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A Threshold-Based Real-Time Incident Detection System for Urban Traffic Networks

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Abstract

As incident detection on a typical busy urban road link or intersection still demands more efficient algorithms, this paper introduces a methodology that can be used to characterize the various traffic patterns (incident or no incident) using typical link passage detectors. Offline urban incident scenarios are generated using a microscopic simulation model assuming varying traffic link flows, signal green phase and cycle times, link lengths. Similar scenarios are also generated for non-incident cases. Three detectors were assumed on each link to extract traffic measures. Comparative numerical statistical analyses were conducted to identify the traffic measures (such as the average speed and flow) that are likely to be affected by the incidents. And further analysis was conducted to quantify the most probable thresholds to be used in the proposed urban incident detection model. The proposed model is validated using simulation data. The performance of the proposed model is assessed using dynamic performance indicators such as the success rate of detecting an incident at a specific cycle time, and the false alarm rate.

Keywords: Urban incident detection model, detector; average speed, regression; detection rate; false alarm rate

1. Introduction

Handfuls of research have been developed and incidents detections algorithms for freeways and urban expressway or tunnels are already there with the commercial traffic control systems. On the other hand, detecting an incident on an urban road link or intersection is very difficult to estimate. Urban roads and intersections are interrupted basically by cross-roads, entry-exit to/from the arterial link, pedestrian cross-walk and traffic control signal systems within very short space and time intervals. The traffic dynamics of the recurrent congested urban link and intersection is very similar to the sudden incident scenario. This makes it difficult to distinguish between an incident and non-incident case with the related traffic parameters. Apparently, the developed research in this area is not that significant and therefore, this paper strives to fill up some of this research gaps.

This paper describes the development of a threshold-based offline urban incident detection model that tries to detect the incident status of each analysis time-step of the incident(s) occurred on a link of a pre-timed signal network. Here, the analysis time step is taken as the cycle time of the downstream signalized intersection of the subject link. The used approach is to develop some simple regression models using the extracted traffic measures data from the fixed detectors.

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2. Literature Review

Most of the developed freeway incident detection algorithms could be generally categorized into some typical groups based on the adopted analytical and heuristic techniques. Different algorithms employ different data requirements, principles, and complexity [Parkany (2005)]. The notable forms of freeway based incident detection methodologies are (a) comparative algorithms (b) statistical algorithms (c) time series algorithms (d) filtering/smoothing algorithms (e) traffic modeling algorithms (f) artificial intelligence algorithms and (g) image processing algorithms. However, to overcome the inherent disadvantage of the point-based detectors, the probe-vehicle based algorithms [Sermons and Koppelman (1996), Hellinga and Knapp (2000)] emerged to detect incidents basically on the urban expressway. The probe-vehicle could be equipped with some GPS (Global Positioning System), AVI (Automatic Vehicle Identification), RFID (Radio Frequency Identification Device), Cellular or other driver based sensor technologies.

For the urban case, Thomas (1998) reformulated the urban incident detection algorithm as a multiple attribute decision making problem with Bayesian scores. But, the success of this method depends on the traffic status dataset from historical traffic pattern for both link and the detector stations. However, this AID algorithm does not consider the status of the arterial traffic control signal system. Lee et al (1998) developed fuzzy-logic based incident detection algorithm that operates in a recursive manner with the average of the traffic parameters of the last 5 minutes. It has a scope to be incorporated into a real-time traffic adaptive control system. However, this algorithm is developed only for a diamond intersection and the applicability of this algorithm is not in general with any traffic control system and the link type. Zhang and Taylor (2006) presented Bayesian network model that updates the incident probability at each detection interval through two-way inference for arterials. The detection rate and false alarm rate are not sensitive to the incident decision thresholds. However, the algorithm is applicable to the mainstream traffic flow of the signalized intersections with pre-defined signal settings only.

Liu et al (2007) presented a CUSUM (Cumulative Sum) algorithm based on non-parametric optimization technique as incident detection algorithm for an urban expressway using the probe vehicle data. However, this algorithm is applicable only for the urban expressway, not for any typical urban arterials that have interruptions of the traffic control signals. Hawas (2007) developed also a neuro-fuzzy-logic incident detection algorithm for urban road network. The algorithm is integrated with an incident management module. The adopted approach is new for the development of incident detection algorithm that does not rely on ‘‘real data’’, but rather it can be fully developed using well-validated ‘‘simulation’’ models. However, the success of this method heavily depends on the extensive dataset for the training of the neuro-fuzzy. Recently, Dia and Thomas (2011) developed neural network models for automatic incident detection on arterial roads based on a data fusion technique to achieve more improvement on typical incident detection rate using the simulated loop detector data and probe vehicle data. Here, the emphases were to evaluate the better performing neural network model type and the loop detector configurations.

In summary, all the developed freeway or urban incident detection algorithms primarily use simulated incident data to have some specific threshold values of some traffic variables for incident identification. The techniques are different in forms of estimation of the relevant parameters. The performance of the algorithm is compared against each other for the three primary key performance indicators like detection rate, false alarm rate and mean time to detect. It is to be noted that these algorithms ,except Hawas (2007), just detect some percentage of the total number of incidents that occurred during the recorded or simulated timeframe and the incident must be detected within a short time frame (example, 5 minutes) considering the whole individual incident as a single data only. However, these algorithms typically do not account for the true start time or the terminating time of an individual incident, nor these do show the incident status of intermediate time-steps of an individual incident. Also, these algorithms typically do not consider the effects of link-lengths, hourly traffic volume and associated green-time and cycle time of the approaching pre-timed intersection.

Therefore, this paper presents a new urban incident detection model that detects the incident status of each single operating time-step (i.e. cycle time of the downstream signal) under a specific signal cycle time, link-length and traffic volume combination. The presented methodology is built on the conceptual assumption that the average detectors’ readings in the case of incident may significantly vary from the counter readings in the case of no incident.

3. Methodology

The adopted methodology that this study followed could be summarized as (a) development of off-line incident scenarios accounting for various network configurations, link volumes, signal settings by simulations (b) carry on detailed data analyses to capture the parameters that are likely to be affected by various incident scenarios (c) carry on detailed regression models to come up with some incident status predicting models (d) carry on validation tests of the proposed models.

3.1. Experimental Set Up of the Incident Modeling

An incident is modeled here as any single lane-blocking event that persists at least for 6 minutes on a typical three-lane urban arterials in the simulation models. Longer time incidents could be detected easily as these might have some significant impacts on the traffic parameters but the primary challenge is to detect the incidents of relatively shorter times. Therefore, as a start, this research focuses on a single-lane blocking incidents of 6 minutes, 8 minutes and 10 minutes initially. A typical pre-timed urban intersection network that consists of four links of similar geometry and traffic conditions (Figure 1) was selected as the scope for initial urban incident detection model development because it represents the simplest case of a signalized network. However, the incident was generated only on a single link within some specific time period.

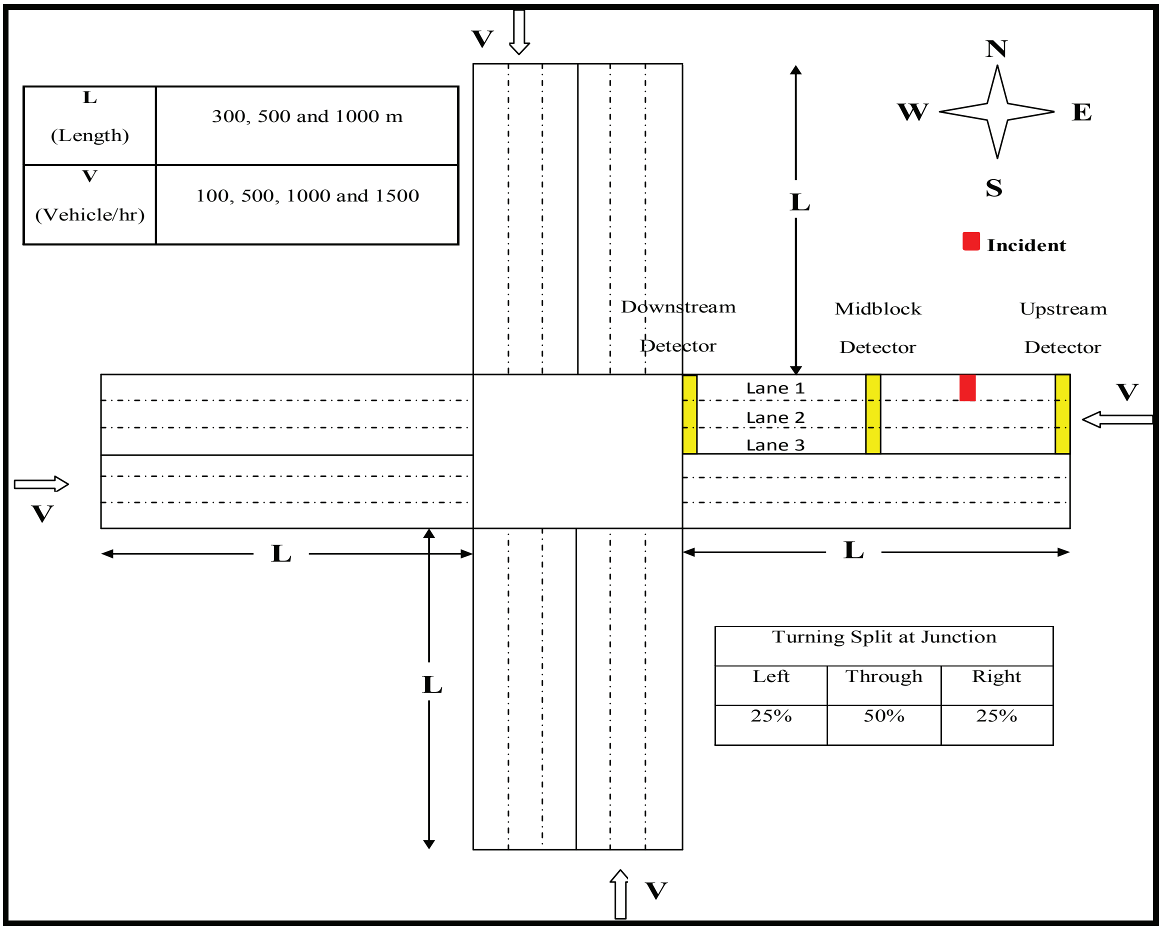

Fig. 1. A signalized (pre-timed) intersection, representing the simplest urban road network, shows four arterial approach links, all detector placements and a sample randomly generated incident location on the westbound approach

3.2 Incident Data Development

In the absence of real field data of incidents, it is a common practice to use simulation data to generate incident scenarios. Therefore, NETSIM micro simulation was used to generate incident data in this study. NETSIM has the capability of generating some long-term events on some designated lane at some specific time for certain durations. NETSIM places the incident randomly on the designated lane. But the limitation is that it has no capability of producing an incident at a designated place [9]. This benchmark simulation program was adopted as it is one of the best available microscopic simulation off-self. At least 5 incidents were generated at random locations of lane 1 of west bound approach (Figure 1) for a specific combination of cycle time, link length and traffic volume. The difference among the five incidents models i.e. when these are generated, how long these lasted and on which lane these occurred are all described briefly in Table 1.

3.3 Incident Data Analysis and Regression Models Development

The detector data were extracted for both incident and non-incident cases for a specific operating configuration. The term 'operating configuration' refers the combination of a specific cycle-time, a specific link length and a specific traffic volume throughout this paper. Some specific traffic measures of importance were chosen to develop some regression models that give the indication of either an incident or non-incident status of a single analysis time-step of that operational traffic hour. The 'Incident Detection Rate' and 'False Alarm Rate' were chosen as the measures of effectiveness (MOEs) of these regression models.

4. Incident Modeling

Table 1 illustrates the overall NETSIM simulation runs with incident and non-incident scenarios employed in this study. Incidents were introduced at random locations of lane 1 of the west bound arterial (Figure 1) at some specific time for some specific durations. Each detector covers all the three lane along its length placed perpendicularly to the direction of traffic flow. When any vehicle hits on any detector of any of the three arterial lanes, the corresponding detector counts the number of vehicle as one unit and it also calculates the corresponding speed of that vehicle.

For simplicity and convenience of the data extraction from the detectors, some assumptions were made in generating incident scenarios in the NETSIM simulation runs. Such as (a) the incident starts exactly when a new signal cycle begins with the green phase of the subject approach (b) the incident exactly terminates when the last cycle-time completes after some specific cycle-time durations of the incident. These assumptions of the incident start and end time match with cycle time enable us to capture the relationship between the traffic measures of importance of the downstream detector during the green phase and the incident status in the proposed model. In summary, the factors varied in the simulation runs were (A) downstream signal cycle Length, the traffic volumes and the approach length to reflect different network configurations. Different incident durations were also considered: 6, 8 and 10 minutes. For each operating configuration, at least 5 incidents were generated at different times and random places on the lane 1 of the subject arterial. The minimum duration of a whole incident was taken as 6 minutes intuitively to reflect the incident as a long-term event in NETSIM. Both incident and non-incident scenarios were run for the same simulation duration and with the same random seed so that the counts/speeds are directly comparable. At this stage of the research, for each specific link length, the volumes levels were chosen in such a manner that no spill-over of the link is happening in the cases of incident-free conditions because of congestions.

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 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.

Table 1. Offline incident scenarios

Input Specifics					Incident Modeling Specifics		
4-phase Cycle Time (Phase Split = data extraction interval)	Incident Duration	Link Length (m)	Link Volume (veh/hr)	Without -incident Simulation Run (simulated cycle times)	Incident Simulation Runs (simulated cycle times)	Incident Run Specifics (incident duration, start and end time) [in cycle times]	Simulation Period (total incidents durations) [in cycle times]
60 sec (15 sec)	6 min (360 sec) i.e. 6 analysis time steps (= 6 cycle times)	300	100	1(30)	6(30)	Run1: (6, 2,7) Run2: (6, 6,11) Run3: (6, 11,16) Run4: (6,16,21) Run5: (6,21,26) Run6: (5,26,30)	180 (35)
			500	1(30)	6(30)		
			1000	1(30)	6(30)		
		500	100	1(30)	6(30)		
			500	1(30)	6(30)		
			1000	1(30)	6(30)		
			1500	1(30)	6(30)		
		1000	100	1(30)	6(30)		
			500	1(30)	6(30)		
			1000	1(30)	6(30)		
			1500	1(30)	6(30)		
80 sec (20 sec)	8 min (480 sec) i.e. 6 analysis time steps (=6 cycle times)	300	100	1(23)	5(23)	Run1: (6, 2,7) Run2: (6, 6,11) Run3: (6, 11,16) Run4: (6,16,21) Run5: (3,21,23)	115 (27)
			500	1(23)	5(23)		
			1000	1(23)	5(23)		
		500	100	1(23)	5(23)		
			500	1(23)	5(23)		
			1000	1(23)	5(23)		
			1500	1(23)	5(23)		
		1000	100	1(23)	5(23)		
			500	1(23)	5(23)		
			1000	1(23)	5(23)		
			1500	1(23)	5(23)		
100 sec (25 sec)	10 min (600 sec) i.e.6 analysis time steps (=6 cycle times)	300	100	1(18)	6(18)	Run1: (6,2,7) Run2: (6,5,10) Run3: (6,8,13) Run4: (6,11,16) Run5: (5,14,18) Run6:(2,17,18)	108 (31)
			500	1(18)	6(18)		
			1000	1(18)	6(18)		
		500	100	1(18)	6(18)		
			500	1(18)	6(18)		
			1000	1(18)	6(18)		
			1500	1(18)	6(18)		
		1000	100	1(18)	6(18)		
			500	1(18)	6(18)		
			1000	1(18)	6(18)		
			1500	1(18)	6(18)		
Total Simulation Runs			-	33	198	-	-

5. 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 is supposed 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. It is to be noted that, the smallest data extraction period is equal to the green (or red) split time of that cycle. So, at every cycle time, there are four data extraction periods. For the upstream detector and mid-detectors, the traffic measures are estimated for each cycle time (i.e. 4 split phases), by manipulating the corresponding traffic measures over the four data extraction periods of the detectors (within that cycle). For example, the analysis time step (i.e. cycle time) vehicle count is estimated by accumulating the vehicular counts reported during the four data extraction periods (i.e. one green phase and three red split phases) within the same cycle. On the other hand, the analysis time step (i.e. cycle time) average speed is estimated as the average of the speed values reported during the four extraction periods i.e. four split phases. But for the downstream detector, the traffic measures of interest during the green-phase only would be used as the analysis data for that cycle time. It is quite reasonable that during the red phases, except the front leading vehicles near the STOP line (i.e. near the downstream detector), no other vehicles would hit the down detector from all 3 lanes during the red phases. Table 2 illustrates the used traffic measures in analysis and in developing the incident-detection regression models.

Table 2. Traffic measures at every-cycle time used in the incident detection models

Detector	Traffic measures of the incident scenarios [for each analysis time-step]		Traffic measures of the no-incident scenarios [for each analysis time-step]		Parameters to be used in the regression models (at each cycle time where 'n' is the total simulated cycle times) for a specific combination	
	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: $Y_3 = DS - \frac{\sum S_3}{n}$

6. Development of Incident Detection Models

This section highlights the development of the incident detection models. At this stage of the research, it was tested that if the simplest form like 'general linear regression model' could predict the incident status rather than using other binary discrete choice regression forms. The calibrated regression models can then be used for predicting incident status of a single time-step. In developing the regression model, the independent variables (as indicated above in Table 2) are the traffic measures extracted from the simulation detectors. The dependent variable of the regression model is either an incident status (yes) or a normal recurrent traffic condition (no incident) of a single time-step. To increase the goodness of fit of the devised regression models, the two binary values (0 and 1) were avoided. The dependent variable of an incident situation is allocated a value of 0.75 (instead of 1), and allocated a value of 0.25 (instead of 0) for the no incident situation. In applying the regression model to predict the incident status, a threshold value is utilized. If the estimated dependent variable is higher that the threshold value (say 0.5) an incident is indicated. A dependent variable of a value lesser than the threshold value is an indication of no incident. The threshold value is chosen to maximize the incident detection rate and minimize false alarms. It was determined with iterative analyses. Initially, the simple value of 0.5000 was set as the intuitive separating point between incident and non-incident status. Then, this value was decreased (or increased) by 0.0001 unit for next iteration until it improves the incident detection rate and keep the false alarm rate within 20%. If threshold value were chosen too small, it results in almost 100% incident detections of all incident-induced time-steps along with excessive high false alarm rate. On the other hand, if the threshold were chosen too high (say, 0.70) there would be no-incident time step and no false alarm as well. The adopted measures of effectiveness of this model are as follows:

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

False Alarm Rate: The percentage of time-steps that the model predicts as incident-induced time-steps 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 model while the associated time step was truly incident-free. It is to be noted that the 'Average Time to Detect' the incidents is the time of one analysis time-step as this model detects whether an individual time-step is incident-induced or incident-free.

The form of linear equation that was tested to fit the predicting equations is:

General Liner Model: $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 Y_1 + \beta_5 Y_2 + \beta_6 Y_3$

Here, βs are coefficients of the associated traffic parameter. Some other notable non-linear forms of equations were also tested. However, it was found that the non-linear regression equations here do not improve the model 'goodness of fit' at all as compared to the general linear additive model. So, the general additive linear regression equation was adopted as the suitable regression model so far. The R^2 values of the regression equations range between 0.08 to 0.30. Due to the unacceptable R^2 values, the goodness of fit is particularly judged by the values of the incident detection rate and the false alarms.

7. Results

The analysis of variance tests revealed that all the traffic parameters of X_1, X_2, X_3, Y_1, Y_2 and Y_3 were found significant or slightly significant in predicting the response (incident status).

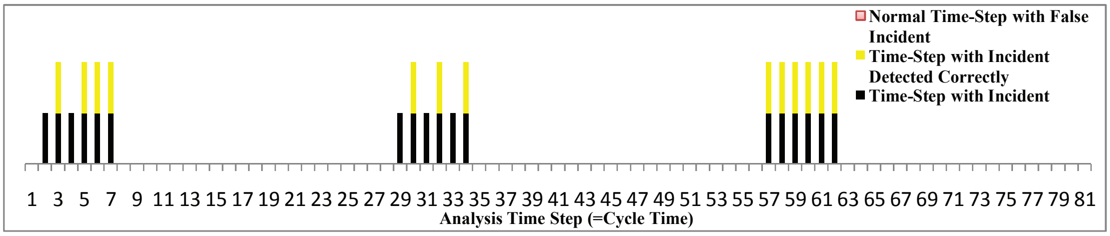

Fig. 2. A typical outcome of the incident status

Figure 2 displays a typical outcome of the incident detection model for each-time step for the case of 80 sec cycle time, 300m link length and 1000 veh/hr. Here, the blank time-step means correctly detected normal incident-free cycle time duration. Table 3 includes the overall threshold based regression models with associated coefficients of each specific operating configuration. It is to be noted that the threshold were found within the range of 0.3564 to 0.5000. The detection rates range from 23% to 87% while the false alarm rates range from 0% to 20%.

Table 3. Effectiveness of regression-based incident detection models

Cycle time	Link length (m)	Veh /hr	Coefficients of regression models							Threshold value	Incident detection rate (%)	False alarm rate (%)
			β_0	β_1	β_2	β_3	β_4	β_5	β_6			
60 sec	300	100	0.336	0.025	0.172	0.022	0.001	-0.017	0.003	0.37	40	17
		500	0.341	-0.002	-0.012	-0.029	-0.003	-0.020	0.001	0.39	46	13
		100	0.301	-0.003	-0.026	-0.030	-0.048	-0.013	0.011	0.42	71	8
	500	100	0.348	-0.008	0.000	-0.006	0.000	0.001	0.000	0.35	23	19
		500	0.326	0.041	-0.004	-0.002	-0.015	-0.027	-	0.42	51	10
		100	0.322	-0.005	-0.011	-0.020	-0.059	0.006	0.009	0.38	66	16
		150	0.328	0.034	-0.023	-0.009	-0.026	0.001	0.027	0.38	69	17
	1000	100	0.335	0.024	0.180	-0.012	-0.003	-0.018	0.000	0.37	40	20
		500	0.345	0.022	-0.007	0.003	-0.032	-0.002	0.001	0.37	40	19
		100	0.343	0.016	-0.026	-0.018	0.030	-0.010	0.003	0.38	60	19
		150	0.331	-0.016	-0.019	0.003	-0.009	-0.014	0.017	0.39	77	16
80 sec	300	100	0.357	0.071	0.182	-0.008	-0.006	-0.016	0.001	0.40	33	18
		500	0.313	0.022	-0.079	-0.009	0.000	-0.038	0.009	0.45	67	5
		100	0.308	0.024	-0.014	-0.019	-0.059	-0.008	0.025	0.43	74	8
	500	100	0.360	0.088	0.180	-0.035	-0.009	-0.015	0.001	0.40	37	20
		500	0.339	-0.031	-0.051	-0.032	-0.058	0.014	-	0.43	74	9
		100	0.311	0.012	-0.012	-0.015	-0.073	0.001	0.015	0.45	70	5
		150	0.342	0.008	-0.025	-0.001	-0.039	-0.003	0.035	0.45	70	1
	1000	100	0.340	-0.072	0.310	0.033	0.007	-0.028	-	0.39	52	20
		500	0.356	0.011	-0.006	-0.003	-0.043	0.004	0.016	0.41	52	20
		100	0.338	-0.007	-0.007	-0.024	-0.066	0.019	0.017	0.40	63	16
		150	0.354	0.029	-0.020	0.000	-0.024	-0.002	0.034	0.42	41	14
100 sec	300	100	0.374	0.018	0.160	-0.043	-0.002	-0.014	0.001	0.43	32	5
		500	0.341	0.015	-0.019	-0.011	-0.008	-0.047	0.018	0.44	71	12
		100	0.321	0.012	-0.035	-0.018	-0.067	-0.001	0.026	0.43	81	0
	500	100	0.389	0.002	0.142	-0.019	0.000	-0.012	0.000	0.42	32	16
		500	0.369	0.035	0.006	-0.008	-0.029	-0.025	0.027	0.45	52	17
		100	0.351	0.043	-0.025	-0.038	-0.060	-0.036	0.032	0.40	81	16
		150	0.355	0.058	-0.026	-0.002	-0.032	-0.014	0.036	0.45	77	3
	1000	100	0.382	-0.052	0.119	-0.044	0.004	-0.011	0.001	0.42	42	16
		500	0.373	0.022	-0.025	-0.010	-0.029	-0.026	-	0.48	39	17
		100	0.309	-0.064	-0.014	-0.031	-0.060	0.011	0.009	0.50	87	0
		150	0.371	0.044	-0.016	-0.014	-0.059	-0.009	0.046	0.43	71	14

It is apparent that the incident detection rate is lower for the cases of low traffic volumes (100 vehicles/hour). At low traffic volumes, there is no significant impact on the detector readings or the adopted traffic measures. Even with long incident durations, vehicles could easily bypass the blocked lane through other free lanes. This relatively lower traffic volume also emerges with high false alarm rates. 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.

From the sensitivity analyses of the numerical values of the regression coefficients in Table 3, it was found that β_0 is significantly sensitive to both cycle time and volume variations. β_2, β_4 and β_6 are significantly sensitive to volume variations only. β_1, β_3 and β_5 are not significantly sensitive to the cycle time, link length and traffic volume variations. This implies a good potential to come up with some general regression models irrespective of any link length variations. Also, the threshold values are significantly sensitive to both of the cycle time and volume variations.

8. Validation Tests

Another set of models were developed to validate the developed threshold-based incident detection models as indicated hereafter.

8.1 Validation

To validate the models, another set of incident scenarios was modeled with NETSIM. These validation scenarios are different from those used to calibrate the models. In the validation scenarios, the incident duration was kept as 8 time steps for all cycle times. The incidents starting and ending time steps are 9 and 16, respectively. The incident durations are 480, 640 and 800 seconds for the cycle times of 60, 80 and 100 seconds, respectively. The incidents were generated not only on lane 1 only, but also on lane 2 (Figure 1) for around half of the scenarios to reflect a significant change in incident occurrences. Some of the Lane-2 incidents were generated along with hourly traffic volumes of 500 and 1000 veh/hr for all link lengths and cycle time of 60 seconds. Some other Lane-2 incidents were generated along with hourly traffic volumes of 100 and 1500 veh/hr for all link lengths and cycle time of 80 seconds. Also, Lane-2 incidents were generated along with hourly traffic volumes of 500 and 1500 veh/hr for all link lengths and cycle time of 100 seconds. In general, the validation scenarios reflect different settings of incident starting times, incident durations, locations and incident blocking lanes from the original models that were used to develop the regression models. These different settings of the inputs also reflect some sort of robustness of these models.

The developed regression models (listed in Table 3) were used to predict the incident status using the data of the validation scenarios. The results indicate that all the Lane-2 operating configurations emerged with an average detection rate of 51% (standard deviation 28%), and an average false alarm rate of 16% (standard deviation 8%). Lane-1 validation scenarios data resulted in 45% average incident detection rate (standard deviation 28%) and 9% average false alarm rate (standard deviation 10%). The lower detection rates (of less than 40%) were found with low traffic hourly volumes (up to 500 vehicles/hour). Except for few cases, the false alarm rates are within acceptable limits. As the hourly traffic volume is the most significant influencing factors for the coefficients of the regression models (in Table 3), some volume-wise generalized regression models were further developed. These models can be used for predicting the incident status irrespective of the cycle-time and the link length. The volume-wise generalized models were derived by averaging the corresponding coefficients and the thresholds of the models in Table 3.

100 veh/hr (threshold: 0.3952):

$$y = 0.3579 + 0.0107X_1 + 0.1606X_2 - 0.0124X_3 - 0.0009Y_1 - 0.0144Y_2 + 0.0007Y_3 \cdots\cdots\cdots (1)$$

500 veh/hr (threshold: 0.4271):

$$y = 0.3448 + 0.015X_1 - 0.0219X_2 - 0.0112X_3 - 0.0241Y_1 - 0.0186Y_2 + 0.0064Y_3 \cdots\cdots\cdots (2)$$

1000 veh/hr (threshold: 0.4217):

$$y = 0.3227 + 0.0031X_1 - 0.0189X_2 - 0.0237X_3 - 0.0513Y_1 - 0.0034Y_2 + 0.0163Y_3 \cdots\cdots\cdots (3)$$

1500 veh/hr (threshold: 0.4207):

$$y = 0.3468 + 0.0262X_1 - 0.0215X_2 - 0.0038X_3 - 0.0315Y_1 - 0.0068Y_2 + 0.0325Y_3 \cdots\cdots\cdots (4)$$

In applying the generalized models (equations 1 through 4) using the data of the validation scenarios, the Lane-1 incidents scenarios resulted in 51% average incident detection rate (standard deviation 24%) and 12% average false alarm rate (standard deviation 8%). Lane-2 incidents scenarios resulted in 42% average incident detection rate (standard deviation 27%) and 17% of average false alarm rate (standard deviation 9%). To a great extent, the generalized models conform to similar results as of the original incident prediction models.

9. Conclusions

In brief, this paper presented an attempt to introduce a new form of urban incident detection models to capture the incident status of each analysis time step. This approach is a combination of simple regression models and threshold values for each specific combination of cycle time, link length and hourly traffic volume. The rationale for developing these models is based on the assumption that the no-incident traffic measures extracted from the detectors' readings significantly vary from the counter readings in the case of incident. Except the relatively lower hourly traffic volumes, the incident detection rate and the false alarm rate came quite satisfactory for all cases. Each operating configuration specific model and also the generalized models were validated. The models proved to be robust with slightly varied input attributes. Thus, this study tried to address some of the gaps in the research areas of urban incident detection models.

However, still good potential remains in obtaining more efficient models for improved detection rates while minimizing false alarm rates. Also, further challenges remain in predicting the incident status with significantly wide variations of the input attributes from the base cases, with the malfunctioning of the detectors and also with variations with detector placements. Next stage of research would focus on comparisons of this simple regression model with binary logit regression models and incorporation of conventional incident and false alarm detection rates using the number of incidents only, not the incident-induced analysis time-steps. Further research would be conducted focusing on comprehensive sensitivity analysis of all the input settings and parameters, reduced traffic parameters with the detectors, testing the impact of the incident placements on a specific lane, varying the incident locations on other lanes, varying incident duration time-steps, varying detector placements, varying cycle lengths, varying traffic flows on other links of the downstream intersection. Also, apart from regression type models, other heuristic methodology like nuero-fuzzy models would be tested to come up with some improved models. Finally, some field data collections of the model parameters could be conducted to test the proposed model(s) in a real traffic conditions upon the availability of the associated roadway devices and signal control system in the UAE.

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