A Fuzzy Logic Model for Real-time Incident Detection in Urban Road Network

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Abstract: Incident detection systems for the urban traffic network are still lacking efficient algorithms or models for better performance. This paper presents a new urban incident detection system based on the application of Fuzzy Logic modeling. Offline urban incident and corresponding non-incident scenarios are generated using a microscopic simulation model assuming varying traffic link flows, phase timing, cycle times, and link lengths. The traffic measures are extracted from three detectors on each link. Statistical significance analysis was utilized to identify the significant input variables to be used in developing the Neuro-fuzzy model. A set of data was generated and used for training of the proposed Neuro-fuzzy model, while another set was used for validation. The performance of the proposed model is assessed using the success and the false alarm rates of detecting an incident at a specific cycle time.

1 INTRODUCTION

The loop detector-based freeway incident detection algorithms in literature could be generally categorized into adopted analytical and heuristic-based techniques (Parkany, 2005). Notable roadway detector-based recent urban incident detection models are mostly based on statistical regression (Ahmed and Hawas, 2012), Bayesian network (Zhang and Taylor, 2006) and fuzzy logic modeling (Hawas, 2007) techniques. Non-parametric optimization technique (Liu et al., 2007) and discriminant analysis (Sermons and Koppelman, 1996) was used for the probe-vehicle based urban incident detection system. Neural network models were also developed (Dia and Thomas, 2011) using both loop detector and probe-vehicle data.

Typically, the focus of these algorithms was primarily on estimating the performance measures using the percentage of the total number of incidents detected or falsely identified incidents for the simulated duration where the whole incident as a single unit. These algorithms do not particularly account for the true start or the terminating times of individual incidents as a criterion of evaluation. Moreover, these do not consider the effects of the link lengths of the approaches, the hourly traffic volumes, the signal settings and the cycle times of the intersections. This study strives to fill in some of these research gaps of urban incident detection areas for more efficient detection model.

This study assumes that the duration of an incident is divided into smaller time steps and the algorithm is operated repeatedly each (shorter time resolution) step to detect incidents. The proposed fuzzy-model is capable of identifying whether there is an incident or not during each time step. The simulation period may be divided to hundreds of such shorter time steps. With this approach the actual incident start and clearance time could be identified to a great extent.

Therefore, this paper comes up with a new form of urban incident detection model using fuzzy-logic. The model detects the incident status each time step, under various signal cycle times, link lengths and traffic volumes combinations.

2 METHODOLOGY

The conceptual assumption is that the average detectors' readings in the case of incident may significantly vary from the counter readings in the case of no incident. A micro-simulation based methodology is adopted. A typical pre-timed urban intersection network that consists of four links of

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similar geometry and traffic conditions (Figure 1) was selected as it represents the simplest case of a signalized urban network. The overall methodology that this study followed could be summarized as with the following steps:

Step 1: Preparing a specific simulation test-bed (with upstream, midblock and downstream detectors) for the base inputs of a specific Cycle Time (sec) of downstream signal, associated link length (m) and hourly traffic volume (veh/hr) combination.

Step 2: Run this specific simulation model without incident and extract the raw detectors count and speed data (at every approach split time of the signal cycle).

Step 3: Run this specific simulation model test-bed again with an incident generated at a specific time with specific incident duration, and hence extract the raw detectors count and speed data.

Step 4: Estimate detectors count and speed data for every analysis time step [analysis time step = cycle time] for the both incident-free and incident-induced runs.

Step 5: Estimate the traffic measures of interest (i.e. independent variables) for every analysis time step.

Step 6: Repeat steps 1 to 5 for a different base input specifics (cycle time, link length and hourly traffic volume) and collect all the traffic measures of interests for all analysis time-steps from all input specific combinations.

Step 7: Develop some statistical significance tests (ANOVA) for extracting the most significant independent variables to be used in the proposed incident detection model.

Step 8: Develop a Neuro-Fuzzy Model [A fuzzy model for each specific base model that is trained with neural net for calibrations.

Step 9: Validate this Neuro-Fuzzy Model with validation data set. This data set is developed following step 1 to step 5 for slightly altered input specifics from the base cases.

Step 10: Comparison of the measures of performance estimated by the calibrated models using the validation data.

2.1 Experimental Set up of the Incident Modeling

An incident is modeled here as a "lane-blocking" event that persists at least for 6 minutes on a typical three-lane urban arterials in the simulation models.

It is quite rational that longer time incidents, reported in previous studies, could be detected easily as these might have some significant impacts on the traffic parameters. The true challenge (and that is one of the premises of this work) is to detect the incidents of relatively shorter times. Herein, we focus on a single-lane blocking incidents of 6, 8 and 10 minutes incident clearance intervals. Such shorter events will be harder to detect.

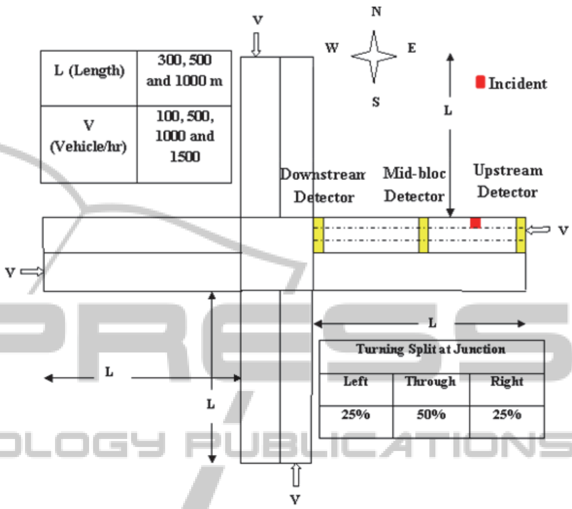

Figure 1: A simple signalized (pre-timed) urban intersection: four approaches, detector placements and a randomly generated incident on the Lane 1 (i.e. rightmost lane in the direction of traffic flow) of the West bound approach.

2.2 Incident Data Development

In the absence of detailed data of real-field detector-based traffic measures, it is a common practice to use well-validated simulation data to generate incident scenarios. Previous studies ((Khan and Ritchie, 1998); (Yuan and Cheu, 2003) and (Zhang and Taylor, 2006)) also used simulation models to generate the incident scenarios. However, these studies used calibrated simulation models from the field data. Similarly, this study also adopted NETSIM to generate incident data. NETSIM places the incidents randomly on the designated lane with specific time duration; however, it cannot be actually used to model an incident at a very specific designated place (Yuan and Cheu, 2003).

2.3 Incident Data Analysis and Fuzzy Models Development

The detector data were extracted for both incident and non-incident simulation cases for various operating configurations models. The term 'operating configuration' refers the combination of a specific cycle time, link length and traffic volume. Specific traffic measures that are likely to vary between incident and no incident cases were chosen to develop the fuzzy-logic models. Incident detection and false alarm rates were chosen as the measures of effectiveness (MOEs) of the calibrated fuzzy-logic models.

3 INCIDENT MODELING

For practicality issues herein, we assume that each detector covers all the approaching lanes for capturing the traffic data. Each detector was placed perpendicularly to the direction of traffic flow. The same logic could be easily adapted in case the detectors are placed on individual lanes. When a vehicle hits a detector, the corresponding detector's count is increased by one. The detector also captures the vehicle's speed.

Only for the simplicity and convenience of the data extraction from the detectors, it is assumed that incidents starting time is the start of the green phase of the incident approach. The incident then lasts for multiples of cycle times (based on the incident duration). The incident terminates concurrently by the end of a cycle time. However, this assumption might have some impact on the time to detect of the incidents.

The detector placements are kept fixed; near the stop-line (downstream detector), at mid-block position (mid-detector) and at end of the link (upstream detector). The vehicle composition is kept also fixed; private-cars 90% and heavy-vehicles 10%. The percentages for left, through and right turns at each approach were fixed as 25%, 50%, and 25%, respectively. The operating speed limit was fixed at 60 km/hr. The pre-timed signal operates on split phase sequencing for the 4 approach legs.

The simulation test beds were varied to reflect various signal cycle time (60, 80 or 100 seconds), approach link length (300, 500 or 1000m) and hourly traffic volumes (100, 500, 1000 or 1500 veh/hr). As the combination of link length of 300 and traffic volume of 1500 veh/hr resulted in link spill back in the no-incident scenarios, and as such it was excluded. We have 11 basic link and volume (LV) combinations for each signal cycle to develop simulation test beds and to extract the detector data needed for model calibration. Thus, the LV combinations, denoted by (Link length: Veh/hr), are (300, 100), (300, 500), (300, 1000), (500, 100), (500, 500), (500, 1000), (500, 1500), (1000, 100), (1000, 500), (1000, 1000) and (1000, 1500). These 11 basic LV models for each cycle time also serve as the base incident-free models. Then, incidents were generated on these base test-beds with different start-times for each incident model. The incident models were run with the same random seed number and initial warm-up period as of the corresponding base incident-free models. Finally, we have 66 incident models for the 60-second cycle time cases, 55 incident models for the 80-second cycle time cases, and 66 incident models for the 100-second cycle time cases.

Each simulated incident model (also, corresponding non-incident base model) was run for the time-period of around ½ hour (i.e. 30 time steps, 23 time-steps and 18 time-steps for the 60, 80 and 100 sec signal cycle times, respectively, where a time step is equal to a cycle time). The exact incident specifics with the 60-second cycle time are denoted here by the *[run no: incident start time, incident duration]*. The exact runs are *[R1: 2, 6], [R2: 6, 6], [R3: 11, 6], [R4: 16, 6], [R5: 21, 6]* and *[R6: 26, 5]*. The 80-second runs are *[R1: 2, 6], [R2: 6, 6], [R3: 11, 6], [R4: 16, 6]* and *[R5: 21, 3]*. The 100-second runs are *[R1: 2, 6], [R2: 6, 6], [R3: 11, 6], [R4: 16, 6]*, *[R5: 21, 3]* and *[R6:17, 2]*.

4 DATA ANALYSIS

The approach used for the data analysis is based on the assumption that it is likely that the traffic measures (extracted from detectors) of the incident-induced cycle-time will vary from the counter traffic average values measured in no incident case. The proposed model operates with a time step (cycle time) resolution; to detect the incident status at every cycle time.

The considered traffic measures are the 'accumulated detector counts' and the 'average detector speeds' for all the three detectors. The data extraction period is equal to the green split time of that cycle. That is, for every cycle time, there are four data extraction periods.

For the upstream detector and mid-lane detectors, the traffic measures are estimated for each cycle time including 4 split phases. For the downstream detector, only the traffic measures during the green phase are used. During the red phases, it is expected that detectors will indicate fixed counts and zero speed. Except for the front leading vehicles near the STOP line (near the downstream detector), no other vehicles would hit the downstream detector during the red phases.

5 DEVELOPMENT OF FUZZY-BASED INCIDENT DETECTION MODEL

A neuro-fuzzy approach was adopted to develop the incident status prediction models presented in this paper. In developing the fuzzy model, the independent variables (as indicated above in Table 1) are the traffic measures extracted from the simulation detectors. The parameters UC, US, MC, MS, DC and DS of Table 1 are the recorded detector data for each of the simulation time-step of the incident models or the operating time-step in reality. The parameters C_1, C_2, C_3, S_1, S_2 and S_3 are also the recorded detector data for each time step with no-incident scenarios out of the corresponding base LV model of each operating configuration. In reality, based on the detector readings of (say) the previous 3 to 5 time steps, the model could identify the closest base scenario for the retrieval of the parameters.

After some comprehensive statistical significance tests with Factor Analysis in Minitab, it was observed that Y_1, X_2, Y_2 and Y_3 in Table 1 are the most significant independent variables in predicting the incident status by some general linear regression (GLM) models. So, the same four independent variables were considered as the input membership functions for the fuzzy logic models.

The dependent variable of the fuzzy model is either an incident status (yes) or a normal recurrent traffic condition (no incident) of a single time-step. Because of the unavailability of the neuro-fuzzy training for the discrete binary dependent variables, the dependent variable of the proposed fuzzy-logic was considered as continuous variable while using the program FuzzyTECH 5.5 (INFORM, 2001).

The 'true' range of the dependent variable of an incident status is allocated the central value of 1 for an incident, and the 'false' range of the dependent variable of a non-incident status is allocated the central value of 0.

In applying the fuzzy-logic model to predict the incident status, a threshold value is utilized. If the estimated dependent variable is higher that the threshold value (say 0.500) an incident is indicated, otherwise it's a normal condition. The threshold value is chosen to maximize the incident detection rate and minimize false alarms. Such threshold was determined through comprehensive iterative analyses. Initially, the value of 0.500 was set as the intuitive separating point between incident and non-incident status. Then, a brute-force search was adopted with 0.001 units of increase/decrease for next iteration until the improvement in the incident detection rate is noticed, while keeping the false alarm rate within some acceptable limits.

The adopted measures of effectiveness of this model are as follows:

Incident Detection Rate: The percentage of time steps that the FLM predicts the incident time steps correctly. The true detection of incident status of a time step is defined as the prediction of an incident status by the model while this time step was truly an incident-induced simulated time step.

False Alarm Rate: The percentage of time steps that the FLM predicts an incident status out of all normal incident-free time steps. The false detection of a time step is defined as the prediction of an incident status by the FLM while this time step was truly incident free.

It is to be noted that the average time to detect the incident is the duration of one time step (which is equal to one cycle time) as this model detects whether an individual time step is incident-induced or incident-free.

6 FUZZY SYSTEM STRUCTURE

The simple FLM structure shown in Figure 2 was adopted. The connecting lines symbolize the data flow.

Four input variables with the associated linguistic terms were identified for the logic as shown in Table 2. The output 'Incident_Status' is an index for incident possibility with two linguistic terms (False and True); the higher the index the higher the possibility of an incident.

6.1 Fuzzification

The linear (L-shaped) membership function (MBF) was adopted for all variables. The membership functions are initially set equally distributed over the range of all possible values. Each variable's term is defined by that single value that corresponds to a term membership value (μ) of 1 as shown in Figure 3.

The Neuro-Fuzzy training algorithm is used to optimize these confidence levels and the membership functions via data training as will be explained later.

Table 1: Traffic measures used in the incident detection models.

Detector	Traffic measures of the incident scenarios [for each analysis time-step (cycle time)]		Traffic measures of the no-incident scenarios [for each analysis time-step (cycle time)]		Parameters to be used in the models (for each cycle time) *n*: total number of simulated cycle times for a specific combination [n= 30, 23 and 18 for the cycles of 60 , 80 and 100 seconds, respectively]	
	Vehicle count measures	Speed measures	Vehicle count measures	Speed measures	Vehicle count measures	Speed measures
Upstream detector [data at each cycle]	Total vehicle count (UC)	Average speed (US)	Total vehicle count (C_1)	Average speed (S_1)	deviation of upstream detector count: $X_1 = UC - \frac{\sum C_1}{n}$	deviation of upstream detector speed: $Y_1 = US - \frac{\sum S_1}{n}$
Midblock detector [data at each cycle]	Total vehicle count (MC)	Average speed (MS)	Total vehicle count (C_2)	Average speed (S_2)	deviation of midblock detector count: $X_2 = MC - \frac{\sum C_2}{n}$	deviation of midblock detector speed: $Y_2 = MS - \frac{\sum S_2}{n}$
Downstream detector [data at each cycle]	Total vehicle count [during green phase] (DC)	Average speed [during green phase] (DS)	Total vehicle count [during green phase] (C_3)	Average speed [during green phase] (S_3)	deviation of downstream detector count: $X_3 = DC - \frac{\sum C_3}{n}$	deviation of downstream detector speed: $Y_3 = DS - \frac{\sum S_3}{n}$

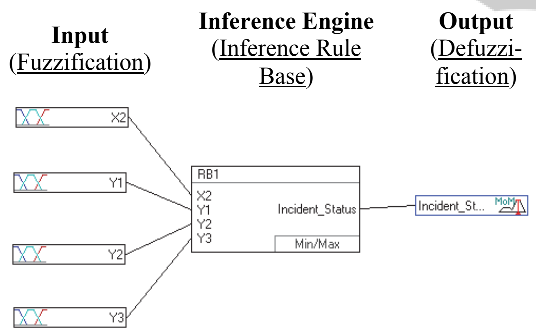

Figure 2: The FLM structure of the urban incident detection model.

6.2 Fuzzy Inference Process

The fuzzy inference consists of three computational steps: Aggregation, Composition, and Result Aggregation (INFORM, 2001). The rules (IF-THEN logics) were generated to describe the logical relationship between the input variables (IF part) and the output variable (THEN part). Initially, all the possible combinations of rules (3*3*3*3*2=162) were set initially with equal degree of support (DoS) of 0.5 as shown in Table 3. The initial value of the DoS for each rule is adjusted by neuro-fuzzy training.

Table 2: The FLM input and output variables, numerical ranges, and linguistic terms.

Variable category	Variable name (Denoted in FLM)	Numerical ranges		Linguistic terms
		Min	Max	
Input variables	deviation of upstream detector speed (Y_1)	-17.96	24.11	Low, Medium, High
	deviation of midblock detector count (X_2)	-14.56	42.28	Low, Medium, High
	deviation of midblock detector speed (Y_2)	-31.51	21.74	Low, Medium, High
	deviation of downstream detector speed (Y_3)	-28.75	43.53	Low, Medium, High
Output variable	Incident Status (Incident_Status)	-1	+2	False, True

Among the several available operators (such as AND, OR, Min–Max, Min–Avg, Gamma), the 'Min–Max' operator resulted in minimum training error.

(a)

(b)

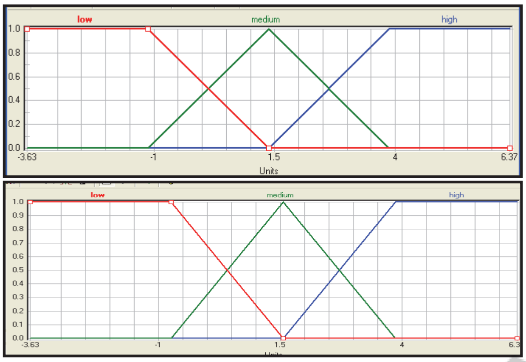

Figure 3: (a) the initial and (b) finally calibrated MBF of input Y_2 (60-second cycle, 50-m link length and 1000 veh/hr scenario).

Table 3: Examples of sample IF-THEN rules.

IF				THEN	
Y_1	X_2	Y_2	Y_3	DoS (initial: final)	Incident_ Status
low	low	low	low	(0.50: 0.97)	False
low	low	low	low	(0.50: 0.98)	True
low	low	high	low	(0.50: 0.49)	False
low	low	high	low	(0.50: 0.50)	True
low	low	high	high	(0.50: 0.45)	False
low	low	high	high	(0.50: 0.50)	True

6.3 Defuzzification

Among the several defuzzification methods, the adopted MoM (Mean-of-Maximum) method delivers the "most plausible" result that is mostly used in pattern recognition problems. The MoM method generates the mean value (z_0) of all output units, whose membership functions (from Figure 4) reach the maximum as follows:

$$z_o = \sum_{j=1}^{k} \frac{z_j}{k}$$

Where

z_j: output unit whose membership functions reach the maximum

k: number of such output units.

6.4 Neuro-Fuzzy Data Training

The neuro-fuzzy system can be viewed as a three-layer feed forward neural network similar to the above traditional fuzzy system (Figure 2) with a layer of hidden neurons used to perform each process. The first layer represents the input variables fuzzification process, the middle hidden layer represents the fuzzy rule inference process and the third layer represents the output variable defuzzification process.

Figure 4: The final values of output (Incident_Status) after nuero-fuzzy training of the MBF (60-second cycle, 500-meter link length and 1000 veh/hr scenario).

The 'calibration' here refers to finding the 'optimal' fuzzy membership shape and the Degree of Support (DoS) for the IF–THEN rules. In the first step, all MBFs and rules were selected for the neuro-fuzzy training to find the optimised FLM. Then, the parameters (step width for DoS and terms) were selected for the training. The whole neuro-fuzzy training was carried out for five cycles with each cycle for 1000 iterations.

The step width for the DoS values has been set to 0.1 for each cycle. The step width for the terms has been set to 5% in the first cycle, which was increased by 5% in later cycles. The maximum and average deviations were observed after completion of each cycle. The cycle, for which the deviation values are less, was selected as the final FLM. After the training phase, the MBFs and the DoS values were determined as shown in Table 3 and Figure 3(b).

7 RESULTS

For the 60-second signal time models, the performance measures, denoted by (FLM threshold, incident detection rate, false alarm rate), for the mentioned 11 LV combinations are (0.500, 26%, 10%), (0.500, 69%, 0%), (0.200, 77%, 24%), (0.200, 46%, 39%), (0.200, 46%, 15%), (0.500, 77%, 9%), (0.500, 31%, 1%), (0.500, 40%, 19%), (0.500, 66%, 9%), (0.500, 34%, 9%) and (0.500, 43%, 9%), respectively. With the 80-second signal time models, the performance measures are (0.500, 41%, 8%), (0.500, 96%, 0%), (0.500, 78%, 0%), (0.500, 22%, 5%), (0.500, 67%, 3%), (0.500, 85%, 6%), (0.500, 70%, 0%), (0.500, 56%, 51%), (0.500, 0%, 0%), (0.500, 0%, 0%) and (0.500, 56%, 1%), respectively. With the 100-second signal time models, the performance measures are (0.500, 0%, 0%), (0.500, 90%, 0%), (0.500, 90%, 0%), (0.500, 61%, 21%), (0.500, 90%, 23%), (0.500, 77%, 17%), (0.500, 81%, 1%), (0.500, 48%, 9%), (0.500, 65%, 5%), (0.500, 87%, 25%) and (0.500, 68%, 10%), respectively. Thus, the incident detection rates range from 0% to 96%, while the false alarm rates range from 0% to 51%. Except for few operating conditions, the average detection rate is mostly above 55%.

The worst performance of the FLM (low detection rate and/or very high false alarm rate) is evident with low traffic volumes. At low traffic volumes, incidents do not significantly impact the detector readings or the adopted traffic measures (especially for the cases of partial blockage). Even with long incident durations, vehicles could easily bypass the blocked lane through other free lanes.

This limitation (low detection rates at low traffic volumes) is quite similar to that of the freeway incident detection models. At such low traffic volumes one may argue that traffic control centre does not necessarily have to respond by control adjustments as the incident does not impact the traffic flow significantly. Also, for the case of 80-second cycle time, the FLM for the case of long link length (i.e. 1000 m) seems performing worse with relatively low detection rates. This may be attributed to the delay in detecting incidents caused by the longer travel times on links.

By excluding the scenarios of low traffic volume (100 veh/hr), the average detection rate of the proposed FLM is 64.3% (55%, 57% and 81% for the signal cycles of 60, 80 and 100 seconds, respectively), and the average false alarm rate is 7%. This FLM seems performing better with lower false alarm rate (7%) as compared to the GLM based regression models (11.7%) developed by Ahmed and Hawas (2012). The average detection rate of the GLM models (64.6%) is close to that of the FLM (64.3%).

8 VALIDATION TESTS

Another set of different incident scenarios was modeled with NETSIM for validation test. This would also test the robustness of the devised FLMs. Here, all scenarios were modeled with 8 time steps incident duration (480, 640 and 800 seconds for the cycle times of 60, 80 and 100 seconds, respectively), where the incidents starting and ending time steps were set to 9 and 16, respectively. The calibration data set was from the lane 1 incidents only, but the validation data set were generated from the incidents of both lane 1 and lane 2. Thus, it reflects significant changes to incident occurrence specifics as compared to the data used for calibration. Some of the lane-2 incidents were generated with hourly traffic volumes of 500 and 1000 veh/hr with various link lengths and cycle time of 60 seconds. Others were generated with hourly traffic volumes of 100 and 1500 veh/hr, various link lengths and cycle time of 80 seconds. Also, some incidents were generated with hourly traffic volumes of 500 and 1500 veh/hr with various link lengths and cycle time of 100 seconds.

The developed FLM of each specific combination (i.e. from the 33 operating configurations) was used to predict the incident status using the data of the validation scenarios. Lane-2 incident validation scenarios resulted in average detection rate of 32% (standard deviation 20%), and average false alarm rate of 14% (standard deviation 17%). Lane-1 validation scenarios resulted in 19% average detection rate (standard deviation 21%) and 8% average false alarm rate (standard deviation 12%).

It is to be noted that the lower detection rates of the validation scenarios (as compared to the results reported in the calibration of the FLM) might be attributed to the insufficient data as for each specific combination of cycle time, link length and volume; only one incident scenario for each combination whereas there were at least 5 incident scenarios in calibration. Furthermore, the calibration data was somehow limited in the sense that it did not consider overall random variations in incident durations, start and end times.

9 CONCLUSIONS

This paper presented an FLM approach that combines simple fuzzy logic models and threshold values for each specific combination of cycle time, link length and hourly traffic volume. Except the relatively lower hourly traffic volumes, the incident detection and the false alarm rates were satisfactory for all the cases.

There is still a significant room for improving the presented FLM to obtain more efficient and robust models. Also, further challenges remain in predicting the incident status with significantly wide variations of the input attributes accounting for other aspects such as the malfunctioning of the detectors and the variations with detector placements. Further research is intended to focus on improving the FLM by considering the impact of random incident locations, durations, and different detector placements. Other improvements could include the generalization of the FLM to account for over-saturated traffic conditions when link spill back occurs. Further research would also consider different settings of the FLM structure in terms of reduced number of input parameters. Also, a general FLM (for various operational conditions) will be strongly needed.

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