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Understanding incident impact on traffic variables to reduce false incident detection

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Abstract

False detection is a major issue of incident detection algorithms (IDA). A better understanding of the incident behavior is needed to minimize this error. This study explores 77 motorway incidents and their impacts on occupancy, flow and speed profile at the nearest upstream and downstream detector locations. The analysis discovers that an incident is likely to create a difference in occupancy and speed profile between the upstream and downstream detectors. At the same time, the incident creates a disturbance in the flow which significantly reduces the roadway capacity. A new IDA is proposed based on the famous California #7 algorithm. The proposed California #7 with flow (CWF) algorithm includes a flow drop test to reduce the false detection rate. Both the algorithms have been properly calibrated and validated with the collected data. The validation result shows a significant improvement in the reduction of the false detection rate. The new IDA avoids minor incidents that have little or no impact on traffic flow.

1. Introduction

Incident Management (IM) is one of the main activities of Traffic falseManagement Centers (TMCs). It includes detecting and verifying the incident, responding with emergency vehicles and information for other motorists, clearing the incident, and monitoring traffic movements until normal operating conditions return. Effective incident management reduces the duration and the impacts of traffic incidents and improves the safety of motorists, crash victims and emergency responders (FHWA, 2010). The success of the incident management plan highly depends on the fastest and accurate identification of the incident. To this end, Incident detection algorithms (IDA) provide indications of the probable presence of incidents by processing real-time traffic data. IDA becomes an integral part of TMC. However, IDA's are often questioned about their success rate. Especially, high false detection rate (also known as a false alarm) is observed in high traffic volume conditions (Deniz and Celokoglu, 2011). Besides the obvious goal of identifying incidents, a reliable IDA should be capable of producing low false alarm under different traffic conditions.

TMC has to respond to each incident alarm and verify it with other sources (e.g., video camera footage) before implementing a response plan. Every false alarm not only increases the workload for the TMC personnel but also decreases their faith over the IDA. Hence, it is important to focus on reducing false detection rate of IDAs. In this regard, a proper understanding of the incident properties and their impact on traffic variables is required.

This paper aims to have a better understanding of different incident behavior and their impact on traffic variables (e.g., speed, flow, and occupancy) and proposes an improved algorithm to minimize false detection. A detailed analysis of the traffic variables before, during and after incident cases will be performed to identify possible changes that provide valuable information about successful incident identification. This information will be incorporated in the widely used California #7 IDA in a way that would better reflect the incident behavior and thus help to reduce false detection.

The remaining of the paper is organized as follows: Section 2 presents a brief overview of the available IDAs, Section 3 shows the impact of the incidents on traffic variables and presents the proposed IDA, Section 4 discusses the findings and limitations, and Section 5 concludes the paper.

2. Brief review of IDA

Over the years many algorithms are proposed and implemented to have IDA that can achieve high incident detection rate and low false detection rate. A brief discussion of these algorithms is presented in this section. Two recommended reviews on this aspect are Mahmassani et al. (1999) and Parkany and Xie (2005). The algorithms can be classified into four broad groups: *comparative, statistical, time series, artificial intelligence algorithms*.

Comparative Algorithms

These algorithms rely on the principle that an incident is detected when a set of selected quantities exceed their respective thresholds. Some famous algorithms in this category are California series (Payne and Tignor, 1978; Nathanail et al. 2017), All Purpose Incident Detection (AIPD, Masters et al., 1991), TxDOT algorithm (Brydia et al., 2005) and DELOS (Chassiakos and Stephanedes, 1993). California #7 and DELOS are probably the two most implemented algorithms in this category. Both algorithms rely on occupancy differences between the upstream and downstream detectors. California algorithms use a tree structure to detect the incidents following a set of rules. DELOS uses a statistical smoothing technique to remove sharp and high-frequency fluctuations in occupancy before comparing those with predefined thresholds. Because they rely on static thresholds, comparative algorithms are incapable of handling fluctuating traffic demands efficiently. Despite these shortcomings, they are extensively used due to their simplicity and ease of application.

Statistical Algorithms:

Statistical algorithms are so named because they are designed to detect significant differences between observed detector data and predicted traffic characteristics. The most popular ones are the Standard Normal Deviate (SND, Dudek and Messer, 1974) and Bayesian Algorithm. These algorithms only rely on data from one detector location which makes them vulnerable to detector errors and data fluctuations.

Time series Algorithms:

Time-series algorithms consider the recent history of a traffic variable and employ statistical forecasting of traffic behavior to provide short-term traffic forecasts. Significant deviations between observed and forecast values are attributed to incidents. Some well-known algorithms in this category are ARIMA (Ahmed and Cook, 1977, 1982), SARIMA, SARMA (Fusco et al., 2016). The success of this model depends on the forecasting ability. A large set of historical data is required to calibrate/train the model.

Artificial intelligence algorithms:

Artificial intelligence (AI) refers to a set of procedures that apply “black box” reasoning and uncertainty in complex decision-making and data-analysis processes. The AI techniques applied in automatic incident detection include neural networks, fuzzy logic and a combination of these two approaches. A recent unsupervised automatic incident detection algorithm that was applied to the same incident database used in this paper can be found in Hernandez-Potiomkin et al., 2018. A large historical dataset is required to train them properly. However, being unsupervised, they do not need manual calibration efforts.

When choosing an algorithm for incident detection, many factors need to be considered such as data availability, complexity in implementation, calibration efforts and false detection rate. In this study, the California #7 algorithm has been chosen as the base IDA. It is one of the most widely used algorithms. It is easy to implement and needs only three parameters to calibrate. Also, the study shows that, if properly calibrated, California #7 can produce a low false detection rate compared to other sophisticated algorithms (Martin, 2001).

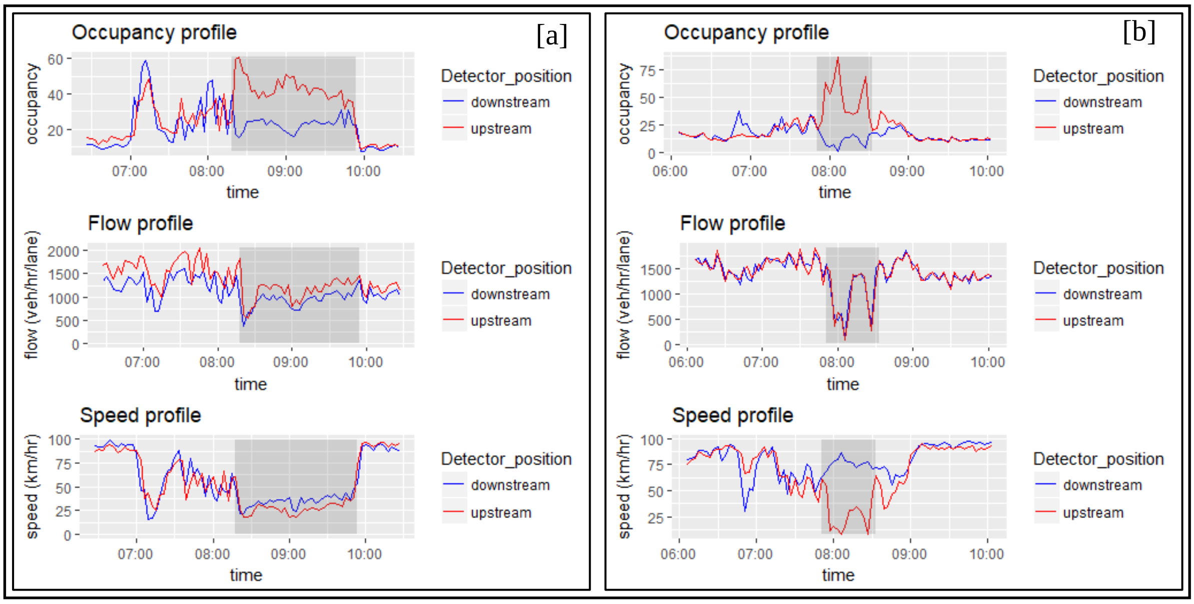
3. Analysis and models

3.1. Impact of the incident on traffic variables

Traffic incident is a broad term. It can include a wide range of situations from roadside plantation to fatal accidents. Hence, a definition of the incident is needed to identify it properly. In this paper, an incident is defined as an abnormal, non-recurrent traffic state at a given segment of the network at a given time. This definition eliminates recurrent traffic congestion that is observed in the morning and evening peak periods. It also eliminates incidents that have little or no impact on the traffic variables. For example, an incident like vehicle breakdown on the emergency stopping lane is not going to impact the mainline traffic flow. Hence, these incidents are hard to be identified as an abnormal situation from usual traffic variables.

The reported incident data used in this study are analyzed with the traffic data collected from loop detectors. Both the incident and detector data are collected on Sydney M4 motorway from January 2014 to July 2016. Due to time constraint, incident data from 8 selected months are analyzed in detail. The selected months are March 2014, March 2015, May 2015, July 2015, Sep 2015, Nov 2015, Jan 2016 and March 2016. The two datasets are matched with time and location of the incident. It is important to identify the exact start and end time of the incident and the upstream and downstream detectors. For this study, a total of 77 incidents that occurred on the Sydney M4 motorway have been selected after manual inspection. Among them, 72 are Accident, and 5 are Breakdown. A point to be noted here is that the recorded start/end time of the incident was not reliable mostly because these values were manually recorded after the incident has occurred. Hence, the start and end time are updated after manual inspection of the incidents based on the change in occupancies. The term occupancy refers to the percentage of time that there is a vehicle over the detector (e.g., 0 for no vehicle and 100 for standstill vehicle on the detector). At the time of the incident, the occupancy in the upstream detector rises, and the downstream occupancy drops. Hence, the start of the incident is considered at the point from where a difference in occupancy between the upstream and downstream detectors starts to increase, and the end is considered when this difference in occupancies faded away. Figure 1 shows an example of two incidents and their impact on average occupancy speed and flow profiles. The shaded area refers to the duration of the incident. For all incident, the nearest upstream and downstream detector data has been used.

Figure 1: Incident impact on occupancy, flow and speed profiles.



* Dark shaded area refers to the duration of the incident.

The incident in Figure 1(a) is recorded as an "accident" occurred on 16 September 2015 at 08:27 AM on the eastbound (towards Sydney CBD) traffic. The incident in Figure 1(b) is also recorded as an "accident" occurred on the eastbound direction of traffic on M4 motorway that occurred on 6 November 2015 at 08:04 AM. In both cases, the usual occupancy behavior is observed. As the incident is likely to create congestion in the upstream, the occupancy rises and the speed drops in the immediate upstream detector. The opposite behavior is observed in the downstream detector where the occupancy drops due to lack of flow.

Interestingly, the speed profile in the downstream detector shows different behavior for the two incidents. The speed drops for the incident in Figure 1(a) and rises for the incident in Figure 1(b). This opposite behavior could be due to the presence of on/off ramp in between the two detectors, the location of the incident, or number of lanes affected by the incident. The incident database does not have enough information to investigate this uncertain speed behavior. On the other hand, the behavior of flow remains consistent for both the incidents. A flow drop, in both upstream and downstream detectors, is observed during the incident period, that is associated with the capacity drop caused by the incident due to temporary blockage of one or more lanes.

After closely analyzing all the incident cases, a consistent flow and occupancy profile is observed; however, the speed profile varied among the incidents. The occupancy profile shows a rise at the upstream detector and a drop at the downstream detector location. This opposite nature of the occupancy profile in the two consecutive detector locations is observed during the incident period. Unlike the occupancy profile, a flow drop occurs in both the detector locations. Although the magnitude of the flow drop varies during the incident period [see Figure 1(b)], the drop is consistent at the start of the incident. Table 1 shows some descriptive statistics of the traffic variables within the incident period.

According to Table 1, the average occupancy difference between the upstream and downstream detectors within the incident period becomes 20.6, and this difference is statistically significant (p-value <0.001). It also shows that the upstream detector speed drops by 26.2 km/hr from the downstream detector and this difference is also statistically significant (p-value <0.001). However, the opposite speed behavior is also observed. To be exact, 9 out of 77 cases the average speed in the upstream detector becomes higher than the downstream speed. No significant difference between the upstream and downstream flows has been observed. The average difference between the two flows is 16.15 veh/hr/lane.

Although traffic flow drops, it shows large fluctuation during the incident period as observed in Figure 1. The maximum flow drop from the no-incident period is also reported in Table 1. In both locations a high flow drop is observed, indicating a significant reduction in capacity during the incident period. Table 1 shows that the average flow drop in upstream and downstream detector location is 748.1 and 663.6 veh/hr/lane respectively. Adding this extra information about the capacity drop in the IDA should help to reduce the false detection rate. More discussion on the benefit of including traffic flow observations in IDA is explained in section 4.2.

Table 1: Descriptive statistics of the traffic variables within the incident period

	mean	SD	min	max	t-test[3]	
					t-value	p-value
Average[1] upstream occupancy	38.63	10.97	3.60	65.50		
Average downstream occupancy	16.70	10.60	1.78	59.17		
Difference[2] in the average upstream and downstream occupancies	21.93	11.14	0.80	54.70	12.531	<0.001
Average upstream flow [veh/hr/lane]	1027.35	311.00	214.92	1547.08		
Average downstream flow [veh/hr/lane]	1043.50	313.47	161.27	1574.67		
Difference in the average upstream and downstream flows [veh/hr/lane]	-16.15	196.13	-575.31	492.03	-0.319	0.750
Average upstream speed [km/hr]	33.98	14.39	11.33	82.77		
Average downstream speed [km/hr]	61.19	22.28	16.42	99.18		
Difference in the average upstream and downstream speeds [km/hr]	-27.20	21.17	-69.97	17.58	-8.940	<0.001
Maximum flow drop[4] on upstream detector [veh/hr/lane]	748.07	409.76	26.67	1980.00		
Maximum flow drop on downstream detector [veh/hr/lane]	663.57	386.93	53.33	1593.33		

[1] Average values are calculated during the incident period
[2] The difference is calculated as upstream variable – downstream variable
[3] Welch two-sample t-test is performed to find whether the difference between the upstream and downstream traffic variables are significant or not. The null hypothesis is that the upstream and downstream detector shows no difference in traffic variables.
[4] Maximum flow drop is calculated as the maximum difference of upstream

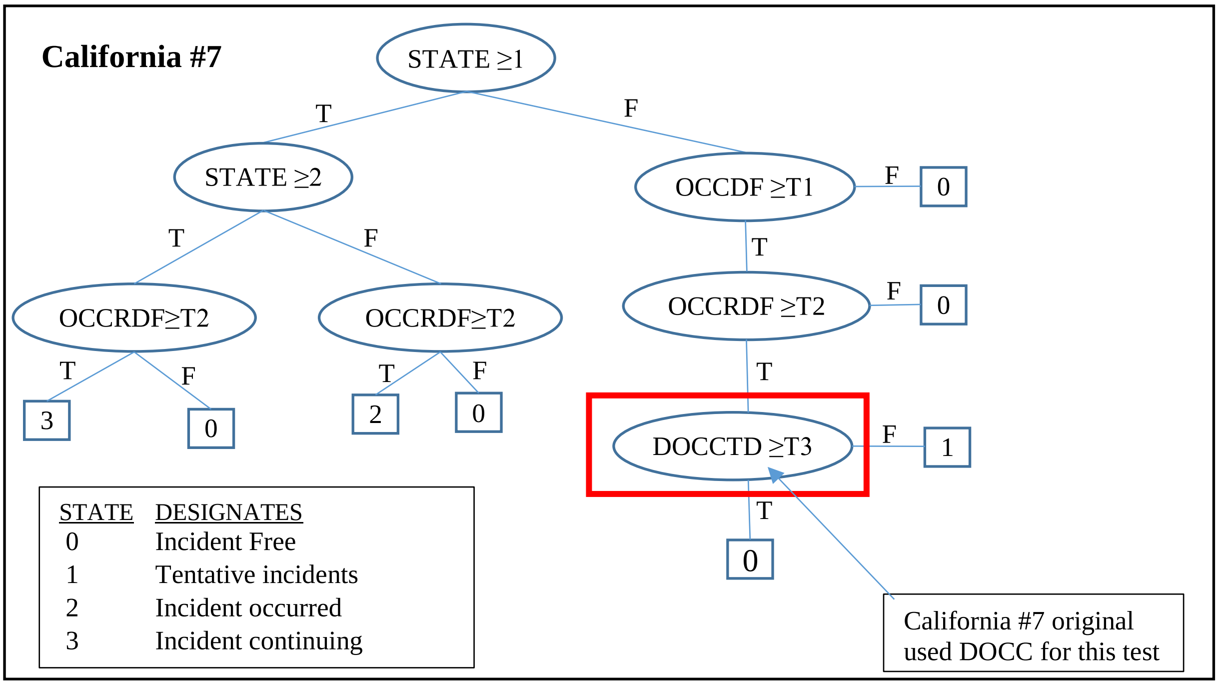
3.2. California #7 IDA

Two versions of California #7 algorithm are found in the literature. The widely used version is named here as 'California #7' and the pioneer version (by Payne and Tignor, 1978) is named as 'California #7 Original'. The only difference between these two versions is the third test to identify the start of the incident. While the original version used the downstream occupancy (DOCC) threshold, the later version used the temporal difference in downstream occupancy (DOCCTD) to avoid compression wave. The algorithm is shown in Figure 2. The variables used in the California #7 are described in Table 2.

Table 2: Variables for California #7 algorithm

$OCC_i(t)$	Occupancy at station i, for time interval t	
$DOCC_i(t)$	Downstream occupancy	$OCC_{i+1}(t)$
$OCCDF_i(t)$	Spatial difference in occupancies	$OCC_i(t) - OCC_{i+1}(t)$
$OCCRDF_i(t)$	Relative spatial difference in occupancies	$\frac{OCC_i(t) - OCC_{i+1}(t)}{OCC_i(t)}$
$DOCCTD_i(t)$	Temporal difference in downstream occupancies	$OCC_{i+1}(t) - OCC_{i+1}(t-1)$

Figure 2: California #7 algorithm (widely used version, Nathanail et al., 2017)



Both the versions of California #7 algorithm only rely on occupancy measures. It takes two time-steps to confirm an incident in the California #7 algorithm. Once a tentative incident is confirmed the algorithm moves the traffic state to 1. There is no difference in the test for determining STATE 2 and 3. In both cases, the incident is confirmed/continued based on the relative difference in the occupancies between the two detectors.

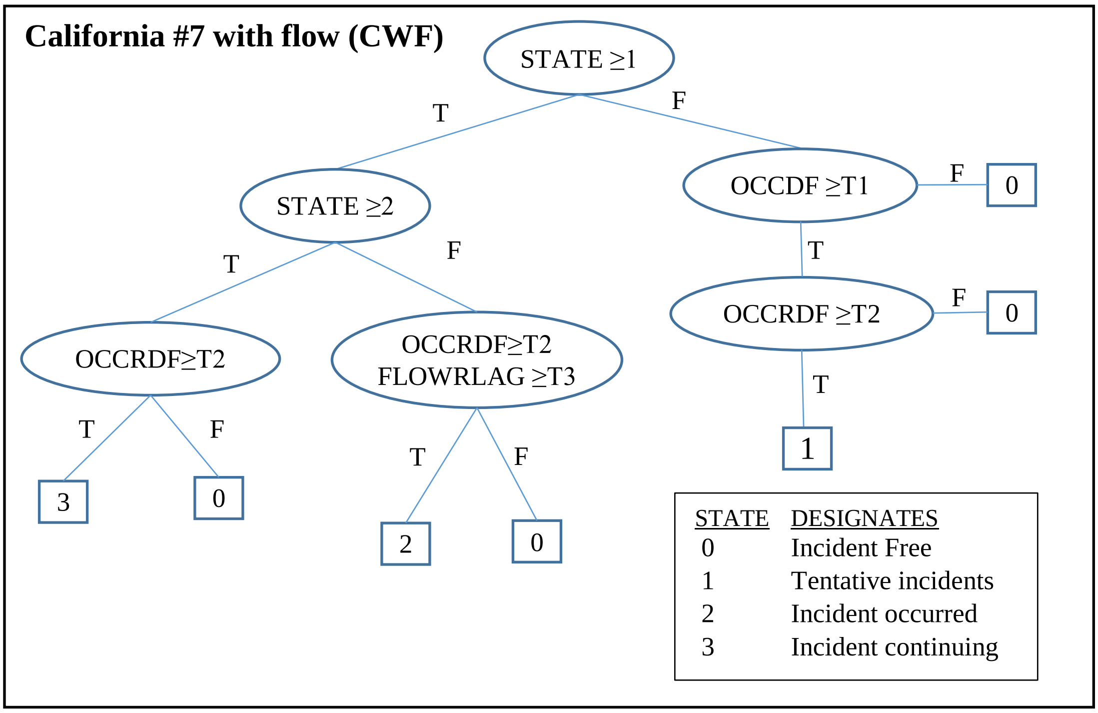
3.3. Proposed IDA

This section presents an extension of California #7 algorithm. A new test is introduced in the second stage (when 1≤ STATE <2) which compares the flow drop from two time-steps before. The analysis in Section 3.1 shows a significant reduction of flow during the incident period at both detector location. To incorporate this flow behavior, it is assumed that a significant flow drop should be observed within two time-steps (that is 6 min in this case) since the occurrence of the incident. This new parameter, named FLOWRLAG, calculates the relative difference of flow between the current and historical flow before two time-steps as shown below.

$$FLOWRLAG_i(t) = \frac{FLOW_i(t) - FLOW_i(t-2)}{FLOW_i(t-2)}$$

The proposed modification is aimed to reduce the false alarm rate by eliminating incidents that have no significant impact on flow [i.e., does not create a flow breakdown]. The tree structure for the California #7 with flow (CWF) algorithm is presented in Figure 3.

Figure 3: California #7 with flow (CWF)



4. Results

4.1. Model performance criteria

For each incident, 4-6 hours of detector data have been collected (depending on the duration of the incident). Each time stamp has an incident flag = 1 (if there was an incident) and 0 (if no incident). We have considered each time step data to assess the model performance. The model performance was judged by the following criteria:

Table 3: Model performance criteria

	IDA incident flag = 0	**IDA incident flag = 1**
Observed incident flag = 0	TN	FP
Observed incident flag = 1	FN	TP

$$Detection\ rate\ (DR) = \frac{\sum TP}{\sum TP + \sum FN} \times 100$$
$$False\ alarm\ rate\ (FAR) = \frac{\sum FP}{\sum TN + \sum FP} \times 100$$
$$Match\ rate = \frac{\sum TN + \sum TP}{\sum TP + \sum FN + \sum TN + \sum FP}$$

Genetic algorithm (GA) has been used to calibrate the IDA. Match rate is used as the fitness function as this function will ensure maximum detection rate and minimum false alarm rate.

4.2. Results

Among the 77 selected incidents, 47 are chosen for the calibration of the IDA's, and the remaining 30 incident data are kept for validation. Data for calibration are collected from 5 months in 2015 (March, May, July, September, and November). The validation data are taken from March 2014, January and March 2016. The calibration and validation results are presented in Table 4 and 5 respectively.

Table 4: Calibration results

	California #7 Original	California #7	CWF
Parameters T1 T2 T3	 9.890764 0.3115387 28.80351	 9.926472 0.3116138 0.2435977	 9.863175 0.311479 -0.1461160
Detection rate [%]	77.54	77.23	74.61
False alarm rate [%]	2.64	2.68	2.24
Match rate [%]	92.22	92.11	91.76

Table 5: Validation results

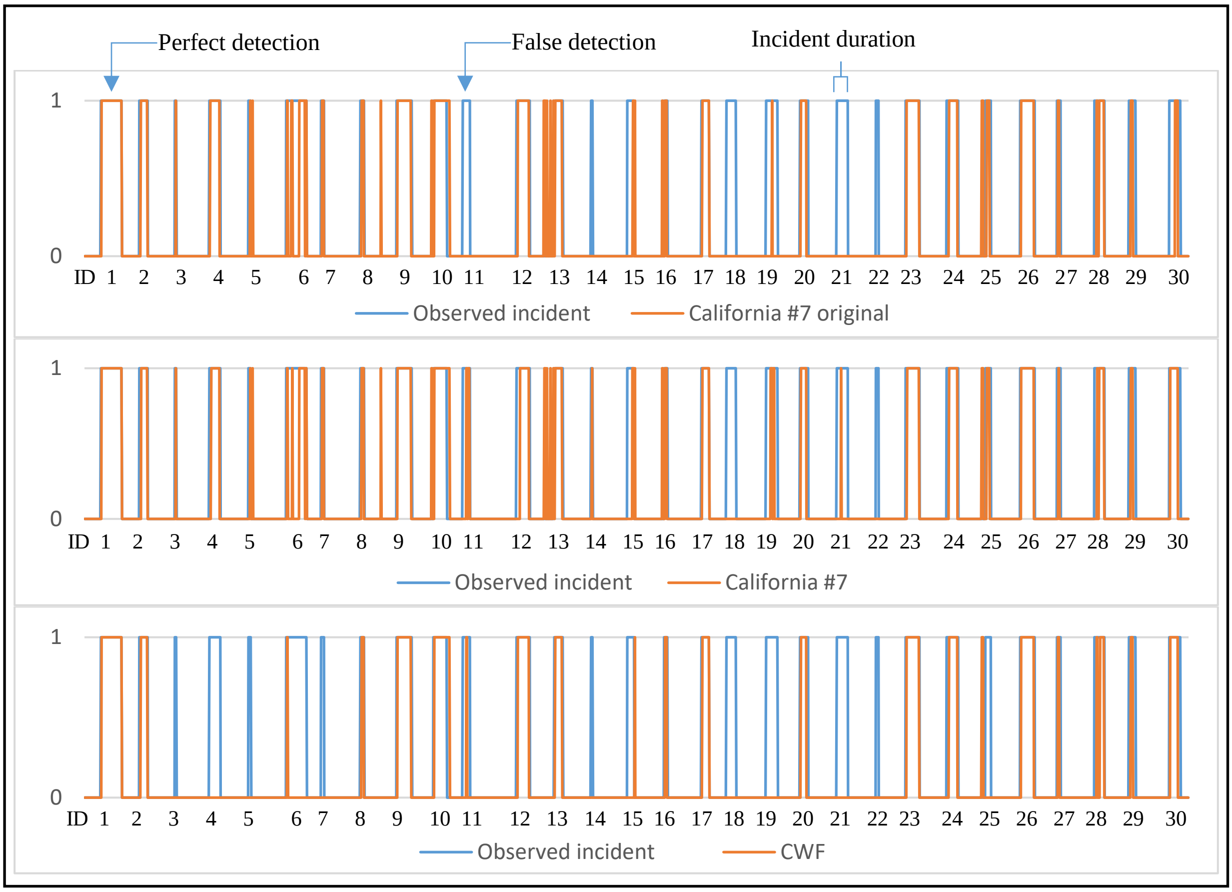
	California #7 Original	California #7	CWF
Detection rate [%]	64.12	66.33	62.76
False alarm rate [%]	2.34	2.45	1.99
Match rate [%]	89.23	89.70	89.15

One point is obvious from the calibration and validation results in the above two tables is that the CWF algorithm shows low detection rate and significantly low false alarm rate than the other two algorithms. Also, the validation performance of the widely used California #7 algorithm is slightly better than the original version. The values in the table are calculated for each observation (i.e., observation at each time period is considered as an incident or non-incident data). To visualize the algorithm performance at the incident level, the validation data are plotted in Figure 4. In this figure, the data from 30 incidents are plotted one after another. An incident and non-incident point are recorded as 1 and 0 respectively.

The validation plot in Figure 4 shows that some of the short-lived incidents could not be captured via the IDAs. California #7 has captured the highest number of incidents (28 out of 30). The original version of California #7 has captured 25 out of the 30 incidents. Both the algorithms show false detection near incident number 13. The CWF algorithm shows the least performance regarding detection (detected 21 out of 30 incidents) but no false detection. To better understand the underlying reason behind the detection process, four cases are analyzed in detail:

Case1: Perfect detection in all three algorithms (incident id 9);
Case 2: No detection in all three algorithms (incident id 18);
Case 3: Detected in California algorithms but not in the CWF (incident id 4);
Case 4: False detection by California algorithms (incident id 13).

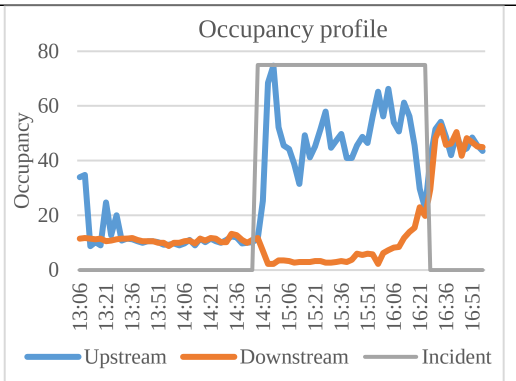
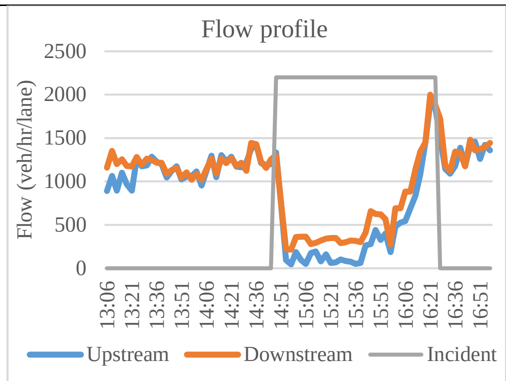
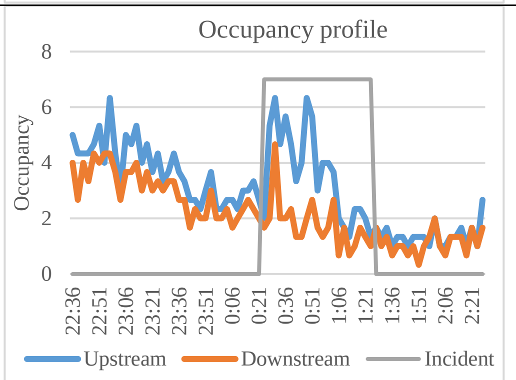
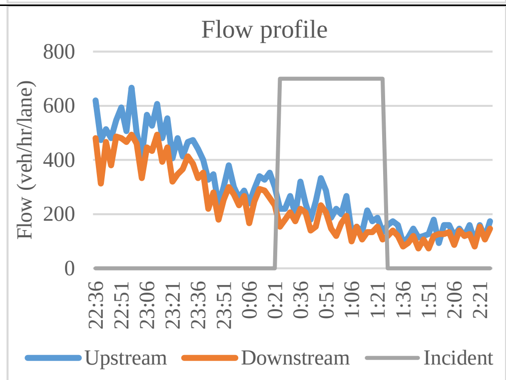
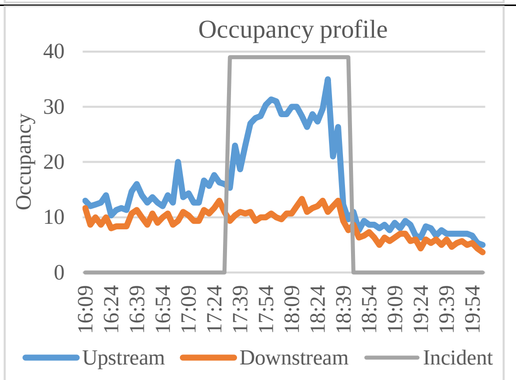
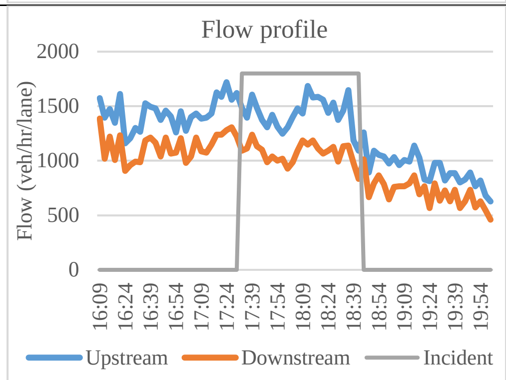
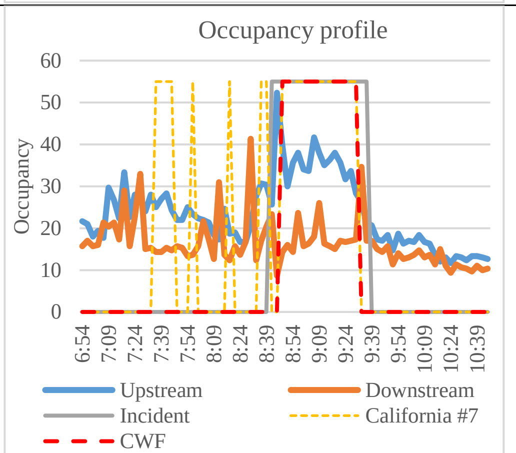
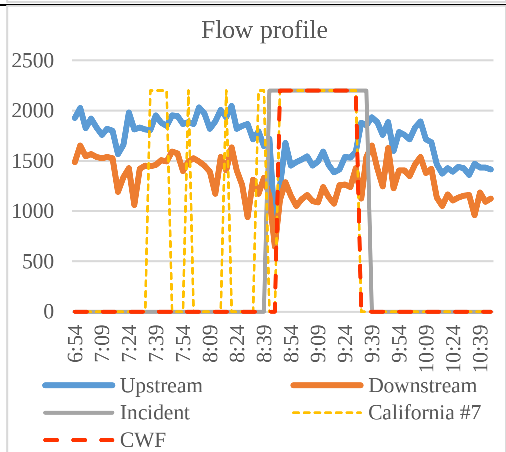
Figure 4: Validation performance of the IDAs *



* In the above plot "0" stands for no incident and "1" for incident. When the line jumps to 1, an incident occurs and when it drops to 0 the incident ends. Sudden rise and drops creates thick band as seen for incident 13.

The occupancy and flow profile for these incident cases are presented in Figure 5. In case of perfect detection (Case 1) the usual occupancy behavior (rise in upstream and drop in downstream occupancy) is observed along with a flow drop in both detector locations. In Case 2 the occupancy difference is observed; however, the difference is not big enough to pass the IDA threshold. Moreover, no capacity drop is observed. The reason behind such low impact on flow and occupancy is mostly due to low traffic at the time of the incident (occurred at midnight). For Case 3 the usual occupancy difference is observed, and the incident was detected via California algorithms. However, no significant flow drop is observed to be detected by the CWF algorithm. Also, there is an off-ramp located in between the two detectors which explains why the flow profile in the upstream detector is always higher than the downstream one. As the incident occurred during the afternoon peak, the rise of occupancy could be either caused by the incident or by the off-ramp congestion. As no major the impact on flow and occupancy is observed, it was not detected by the CWF algorithm.

Figure 5: Understanding incident detection

Case 1 - Perfect detection [Incident id = 9]		
Case 2 – No detection [Incident id =18]		
Case 3 - No detection by CWF [Incident id = 4]		
Case 4 – False detection [Incident id = 13]		

The most interesting case would be Case 4 where the false detection for California algorithms is observed. Relying on occupancy difference alone makes the California algorithm vulnerable to false detection of cases where the occupancy differences could be associated with some other reasons including stop-and-go traffic oscillation. At the beginning of Case 4, the occupancy differenced were identified as an incident by the California algorithm even though no trace in the change of flow is observed. This occupancy difference is not related to the actual incident that occurred about an hour later where both the change in occupancy and drop of capacity is observed. Unlike the California algorithm, the CWF has captured only the true incident without that false detection. This example explains the need of including capacity drop test along with the usual occupancy tests to reduce false incident detection.

4.2. Practical implications of the research findings

This research presents some detailed analysis of the impact of incidents on traffic variables. Findings from this research should apply to all motorways and highways that do not have traffic lights. The precise relationship between the incident and traffic variables (mostly occupancy and speed) can be used to develop better IDAs. One example of such an improved algorithm is presented here. The CWF algorithm has successfully reduced the false incident detection rate. Thus, it can be used at TMC to identify incidents that would have a significant impact on traffic flow. With a low false alarm rate, the CWF algorithm is likely to regain the faith of the TMC personnel. The study also identifies some reliable traffic variables for IDA. For example, the drop of flow is identified as an essential variable which has not been explored much in previous research on IDAs.

By modifying the threshold values the new algorithm can be applied to detect incidents that have a large or small impact on the traffic flow. The dependency on the static threshold values is a well-known drawback of these algorithms. However, compared to the black-box approach of automatic incident detection, the threshold-based algorithms are easy to manage. More importantly, as the parameters have intuitive meaning, the threshold values can be adjusted to modify the detection capability. Moreover, the parameters used in the CWF algorithm is normalized to be applicable for any other motorways.

5. Conclusion

This research aims to understand the impact of traffic incidents to have a better incident detection algorithm that will drastically reduce the false detection rate. To achieve that, detail analysis of some selected incidents is performed, and their impact on occupancy, flow and speed profile is closely observed. The analysis discovers the fact that an incident is likely to create a difference in occupancy and speed between the upstream and downstream detectors. While the occupancy in the upstream detector rises during an incident, the speed is likely to drop, and the opposite is observed in the downstream detector. At the same time, the incident creates a disturbance in the flow which shows a significant reduction in roadway capacity.

Findings from this analysis have been incorporated to develop a new IDA. The detection rate of the CWF algorithm is lower than the California #7 as it only identifies the incidents that have a significant impact on flow. However, the false detection rate has drastically reduced compared to the base. The validation performance shows that the CWF algorithm has 5.3% lower detection rate and 18.8% lower false alarm rate compared to California #7. The new IDA avoids minor incidents that have little or no impact on the roadway capacity. It also avoids recurrent traffic jams as the jam characteristics on flow and occupancy is different than incident (no sudden capacity drop and no large difference in occupancies between two consecutive detectors).

The quality of the incident data may not ensure a perfect start/end time of the incident which is needed for proper calibration of IDA. In this respect, a cross-validation technique by using more than one IDA can be used. One such attempt has been taken in Hernandez-Potiomkin et al. (2018). Future work should also involve applying the CWF algorithm to a continuous set of data (for example one month of traffic data) and observe its performance. The inclusion of flow in IDA seems promising in this study. Future study should also test other measures such as speed difference, flow difference, and other combinations.

Acknowledgments

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