Development of an Automated Approach for Quantifying Spatiotemporal Impact of Traffic Incidents

Hong Yang, Ph.D.
(Corresponding author)
Assistant Professor
Department of Modeling, Simulation & Visualization Engineering (MSVE);
Transportation Research Institute (TRI),
Old Dominion University
4700 Elkhorn Ave,
Norfolk, VA 23529
E-mail: hyang@odu.edu
Phone: +1-(757)-683-4529

Kaan Ozbay, Ph.D.
Professor, Department of Civil & Urban Engineering;
Center for Urban Science + Progress (CUSP),
New York University (NYU)
One MetroTech Center, 19th Floor
Brooklyn, NY 11201
Tel: +1-(646)-997-0552
Email: kaan.ozbay@nyu.edu

Kun Xie, Ph.D. Candidate
Department of Civil & Urban Engineering,
Center for Urban Science + Progress (CUSP),
New York University (NYU)
One MetroTech Center, 19th Floor
Brooklyn, NY 11201
Email: kun.xie@nyu.edu
Phone: +1-(646)-997-0547

Yifang Ma, M.Sc.
Center for Urban Science + Progress (CUSP),
New York University (NYU)
One MetroTech Center, 19th Floor
Brooklyn, NY 11201
Email: ym30@nyu.edu
Phone: +1-(646)-997-0548

Word count: 4678 Texts + 2 Table + 3 Figures = 5928
Abstract: 170
Resubmission Date: November 15, 2015

TRB16-5943
Transportation Research Board’s 95th Annual Meeting, Washington, D.C., 2016
ABSTRACT
Traffic congestion on roadways seriously affect travel experience and cause economic and environmental problems. Part of the recurrent congestion is due to roadway bottlenecks such as lane drops or exit/entry ramps. Another major type of congestion is induced by traffic incidents such as traffic crashes. The former can be remedied by removing physical bottlenecks through the improvement of roadway capacity, geometry etc. However, the latter usually randomly occurs due to the high level of stochasticity of incident events. Therefore, it is a challenge to capture these non-recurrent congestion hot spots due to incidents. Nevertheless, the availability of real-time traffic sensor data provides the opportunity to address this issue through the use of data-driven solutions. Thus, the main objective of this study is to develop an automated approach to quantify incident induced congestion using sensor data. A practice-ready data-driven non-recurrent congestion quantification algorithm is developed and its implementation is demonstrated through real-world case study. It has been shown that the proposed automated approach can be used to efficiently identify incident-induced congestion.
INTRODUCTION
Traffic incidents such as crashes and disabled vehicles can greatly disrupt normal flow of traffic. Many of these disruptive events can directly lead to physical impedance in terms of lane blockage. In addition, even minor incidents occurring on shoulders can also affect traffic flow by distracting drivers, changing driver behavior and ultimately degrading safety and quality of service. According to a 2005 FHWA research report, traffic incidents account for about a quarter of non-recurrent congestion on freeways. In many large metropolitan areas, incident-related delay can cause between one-half to two-thirds of the total travel delay. In addition, the presence of these incidents also lead to the high risk of secondary incidents (crashes). To address these issues, transportation agencies have been developing a number of traffic incident management (TIM) programs for reducing extremely negative impact of incidents.

To help transportation agencies develop more efficient TIM programs, the need to examine traffic incidents’ impact drew great attention of researchers in multiple disciplines such as transportation engineering, computer science and operational research. Analyzing the impact of incidents on traffic flow can help transportation agencies to monitor the performance of traffic operations and develop efficient incident response strategies to reduce the risk of congestion caused by primary and secondary incidents. However, one of the challenges in achieving the goal of effective incident management is the accurate quantification of the spatiotemporal impact of each incident. A frequently used approach is the use of a deterministic queuing diagram approach that relies on the examination of capacity reduction due to an incident, the actual traffic demand, and queuing models to deduce the magnitude of the impact. However, there are several difficulties associated with the use of such an approach. For example, (a) the capacity reduction varies stochastically and dynamically according to the number of lanes blocked, type of the incident, progression of the incident clearance operations, etc.; and (b) detailed incident information might not be available in a timely manner to support the measurement of capacity reduction. Many analytical models are also site-specific and difficult to transfer.

In order to provide a more practical approach that can be used by agencies on a day-to-day basis, this study aims to develop an automated method that can capture the spatial and temporal extent of incident-induced traffic congestion. The proposed method takes advantage of traffic sensor data to dynamically identify the time-dependent progression of the incident impact. Its implementation has been demonstrated through real-world case study. The step-by-step algorithm provides a practice-ready procedure to develop incident-related congestion quantification method.

LITERATURE REVIEW
Numerous empirical observations suggest that a primary cause of day-to-day variability in travel time is attributed to traffic incidents such as crashes that block lanes for extended periods. Researchers have made great effort towards developing algorithms/approaches to detect the occurrence of these incidents causing delays. However, these incident detection studies offer very limited information about the impact of incidents on traffic congestion. Clearly, knowing when and where congestion will occur under the incident condition will be very helpful for traffic incident management. Motivated by this question, a number of studies have examined the impact of incidents on traffic congestion.

A large number of studies focused on examining incident induced delays, primarily based on queuing theory and shock wave analysis. For example, the deterministic queuing model is one of the frequently used approaches for estimating incident induced delays. Fu and Rilett developed a dynamic and stochastic model within a traditional deterministic queuing model approach for predicting incident induced delays. Wang et al. used modified deterministic queuing theory to develop an algorithm for quantifying travel delays caused by different incident categories. These queuing models require the identification of capacity reduction, demand change, and a balance...
equation to determine the extent of the delay (18). These requirements limited the application of the queuing models because capacity reduction changes dynamically due to the stochastic nature of incidents and it is also difficult to measure traffic demand changes due to possible diversion (18, 19). Many studies (20, 21) made an attempt to use shock-wave theory to predict travel delays. However, as revealed by Messer et al. (20), inaccuracy in estimating wave speeds can cause serious misinterpretation of the incident-induced delays. Similarly, Al-Deek et al. (22) investigated both single and multiple incident delays based on shock wave analysis and suggested that the use of homogeneous traffic data for estimating wave speeds can lead to unrealistic estimates in congestion. Chow (23) evaluated the performance of using queuing models and shock wave analysis in estimating incident-induced delays and suggest that the use of time-dependent flow-density relationship can lead to more realistic estimates in the total incident delays.

Another set of research projects have primarily focused on the analysis of the duration of incidents. For example, Garib et al. (24) developed linear regression models to estimate magnitude and duration of freeway incident delays. Traffic flow conditions and detailed incident characteristics such as incident type, degrees of severity, location, etc. were used to find the magnitude and duration of incident delays. Khattak et al. (25) developed a truncated regression model for estimating incident duration considering the unobserved impact of minor incidents. Ozbay and Kachroo (26) tested the linear regression model to predict incident duration based on incidents from northern Virginia and suggested the needs to group incidents by types and severity. Ozbay and Kachroo have for the first time in the literature proposed the use of non-parametric approach namely “decision trees” to classify incident durations according to factors determined to affect incident durations of each category. This pioneering work by Ozbay and Kachroo was adopted in some studies (27-30) that also used nonparametric approaches for forecasting incident duration. For example, Valenti et al. (28) compared five models to predict incident duration. Three nonparametric models including artificial neural network (ANN), support/relevance vector machine (RVM), and k-nearest-neighbor (KNN) were tested. The prediction errors were found to change with different incident durations. Models based on decision tree (26, 28), probabilistic distribution (31, 32), hazard function (33), Bayesian classifier (34), and fuzzy logic models (35) are also frequently explored by researchers. The success of aforementioned methods heavily relies on the use of detailed incident information and prevailing traffic conditions. However, this is often a challenge because many factors related to traffic and incidents are highly uncertain and are difficult to objectively and timely quantify (36). Ozbay and Noyan (37) proposed a novel approach namely Bayesian Networks, to address these uncertainty and time dependence problems. They estimated a Bayesian Network based duration estimation model using the Northern Virginia data used in Ozbay and Kachroo (26). It is important to emphasize that all of the developed models are often facility specific and calibration is required for their use at other facilities.

Considering its flexibility, a few studies examined the potential of using traffic simulation models in the analysis of the effects of incidents and corresponding incident management strategies. For example, Cragg and Demetsky (38) tested CORSIM for assessing incident impact and traffic diversion strategies. Ozbay and Bartin (39) developed a simulation program in SIMAN to determine total delays due to incidents and to assess the performance of different incident response strategies. Kabit et al. (40) developed a Vissim simulation model to quantify impacts of a major incident and the associated costs. Lee et al. (41) simulated incident impact in Paramics and used data mining techniques (i.e. high-dimensional stacked bar charts) to visualize the impact. Yu and Kim (36) proposed a micro-simulation model to predict freeway incident impact and found that the estimated travel time was relatively accurate but the estimation of queue based on this approach was not reliable. Zhang et al. (42) predicted incident delays on freeway using TSIS simulation (Traffic Software Integrated Systems). Fries et al. (43) used a Paramics based simulation to assess the impact of quick clearance criteria deployed in South Carolina as a result of the legislation recently passed in
the State. In a follow-up study Ma et al. (44) again used a simulation model developed in Paramics to understand the impact of freeway service patrol in South Carolina. Ozbay et al. (45) used a customized simulation model to quantify the effects of various technologies used of traffic / incident management. These studies demonstrate the great promise of using simulation-based approaches to examine incident impact. Nevertheless, the needs for detailed traffic and incident data, incident duration prediction as well as simulation model calibration limited their large scale use.

Some recent studies (15, 46-48) began to investigate archived traffic sensor data and incident records for quantifying incident impacts. Chung and Recker (47) applied the integer programming technique in estimating the temporal and spatial extent of incident delays induced on freeways. It made an effort to utilize available inductance loop detector data for quantifying congestion. Pan et al. (48) also examined the archived incident and traffic data to quantify the impact of traffic incidents. With the availability of massive sensor data, more data-driven and location agnostic approaches are expected to be developed to quantitatively and timely capture the spatiotemporal impacts of traffic incidents.

METHODOLOGY
In order to automatically quantify impact of an incident on the traffic flow, this study proposes a data-driven algorithm to analyze sensor data under incident-free as well as incident conditions. The algorithm consists of four major steps summarized below.

Step 1: Use of sensor data to build speed contour map (SCM). Assume each sensor measurement represents traffic information of the upstream segment (the segment between current sensor and the adjacent sensor upstream). Denote the speed measurement \( V \) of \( j^{th} \) segment at \( i^{th} \) time period as \( V_{ij} \), \( \forall i = 1,2,3,...,T \) and \( \forall j = 1,2,3,...,S \). The original speed measurements are then coded by a continuous range of spectral colors (i.e., from red to green) to represent speed from low to high. This helps visualize the spatiotemporal changes of speed, which in turn facilitates the highlight of congested area (both recurrent and incident induced congestion).

Step 2: Creation of a representative speed contour map (RSCM) for incident-free conditions based on historical sensor data. For each segment at each time period, sample the corresponding historical speed measurements associated with no incident conditions (for instance, 1-year speed measurements at the same time period). The sampled measurements together generate a distribution of historical speed. Considering day-to-day variation of traffic, this study proposes to use \( p^{th} \) (i.e. 50\(^{th}\)) percentile of the sampled speed measurements of the segment as its representative speed \( \hat{V}(i,j) \).

Step 3: Generate the binary speed contour map (BSCM) by comparing \( V(i,j) \) with \( \hat{V}(i,j) \) obtained in previous two steps. If \( \hat{V}(i,j) - V(i,j) > \Delta V \), the current speed measurement is converted to \( V(i,j)=1 \), otherwise \( V(i,j)=0 \). These constraints help classify whether the segment is congested (abnormal) at the \( i^{th} \) time period. If the speed is \( \Delta V \) mph less than the representative speed, it is assumed that the corresponding segment is congested. Obviously, the selection of \( \Delta V \) is very important. It really depends on how agencies / traffic engineers define the abnormal traffic condition. For instance, one can assume 25 percent (or more) of reduction in the representative speed denotes the abnormal condition (i.e. incident condition). Alternatively, one can also consider multi-level \( \Delta V \) to classify the abnormal conditions for heavy, moderate, and light congestion etc. Once the appropriate criteria are specified, the original SCM is then converted to the BSCM based on the
aforementioned conversion functions. FIGURE 1 (a) shows an example of a binary speed contour map, and the orange cells represents observed congestion based on the speed changes.

**Step 4:** Automatically identify the spatiotemporal impact of incidents. TABLE 1 presents the pseudo code of the proposed algorithm. Briefly, given an incident occurrence at \((i, j)\), the algorithm first finds the neighbor cells (NC) of the target cell \((i, j)\). For instance, we can find all the eight neighbors of the incident \((i, j)\) shown in FIGURE 1 (b). Among these neighboring cells, we can find the first cell \((t, s)\) in the search sequences denoted by the arrows that represent a congested condition \(V(t, s) = 1\), for example, the cyan highlighted cell shown in FIGURE 1 (c). Then the cell \((t, s)\) is reset as the target cell and a new search process is performed to identify its neighbor cells with congested conditions. The recursive identification function is called whenever a congested cell is found. Following the recursive process, the impact area can be automatically identified. For example, FIGURE 1 (d) shows the final searching sequence in order that captures all the congested cells.

![FIGURE 1 Framework of quantifying incident impact on traffic flow.](image-url)
TABLE 1 Pseudo Code of Incident Induced Congestion Identification Algorithm

**Input**: Given an incident \((i, j)\):

**Start**: Identification Algorithm

**Define** an empty \(List\);

**Identify**\((i, j, List)\)

\{
  **If** \(V(i, j) = 1\) and \((i, j) \not\in List\):

  **List** \(\leftarrow (i, j)\);

  **Find** neighbors cells \((NC)\) of target cell \((i, j)\), see FIGURE 1 (b):

  \[NC \leftarrow (i - 1, j), (i - 1, j + 1), (i, j + 1), (i + 1, j + 1),
     (i + 1, j), (i + 1, j - 1), (i, j - 1), (i - 1, j - 1);\]

  **If** \(V = 0\) for all \(NC\):

  **Terminate program**;

  **Else** \{ **Find** 1\(^{st}\) \(NC = (t, s): V(t, s) = 1\) and \((t, s) \not\in List\), see FIGURE 1 (c):

  **Recursion**: \(List \leftarrow **Identify**(t, s, List); \}

\}

**Output**: \(List\);

---

The proposed approach assumes that the incident occurring within a congestion area [FIGURE 2 (a)] or outside a congestion area [FIGURE 2 (b)] will not be the cause of the congestion. In real-world conditions, an incident may not immediately induce a queue. Thus the proposed algorithm can be easily adjusted to address this time-lag problem by expanding the first searching window: instead of initializing the first searching within \(i \pm 1\), one can expand the search to \(i \pm \Delta t\) if the cells within \(i \pm 1\) are \(V' = 0\), where \(\Delta t > 1\). To be conservative, \(\Delta t\) can be two or more time intervals after the occurrence of the incident. For example, with a small time lag scenario as shown in FIGURE 2 (c), the proposed approach can be implemented whereas the large time lag scenario in FIGURE 2 (d) will be excluded.
CASE STUDY
To test the performance of the proposed algorithm, the highway section of the I15-S between milepost 54.6 and milepost 130.6 in California was studied. The speed limit is 70 mph. Incident records and traffic data including the speed, flow and occupancy measurements aggregated in 5-minute intervals from the 95 mainline sensors were obtained from the Freeway Performance Measurement System (PeMS) of the State of California (49). Data collected between January, 2011 and June, 2011 were extracted for the case study. For the speed measurements at a given section and time interval, the corresponding measurements in other days of the 6 months were used to generate the historical speed distribution and 50\textsuperscript{th} percentile speed was assumed to be the representative speed for the non-incident condition. In addition, if the observed speed measurement is 25 percent less than the representative speed, it was assumed that the traffic condition was abnormal. FIGURE 3 (a) shows the original speed contour map and 12 incidents (blue dots) occurred on March 19, 2011. The description of these incidents are presented in TABLE 2. FIGURE 3 (b) shows the developed binary speed contour map. Implementing the proposed algorithm, the impact of each incident is detected and highlighted in cyan [see FIGURE 3 (c)]. It was identified that only two crashes induced congestions: (1) Crash \textit{A} occurred at 9:11 am at milepost 116.429 and (2) Crash \textit{B} occurred at 13:23 at milepost 130.443. The reported duration of crash \textit{A} was 386 minutes (until 15:37) whereas the identified impact on traffic flow last until 15:00 and the spatial impact reached the milepost 119.264. This was a serious crash involving an ambulance as one of the response vehicles. Similarly, the duration of crash \textit{B} was 58 minutes (until 14:21) whereas its impact lasted until 14:05 and reached the milepost 130.6. After screening all incidents, we observed that all other incidents of shorter durations did not induce congestion.
<table>
<thead>
<tr>
<th>Incident.Id</th>
<th>Start.Time</th>
<th>Duration (mins)</th>
<th>Abs.PM</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>11883727</td>
<td>4:21</td>
<td>31</td>
<td>119.673</td>
<td>1179 - Traffic Collision - Ambulance Responding</td>
</tr>
<tr>
<td>11883783</td>
<td>5:14</td>
<td>2</td>
<td>102.353</td>
<td>1179 - Traffic Collision - Ambulance Responding</td>
</tr>
<tr>
<td>11883813</td>
<td>5:34</td>
<td>0</td>
<td>100.064</td>
<td>1183 - Traffic Collision - No Details</td>
</tr>
<tr>
<td>11883817</td>
<td>5:36</td>
<td>0</td>
<td>102.353</td>
<td>1183 - Traffic Collision - No Details</td>
</tr>
<tr>
<td>11883829</td>
<td>5:41</td>
<td>42</td>
<td>119.473</td>
<td>1182 - Traffic Collision - No Injuries</td>
</tr>
<tr>
<td>11883887</td>
<td>6:26</td>
<td>11</td>
<td>100.064</td>
<td>1183 - Traffic Collision - No Details</td>
</tr>
<tr>
<td>11884150</td>
<td>9:11</td>
<td>386</td>
<td>116.429</td>
<td>1179 - Traffic Collision - Ambulance Responding</td>
</tr>
<tr>
<td>11884815</td>
<td>13:23</td>
<td>58</td>
<td>130.443</td>
<td>1183 - Traffic Collision - No Details</td>
</tr>
<tr>
<td>11884960</td>
<td>14:09</td>
<td>0</td>
<td>102.553</td>
<td>1182 - Traffic Collision - No Injuries</td>
</tr>
<tr>
<td>11885260</td>
<td>15:50</td>
<td>16</td>
<td>61.527</td>
<td>1182 - Traffic Collision - No Injuries</td>
</tr>
<tr>
<td>11885558</td>
<td>17:45</td>
<td>20</td>
<td>111.656</td>
<td>1183 - Traffic Collision - No Details</td>
</tr>
<tr>
<td>11885848</td>
<td>19:50</td>
<td>17</td>
<td>114.521</td>
<td>1179 - Traffic Collision - Ambulance Responding</td>
</tr>
</tbody>
</table>

**FIGURE 3** Investigating I15-S incident impact on traffic.

In order to verify the performance of the proposed approach, incidents and congestion under different conditions were also examined. In general, there are four scenarios: (a) incidents induced congestion, (b) congestion induced incidents, (c) incidents causing no congestion, and (d) congestion causing no incidents. As the proposed approach focuses on identifying the spatiotemporal impact of incidents, it should be able to capture scenarios (a) and (c) only.
FIGURE 4 Verifying the performance of the proposed approach.

In FIGURE 4(a), there was an incident that occurred at 6:45 am at the milepost 111.656 on February 23, 2011. The incident duration was 25 minutes. It can be seen that the congestion area induced by the incident was identified in FIGURE 4(a). The maximum queue was about 1.5 miles and the maximum temporal impact lasted about 105 minutes. Similarly, FIGURE 4(b) illustrates that an incident occurred at the end of the queue. Thus, the congestion area that started around the milepost 92 in the afternoon was not attributed to the incident, and therefore, the proposed approach excluded this scenario. FIGURE 4(c) shows that two incidents occurred without inducing any congestion. Two congestion periods that occurred in the afternoon were not classified as incident induced congestion. Under no incident condition in FIGURE 4(d), the congestion areas were not classified as incident induced congestion. As for more validation, it is suggested that a sensitivity analysis can be further performed with different threshold values to depict congestion occurrence as well as different sizes of training data.

CONCLUSIONS

Incident induced congestion is one of the major sources of traffic delays. Quantifying incident induced delays helps monitor performance of the roadways and assess various congestion mitigation measures. This paper developed a new approach to automatically identify the spatiotemporal impact of each incident. The case study demonstrated its performance of screening all incidents and
quantifying the ones with notable impact on traffic. The proposed algorithm integrated incidents (without requiring too much detailed information) with the traffic sensor data to provide agencies / traffic engineers with a data-driven approach for developing incident-induced performance measures in terms of traffic operations. The use of simple yet informative heat maps makes it extremely easy to identify and understand the extent of the spatio-temporal impacts of these accident events in an efficient way. Additional uses of the developed approach include identifying secondary incidents based on the quantified impact area. It can also be extended to explore incidents induced by traffic congestion. Besides, it should be mentioned that the approach was tested using sensor data from instrumented highways. In case of other highways with few or without sensors, third-party data sources, for example, virtual sensor data (50), can be used to make this kind of analysis possible. In addition, one can also use clustering algorithms to obtain clusters of monthly/seasonal sensor data and implement the proposed approach to develop different speed maps for each clusters.

ACKNOWLEDGEMENTS
The contents of this paper only reflect views of the authors who are responsible for the facts and accuracy of the data presented herein. The contents of the paper do not necessarily reflect the official views or policies of the any agencies. The support provided by New York University (NYU, Department of Civil & Urban Engineering, and the Urban Mobility and Intelligent Transportation Systems (UrbanMITS) laboratory at NYU is appreciated.

REFERENCES


