect of incident is to examine variation on traffic flow in terms of speed, occupancy or density. The present study aims to develop incident detection algorithms, by making use of varying traffic flow theories that represent realistically the spatio-temporal variation of traffic flow, and evaluate their performances within a holistic approach where flow modelling and crash modelling frames will be integrated by coupling specific simulation platforms.

The approaches that will be developed for determinig incident is basically the algorithmic process having component of both traffic flow modelling and prediction. Traffic flow simulation on highway network that has different scale with scenario of various non- recurrent congestion will be made in terms of existing traditional flow modelling approaches and simulation software that constituted by benefitting from these. The process of incident detection, inspection and management will be modelled through including methods that detect unexpected and serious variation on traffic flow. Therefore, in the present study, incident detection algorithm will be examined that tests various estimated methods whether intuitional or not as well as it wil be compared with a new approach which determines variation on flow conditions. In order to test and compare, 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 below

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

Detection rate is the ratio of detected incident periods to the total incident periods. Formula of DR is given below

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

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

$$\text{MTTD} = \sum_{i=1}^{n} (\text{ta} - \text{t inc})/\text{n}$$

where n is the number of detected incidents, ta is the time that incident detected and t inc is the time that incident occurred.

Both in traffic production for scenarios which are created and tested ,and calibrations of flow modelling in sample itinerary and network components with real measurements,the softwares according to study aim that can simulate accident\incident will be utilized. Therefore;location temporal change of traffic flow dynamics can be expressed differently benefiting from slim-size,mixed and coarse-size flow theories. The calibration on flow modelling studies will be done with microwave sensor data which collects traffic information such as volume and speed and occupation in different section on istanbul urban highway-expressroad network and which was obtained from the Istanbul Metropolitan Municipality. With the help of these sensors placed along the urban highway-express road network and capable of highly accurate measurements, traffic flow measurement and variables can be determined in real-time. Directorate of Traffic and Transportation Department under the tübitak project no:111m415 and will be received under proposal,in case data is problematic and insufficient will be done with data obtained by the camera will reccord in the field. Therefore;with continuous position-temporal variation of the current variables representing the flow condition,the transitions between steady-unsteady flow conditions and such as zero volume-congestion as a result of accident-incident discontunities may occur can be identified . The accidents/incidents can be made synthetically with scenarios which will be defined by differentiating the factors such as flow characteristics, road geometry and driver behavior and it can be modeled in the simulation environment. Dynamics of vehicle crash,will be examined in the crash simulation enviroment and the outputs of particular vehicle will provide input to the flow simulation environment. On this occasion, crash-based calibration of flow model can be done. On the other hand,the dynamic of any clashes occuring in the variable traffic flow conditions,can be examined with the traffic flow-based calibration by utilizing the related simulation's traffic flow measurement. mentioned bidirectional interaction,it will gain a integrated and simultaneous proccessing structure by assembling the related simulation software.The current variables either among themselves,or depending on time,or the position on the road (path length),or the different combinations of crash model outputs, will be discussed detecting both immediate and soft transitions in flow conditions as an output. Incident detection algorithm that dynamically identify changes in the current conditions with proper variables will be improved and the output compared with methods mentioned before and to test by means of determined scenario

The detection method to be proposed,as shown in Figure 3.1 along with 3.6 in the previous subsection and that classify flow condition according to the predetermined threshold decision process will be express in the flow diagram and code will be written. To be proposed simple flow of control-management process as shown in Figure 3.7. In addition to the code to be written for determining incident,a top-level code will be written again in order to simulate an automated control and management system (flow shown in dashed lines in Figure 3.7).

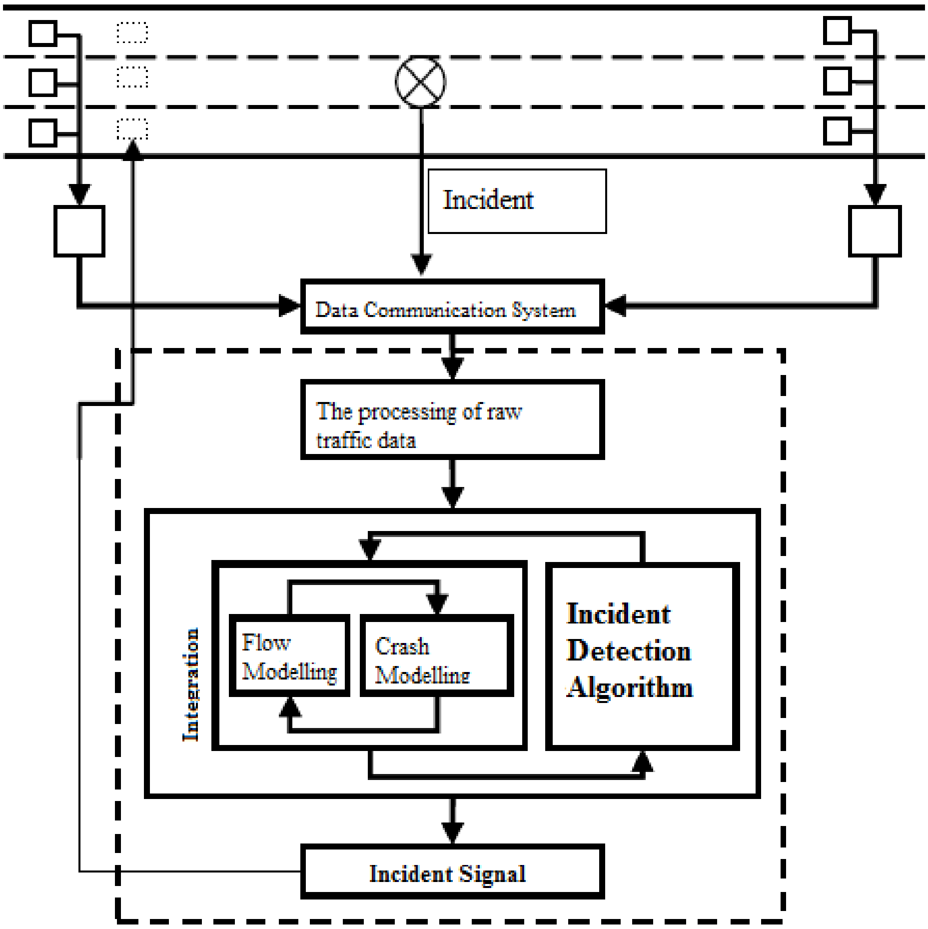

Fig.3.7. Proposed Integrated Model and Incident Management Process

References

1. Cook, A. R., Cleveland, D. E. (1974). Detection of Freeway Capacity Reducing Incidents by Traffic Stream Measurement. In *Transportation Research Record 495* (1–11). Washington, D. C.: TRB, National Research Council.

2. Ezell, S. (2010). Explaining international IT application leadership: Intelligent transportation systems. The Information Technology & Innovation Foundation.

3. Levin, M.. Krause, G.M. (1978). Incident Detection: A Bayesian Approach. In *Transportation Research Record 682* (52–58). Washington, D.C.: TRB, National Research Council.

4. Mahmassani, H.C., Haas, C. (1999). *Evaluation of incident detection methodologies.* Austin, TX: Center for Transportation Research, University of Texas at Austin (Research Report no. 1795–1).

5. O.Deniz, H.B.Celikoglu (2012), *Overvıew To Some Incıdent Detectıon Algorıthms: A Comparatıve Evaluatıon Wıth Istanbul Freeway Data* .“Reliability and Statistics in Transportation and Communication”. Transport and Telecommunication Institute, Lomonosova 1, LV-1019, Riga, Latvia.

6. Chang, E. C. P. (1994). “Fuzzy Systems Based Automatic Freeway Incident Detection”. *IEEE International Conference on Systems, Man, and Cybernetics*, San Antonio, Texas, pp. 1727-1733.

7. California Center for Innovative Transportation at the University of California at Berkeley and CalTrans. (2011). Detection Algorithms - Report. Title. Date of Retrival: 01.03.2012. Access from 8. Payne, H. J., and Tignor, S. C. ~1978!. ‘‘Freeway incident-detection algorithms based on decision trees with states.’’ *Transp. Res. Rec.,* 682, Transportation Research Board, Washington, D.C., 30–37.

9. Dia, H., and Rose, G. ~1997!. ‘‘Development and evaluation of neural network freeway incident detection models using field data.’’ *Transp.Res., Part C,* 5~5!, 313–331.

10. Xu, H., Kwan, C. M., Haynes, L., and Pryor, J. D. ~1998!. ‘‘Real-time adaptive on-line traffic incident detection.’’ *Fuzzy Sets Syst.,* 93, 173–183.

11. Cohen, Simon; Ketselidou, Zoe. A Calibration Process for Automatic Incident Detection Algorithms. *Microcomputers in Transportaton* (7-254), 1993.

12. Geng, Jason; Lee, T.N.; Freeway Traffic Incident Detection Using Fuzzy CMAC Neural Networks. Published by IEEE, 1998. (1164-1169).

13. Ullman, Gerald L. An Assessment of Potential Use and Benefits of a Statewide Call Box System in Texas. *Texas Transportation Institute,* College Station, TX, 1999.

14. Versavel, J. 2000. Sparing lives, saving time: a unified approach to automatic incident detection. *Traffic Technology International.* Issue: The 2000 International Review of Advanced Traffic Management. (189).