Development of a Secondary Crash Identification Algorithm and Occurrence Pattern Determination in Large Scale Multi-Facility Transportation Network

Afrid A. Sarker [a,c], Alireza Naimi [a,c], Sabyasachee Mishra [a,c*], Mihalis M. Golias [a,c], Philip B Freeze [b]

[a] Department of Civil Engineering, University of Memphis, 3815 Central Avenue, Memphis, TN 38152, United States
[b] Tennessee Department of Transportation, Nashville, TN 37243, United States
[c] Intermodal Freight Transportation Institute, University of Memphis, Memphis, TN 38152, United States

Abstract

Secondary crash (SC) occurrences are non-recurrent in nature and lead to significant increase in traffic delay and reduced safety. National, state, and local agencies are investing substantial amount of resources to identify and mitigate secondary crashes in order to reduce congestion, related fatalities, injuries, and property damages. Though a relatively small portion of all crashes are secondary, their identification along with the primary contributing factors is imperative. The objective of this study is to develop a procedure to identify SCs using a static and a dynamic approach in a large-scale multimodal transportation networks. The static approach is based on pre-specified spatiotemporal thresholds while the dynamic approach is based on shockwave principles. A Secondary Crash Identification Algorithm (SCIA) was developed to identify SC on networks. SCIA was applied on freeways using both the static and the dynamic approach while only static approach was used for arterials due to lack of disaggregated traffic flow data and signal-timing information. SCIA was validated by comparison to observed data with acceptable results from the regression analysis. SCIA was applied in the State of Tennessee and results showed that the dynamic approach can identify SCs with better accuracy and consistency. The methodological framework and processes proposed in this paper can be used by agencies for SC identification on networks with minimal data requirements and acceptable computational time.

Keywords: secondary crashes, dynamic approach, kinematic shockwave, crash pairing, impact area

[*] Corresponding author.: Tel.: +1 901 678 5043
E-mail addresses: aasarker@memphis.edu (A.A. Sarker), alienaimi@gmail.com (A. Naimi), smishra3@memphis.edu (S. Mishra), mgkolias@memphis.edu (M.M. Golias), Phillip.B.Freeze@tn.gov (P.B. Freeze)

1. Introduction

Traffic crashes are a major source of congestion on freeway and arterial systems. A "*primary crash (PC)*" leads to reduction of roadway capacity and may result in what is known as a "*secondary crash (SC)*". In this paper, the terms '*crashes*' and '*incidents*' are used interchangeably. SCs are defined as crashes that occur in close proximity of the primary incident's location as a result of either queuing (in the same direction) or driver distraction (in the opposite direction) (Margiotta et al., 2012). Earlier studies suggest that up to 15% of reported crashes have occurred partly or entirely as the result of a PC (Raub, 1997a). Though a relatively small percentage of all crashes are secondary, it is important to identify contributing factors and characteristics, and mitigate their effects on congestion, delay, fuel consumption and emission. SCs are non-recurring in nature and contribute up to 50% of congestion in urban areas (Kwon et al., 2006; Ozbay and Kachroo, 1999; Skabardonis et al., 1998). Reducing the occurrence of SCs is a major concern for traffic incident management (TIM) agencies, especially when dispatching rescue vehicles to clear the affected traffic lanes[1] (Dunn and Latoski, 2003; Owens et al., 2010). United States Department of Transportation (USDOT) estimates that 18% of freeway traffic related fatalities are attributed to SCs (Chimba et al., 2014). Limiting the impact of nonrecurring events, such as SCs and disabled vehicles, through effective incident management is one of the objectives of emergency response professionals (Raub and Schofer, 1997). Understanding the characteristics of primary and secondary crashes can help decision-makers select better traffic operation practices and safety programs. The first step towards achieving these goals is to identify SCs and their contributing factors such as crash severity, clearance time, and facility type. It is extremely important that SCs are identified with great accuracy otherwise any steps taken towards mitigation might prove inefficient.

Past research on SCs considered short segments of freeways in small regional scales for easier delineation of direction, and spatiotemporal thresholds. The most challenging task was identification of SCs in terms of these thresholds, and directional criteria (Zheng et al., 2014). The latter, often a complex

[1] Recently, one of the performance measures used by TIM agencies is reduction of SCs.

process, is the task of attaching the precise location of a crash to a specific lane. Precise lane and direction identification may be relatively easier for freeways, but poses a challenge for undivided medians. Therefore, arterials were excluded in most of the published research to date even though they encounter a significant number of SCs and their identification warrants further research.

The objective of this paper is two-fold. First, development of a methodological framework to precisely identify SCs in a large scale network using minimal available data for planning agencies within acceptable computational times. Second, application of the proposed methodology in a case study using crash, traffic flow, incident management, and roadway network data to demonstrate identification of SCs, and their patterns of occurrence. Keeping these two-fold objectives in mind, this paper proposes a procedure to identify SCs using the static and the dynamic approach. The former approach assumes pre-specified spatiotemporal thresholds, based on past experience or engineering judgment, while the latter determines these thresholds based on real-time traffic conditions using kinematic shockwave theory. The rationale for presenting the static approach is to provide quantitative results (i.e., percentage of error) and identify spatiotemporal thresholds that agencies can utilize in the absence of a dynamic approach. While the dynamic approach is more realistic in identifying SCs, in its absence agencies can use the spatiotemporal thresholds presented in this study for different types of roadway functional classes. Even though thresholds reported herein may not be fully transferable to other states they can be used in cases (limited data) where the dynamic approach cannot be implemented or for validation purposes. In addition, the static approach provides a basis of comparison with the dynamic approach for identification of SCs.

The rest of the paper is organized as follows. The next section discusses practices and published research on identifying SCs. The third section, presents the proposed methodology followed by a case study in the fourth section. The fifth section compares SC identification accuracy and consistency of the static and the dynamic approach. The sixth section presents validation of the proposed methodology followed by some limitations of this research in the seventh section. The final section concludes the paper, summarizing findings, and presenting future research directions.

2. Literature Review

In this section we present SC identification from the relevant literatures along with different criteria for spatiotemporal thresholds. Recent techniques used for SC identification are also discussed.

2.1. Spatiotemporal threshold

The first step in defining a SC is selection of spatiotemporal thresholds (relative to a PC). Two types of thresholds have been prominent in the literature: static (predefined) and dynamic (varies based on incident characteristics and queuing of vehicles). Several studies (Chang and Rochon, 2003; Hagen, 2005; Hirunyanitiwattana and Mattingly, 2006; Karlaftis et al., 1999; Moore et al., 2004; Pigman et al., 2011; Raub, 1997b; Zhan et al., 2009, 2008) illustrate the use of static thresholds in SCs classification (reaching up to 2 miles and 2 hours after the occurrence of a PC) with some studies only considering crashes in the same direction as the primary incident (Hirunyanitiwattana and Mattingly, 2006; Karlaftis et al., 1999).

The dynamic approach, on the other hand, has been used to identify SCs based on the influence area of the primary incident that depends on vehicle queue length, and other incident and traffic data (Khattak et al., 2011, 2010; Zhang and Khattak, 2010). An Incident Progression Curve (IPC) was proposed in 2007 and 2010 by Sun and Chilukuri (Sun and Chilukuri, 2010, 2007), to identify the dynamic impact area of a PC. Dynamic thresholds were modeled as a multivariate function of various parameters (e.g. primary incident duration, number of blocked lanes etc.). The use of IPC reduced SC misclassification (false positive and negative) significantly. Another study developed queuing models to determine the impact area of a primary incident using estimated queue length and incident duration (Zhang and Khattak, 2011).

The likelihood of SC occurrence is commonly associated with primary incident duration. Modeling incident duration is crucial in the process of developing prediction models for SC occurrence. One of the effective techniques used in the past to estimate incident durations has been hazard-based models (Chung, 2010; Jones et al., 1991) and recently Chung (2010) utilized accelerate failure time metric model to account for the influence of the explanatory variables. One particular advantage of hazard-based duration modeling is that it allows the explicit study of the relationship between incident duration and the explanatory variables. Most studies developed a correlation between incident duration and SC likelihood, considering the influence area to be independent of prevailing traffic conditions and incident characteristics. However, recently published research (Imprialou et al., 2014; Vlahogianni et al., 2010) identified real time traffic conditions as critical component in accurate estimation of the influence areas.

2.2. Recent SCs identification techniques

Yang et al. (2014) identified SCs using speed contour plots with approximately 75% and 50% of SCs occurring within two hours after and two miles upstream of the PC respectively (Yang et al., 2014b). Overall, 42% of SCs were found to occur within two hours of the onset of a PC and within a distance of two miles upstream. 58% of SCs occurred beyond these frequently used spatiotemporal thresholds. In addition, more than half of SCs occurred from PC-induced queues lasting more than two hours. Results also revealed that rear-end crashes were the dominant SC type and that the major contributing factor was "*following too closely*". Other significant contributing factors included improper lane change, distracted driving and unsafe speeds (Yang et al., 2014a). Speed contour plot analysis limits the scope of SC identification to urban freeways as real time network speeds are needed. Obtaining such data is challenging for arterials and, even more so, for suburban freeways.

Hirunyanitiwattana and Mattingly (2006) compared differences in the characteristics of secondary and primary crashes with respect to time-of-day, roadway classification, primary collision factors, severity level and type of crash. The study revealed a higher SC rate (expectation) in regions with high traffic volumes during morning and evening peak hours. The study concluded that a PC occurring in an urban area on a high speed facility is likely to have a high probability of inducing SCs. Sensitivity analysis measuring the impact of queue length and clearance time on the estimated number of SCs revealed that reduction in queue clearance time from 60 to 15 minutes reduced the number of SCs by approximately 43%.

The literature review reveals that in the very early stages, when the concept of "secondary crash" was introduced, studies proposed spatiotemporal thresholds, independent of the facility type, crash severity, clearance time, and flow characteristics; all of which are crucial determinants of SCs. While implementing static thresholds is relatively simpler and not computation-intensive, it comes with the risk of identifying SCs with significantly high numbers of false positive and negative (type I and II errors respectively).

The dynamic approach proposed in this paper (section 3.2) is queue length based hence displays some similarity with past literature (Zhan et al., 2009; Zheng et al., 2014). However, the proposed methodology and scope have significant improvements from past literature. First, we have utilized lane closure information based on crash severity and number of vehicles involved to determine the reduction in capacity and subsequently the traffic flow state after the PC which leads to more accurate identification of SCs (in contrast to fixed number of lane closures). Second, we present a comprehensive comparison of five cases of SC occurrence on large-scale networks. Third, we present a comparison of the static (with varying spatial and temporal threshold) to the dynamic approach for freeways including the effect of rubbernecking on SCs. Fourth, the dynamic approach is validated using video detected SC data from the Traffic Management Centers (TMCs) in TN, USA. In the validation process, it is verified whether each of the observed SC would be identified as a SC if SCIA is applied in that study area. Validation results suggest that SCIA replicated the observed SC data well.

Next, we present the proposed methodology to identify SCs on freeways and arterials in large size networks.

3. Methodology

A pictorial representation of the proposed methodology and a step-by-step workflow is shown in Fig.1 and then described in the following subsections. Before proceeding with the methodology, we present the notations used throughout the paper.

Notation	Description
$a_{bf,s}$	Backward-forming or "Back of the queue" shockwave speed in the same direction
$a_{br,s}$	Backward-recovery or "Front of the queue" shockwave speed in the same direction
$a_{bf,o}$	"Back of the queue" shockwave speed in the opposite direction
$a_{br,o}$	"Front of the queue" shockwave speed in the opposite direction
BLM	Beginning log mile
D	Impact area
dS	Distance between two paired crashes
dT	Time interval between two paired crashes
I	Set of all the crashes
i	A primary crash
j	A potential secondary crash
$(k_{ini})_s$, $(q_{ini})_s$ $(u_{ini})_s$	Density, flow, and speed of lane in the same direction prior to primary crash
$(k_{int})_s$,$(q_{int})_s$,$(u_{int})_s$	Density, flow, and speed of lane in the same direction after primary crash but prior to clearance
$(k_{sat})_s$,$(q_{sat})_s$, $(u_{sat})_s$	Density, flow, and speed of lane in the same direction representing optimal (saturated) condition
$(k_{ini})_o$,$(q_{ini})_o$,$(u_{ini})_o$	Density, flow, and speed of lane in the opposite direction prior to primary crash
$(k_{int})_o$,$(q_{int})_o$,$(u_{int})_o$	Density, flow, and speed of lane in the opposite direction after primary crash but prior to clearance
$(k_{sat})_o$,$(q_{sat})_o$, $(u_{sat})_o$	Density, flow, and speed of lane in the opposite direction representing optimal (saturated) condition
S_i	Set of secondary crashes for i
Pri_j	Primary crash for the identified secondary crash j
ql_1	End of impact area at the time of crash j
ql_2	Start of impact are, at the time of crash j
t	Duration between primary and secondary crash occurrence
t_1	Time of occurrence of primary crash
t_2	Time of occurrence of secondary crash
T_c	Primary crash clearance duration

3.1. Static Approach

Identification of SCs using a static approach requires selection of pre-specified spatiotemporal threshold values. In addition, directionality and location (impact region) of a PC play a crucial role and needs to be predefined. Directionality refers to the direction of the PC as compared to the SC (i.e. same or opposite direction). Location refers to the upstream or downstream location of the SC with respect to the direction of flow and location of PC. For the static approach, five possible combinations of directionality and location were considered in this study (graphically depicted in Fig. 2), capturing all possible types of SCs. These five cases are defined as follows:

- <u>Case-1: Same Direction-Upstream</u>: SC occurs in the upstream same direction of the PC

- Case-2: Opposite Direction-Upstream: SC occurs in the upstream opposite direction of the PC
- Case-3: Opposite Direction-Downstream: SC occurs in the downstream opposite direction of the PC
- Case-4: (Combination of cases 1 and 2): SC occurs either in the downstream or upstream opposite direction of the PC
- Case-5: Cases 1, 2, and 3 combined

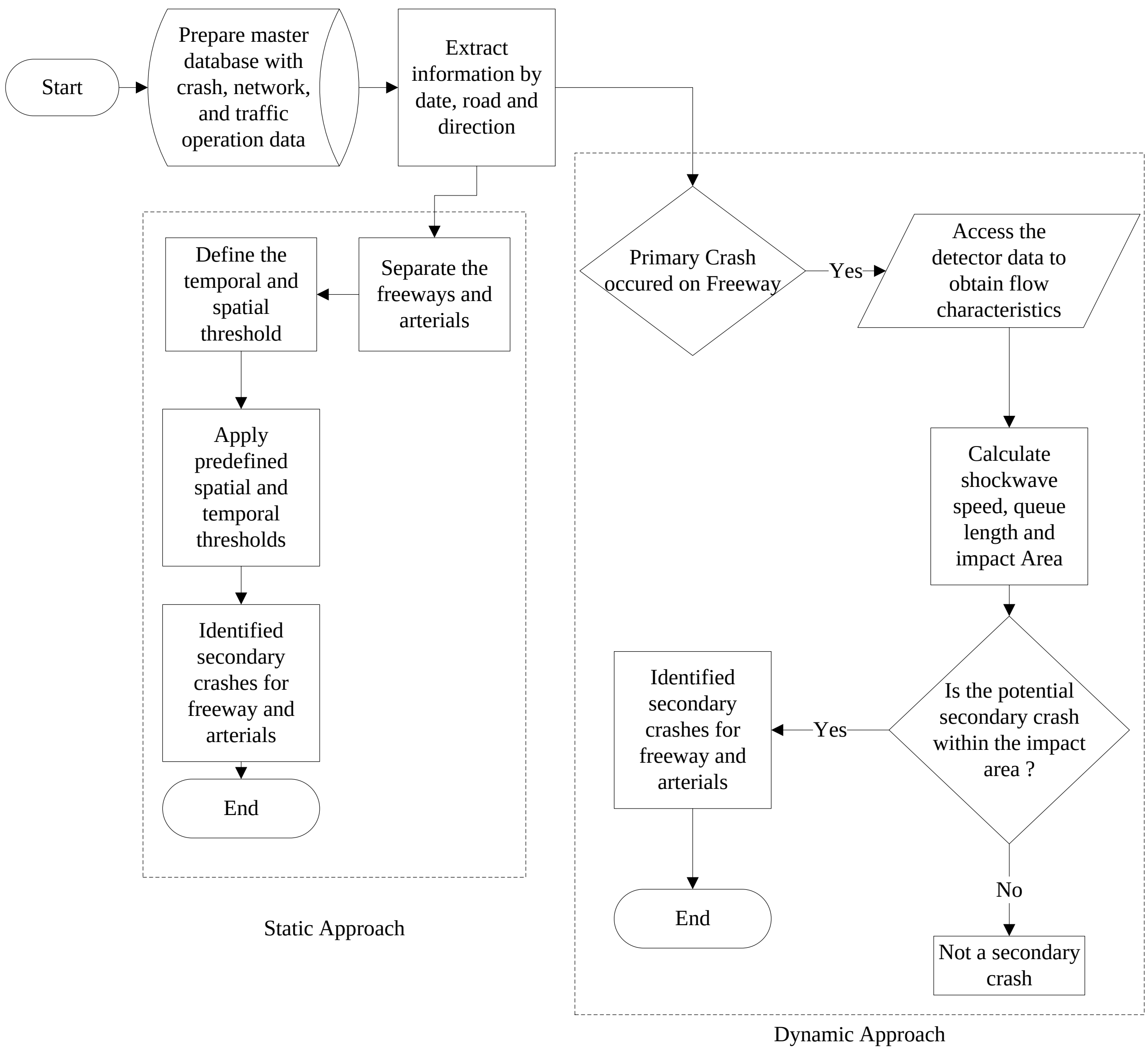


Fig. 1. Flow chart showing the methodology.

For the static approach, in all five cases, spatiotemporal thresholds are predefined by the user. As an example, one can consider a one mile/one hour threshold. Previous research suggests that SC occurred in the opposite direction because of 'rubbernecking' effect. Rubbernecking represents the phenomenon when drivers in the opposite direction slow down to observe the PC causing congestion, reduction in capacity, and associated delays (Chung and Recker, 2013; Colon et al., 2013; Masinick and Teng, 2004; Saddi, 2009; Shah et al., 2015). Rubbernecking effects depends on the facility type, traffic conditions, type and severity of an incident, and has a significant potential of inducing SCs in the opposite direction of a PC. Research conducted by department of transportation in California, Virginia, Washington, and Nevada suggest that about 16% of SCs are caused on freeway grade and median separated urban segments (Saddi, 2009). In a case-study in Washington state, a real-time incident was analyzed which showed that PC occurring on an urban freeway led to a formation of 3-mile long queue in the opposite direction within 15 minutes. SCs on opposite direction of PC would be even more prominent on painted, curbed, and no median arterials.

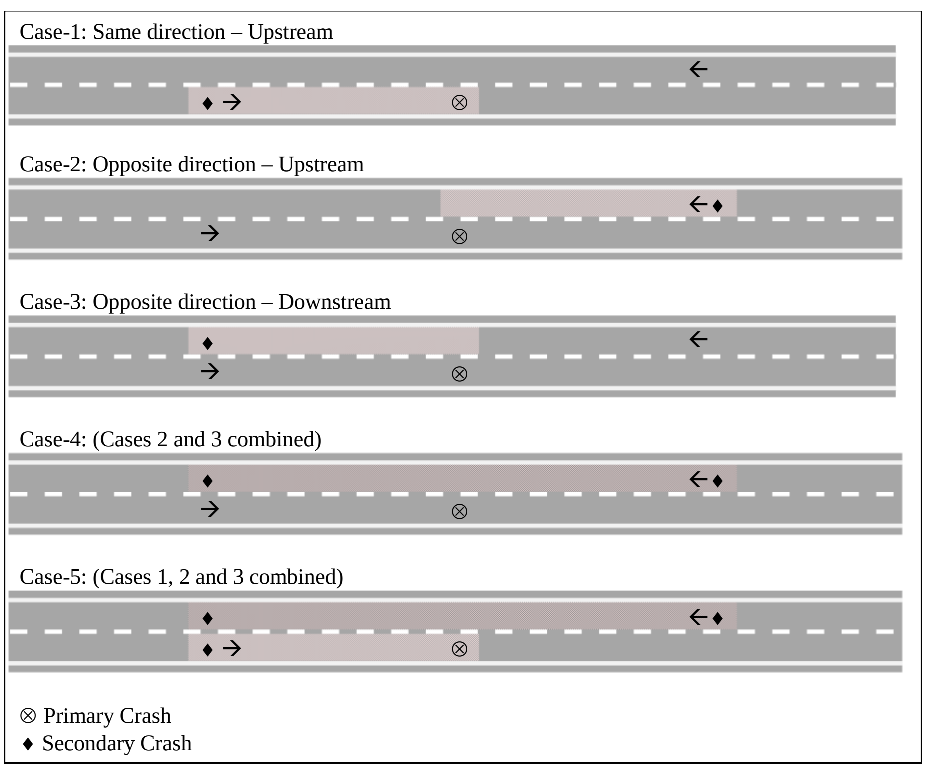


Fig. 2. Pictorial representation of directionality and locations of SCs.

3.2. Dynamic Approach

The dynamic approach in SC identification aims to better capture effects of traffic characteristics (e.g. flow, speed, and density), that change over time and space, and affect both queue formation from a PC and SC occurrence. With a given state and lane specific traffic flow parameters, continuously monitored by sensors or other devices near the crash location (flow, density, speed, number of lanes, location of the crash on a specific lane etc.), it is possible to calculate queue lengths using shockwave theory (Lighthill and Whitham, 1955). In this subsection, we present a dynamic approach to estimate the impact area of a PC created by a "Back of the queue" shockwave and "Front of the queue" shockwave. Back of the queue shockwave leads to formation of queue due to PC. Once the PC is cleared, a front of the queue shockwave is set in motion and eventually catches up with the back of the queue shockwave resulting in dissipation of the queue.

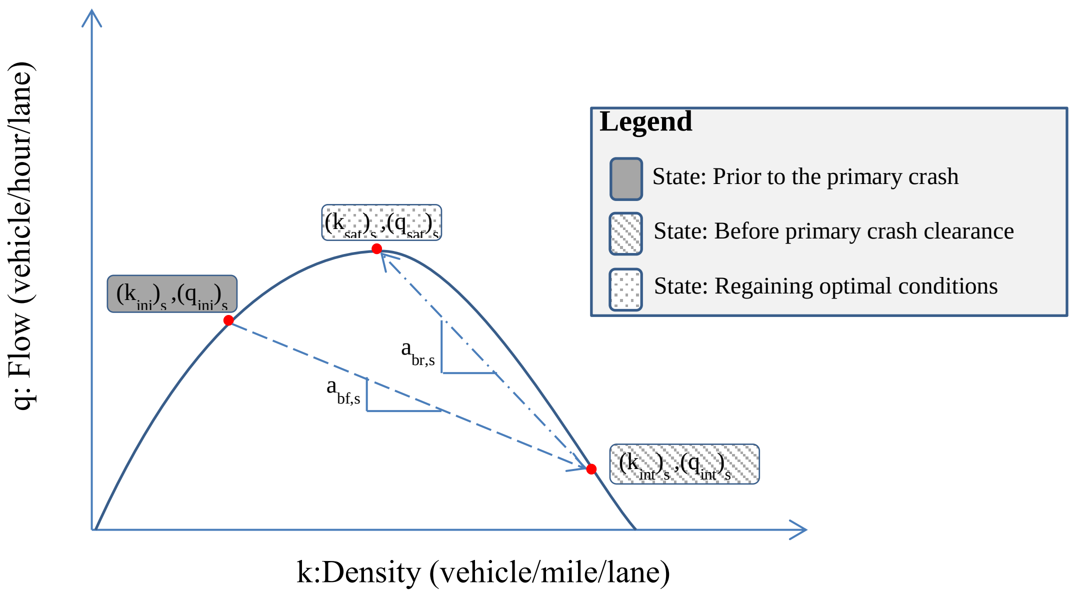
Arterials encounter different traffic flow dynamics compared to freeway because of (un)signalized intersections, the shockwave principles used in this paper for the dynamic approach of SCs are not applicable for arterials. The limitations for arterials include: (1) lack of availability of real time data and traffic flow characteristics at disaggregated time steps, (2) (un)signalized intersections causes discontinuity in traffic flow, (3) turning movements dissipate the traffic flow from one roadway to another, (4) no detailed signal timing information, and (5) no detailed highway geometry and link information. Considering these limitations, the static approach using appropriate spatiotemporal threshold may provide relatively more accurate estimation of SCs on arterials. However, in future with availability of more data the dynamic approach proposed in this paper can be extended for application on arterials. Next we discuss the steps required to estimate the impact area using the shockwave principle.

3.2.1. Estimation of shockwaves

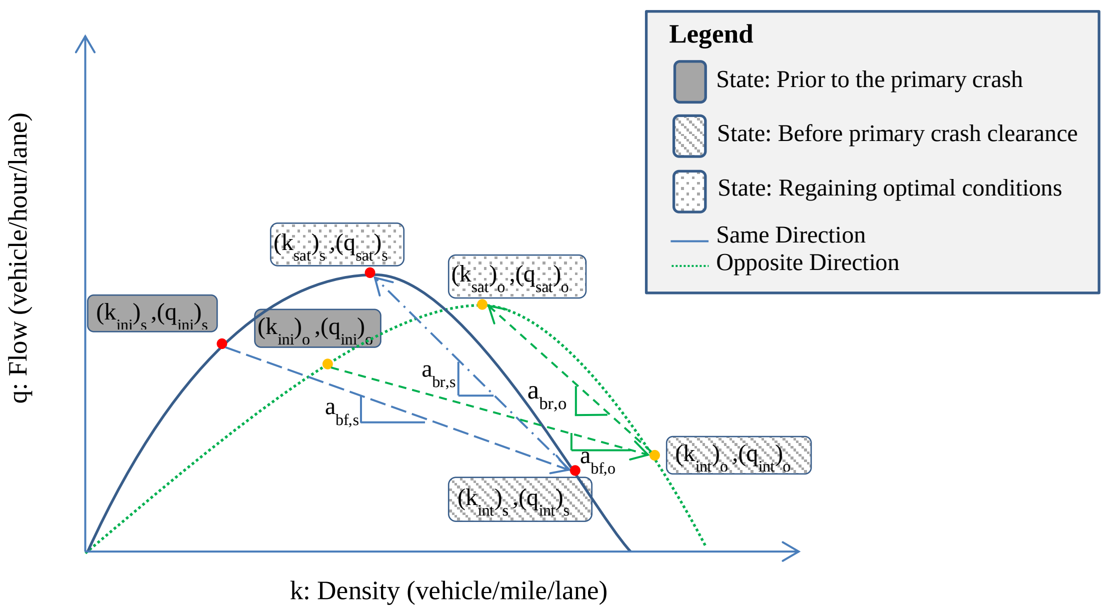
A generalized density-flow curve is shown in Fig. 3(a) where $(k_{ini})_s$ and $(q_{ini})_s$ are the initial conditions of density and flow where the initial speed, $(u_{ini})_s$ is the slope of the curve. After the PC when one or more lanes are completely closed (often the case), that intermediate traffic state is represented by $(k_{int})_s$, $(u_{int})_s$

and $(q_{int})_s$ (until the clearance period). For freeways, lane specific traffic flow data are available which are used to capture the traffic flow conditions (flow, speed, density) before and after the crash. The methodology for dynamic approach makes sure that any flow/density state, represented by the parabola, can be used. Speed of back of the queue shockwave, is equal to:

$$a_{bf,s} = \frac{(q_{ini})_s - (q_{int})_s}{(k_{ini})_s - (k_{int})_s}$$



(a) Determining shockwave speed in same direction using traffic flow characteristics.



(b) Determining shockwave speed in opposite direction using traffic flow characteristics.

Fig. 3. Shockwave speed for single and bi-directional traffic.

After the PC is cleared, flow conditions will eventually reach saturated condition represented by $(q_{sat})_s$, $(u_{sat})_s$ and $(k_{sat})_s$. (explained in section 4.1.2) meaning a front of the queue shockwave will set off with a speed of:

$$a_{br,s} = \frac{(q_{int})_s - (q_{sat})_s}{(k_{int})_s - (k_{sat})_s}$$

A similar approach can be adopted to analyze shockwaves in the opposite direction as shown in Fig. 3(b) which demonstrates traffic states for bi-directional traffic. HCM 2010 also refers to the rubbernecking factor that leads to the reduction of capacity in the opposite direction of the incident. The reduction in capacity ranges from 5% for a single-vehicle crash to 25% for a multivehicle crash. Using the reduction in capacity based on features of PC the flow conditions in the opposite direction to PC, represented by $(k_{int})_s$, $(u_{int})_s$ and $(q_{int})_s$ are calculated.

3.2.2 Impact Area Estimation

Determining the impact area of a PC requires the clearance time (T_c) and the time difference between occurrence of PC and the “potential” SC ($t = t_2 - t_1$). The impact area (d) is defined as:

$$a_{br,s} \times (t-T_c) \leq d \leq a_{bf,s} \times t, \text{ when } t > T_c$$

$$0 \leq d \leq a_{bf,s} \times t, \text{ when } t < T_c$$

In this paper, when estimating the impact area, clearance time for the primary incident was available through an incident management database. Clearance time varies and depends on crash type and severity, number of vehicles involved, number of lanes, availability of shoulder area etc. Fig. 4 shows the impact area (shaded area between the back of the queue and front of the queue shockwaves) which captures the portion of the queue, from the primary incident, which can induce a SC. Note that: a) the front of the queue shockwave does not set off until the primary incident is cleared (i.e. size of the impact area depends on the PC clearance time) and, b) higher speed of front of the queue shockwave results in faster queue dissipation.

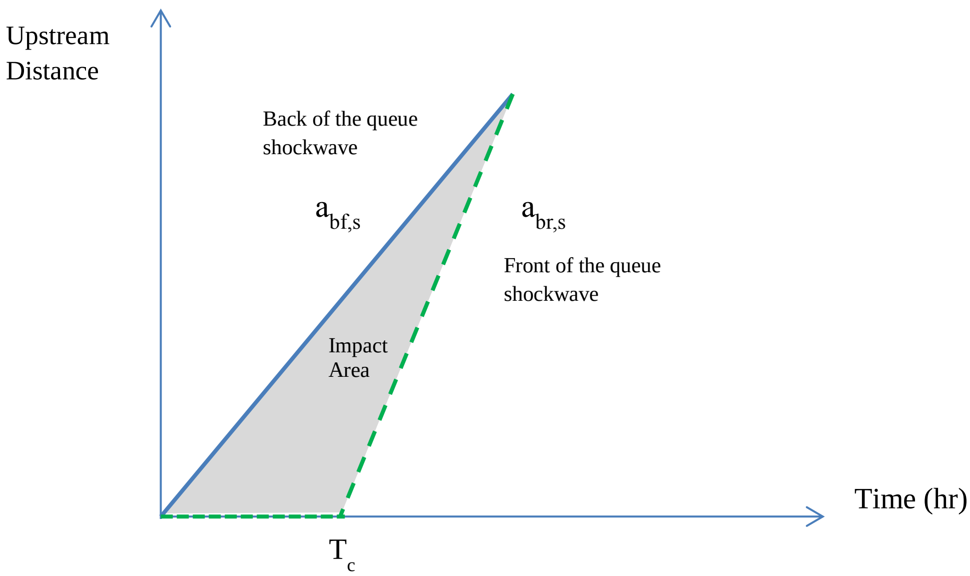


Fig. 4. Graphical representation of impact area.

4. Case Study

The proposed methodology presented in the previous section was applied and evaluated using the transportation network of Shelby County, Tennessee (TN), in the United States (U.S.). Shelby County is an ideal case study candidate as the most populous county in the state of TN, home to one of the largest freight intermodal hubs in the US, and the largest metropolitan planning organization in the tri-state encompassing portions of Tennessee, Arkansas and Mississippi, with a significant portion of inter-state traffic. The following describes data collected for the case study:

- Crash data: Three years (2010-2012) of crash data, from the Tennessee Roadway Information Management System (TRIMS); a total of 91,325 crashes.
- Freeway Traffic Data: Lane specific traffic data by minute (speed, flow, occupancy etc.) aggregated into 15 minute intervals.
- Arterial Traffic Data: Traffic data on arterials were not available in such detailed manner as freeways. Link speed and flow were obtained from the Metropolitan Planning Organization (MPO) travel demand model.

- Incident Management data: Data on all reported incidents (e.g. time of crash occurrence, time taken for the rescue vehicle to reach incident location, clearance time, etc.) were available from the incident management system in TN.
- Roadway Network: A detailed transportation network (20,289 links/1,619 miles) with 20 different functional classes of roadways (1,337 miles of arterials and 282 miles of freeways) was available from TDOT.

A geodatabase was developed from these five data sets with facility types categorized into two groups: freeways or arterials. In this study, rural and urban interstates, and expressways were grouped into the freeways category, while rural and urban principal and minor arterials were grouped into the arterials category.

4.1. Secondary Crash Identification Algorithm (SCIA)

The algorithm developed to identify SC (***SCIA***), shown in Fig. 5, involves two major steps: a) crash pairing, and b) SC identification which are discussed in the following sections. Both steps are discussed in detail next.

4.1.1. Step 1: Crash pairing

The first step of ***SCIA*** involves crash pairing which identifies candidate SCs, given a PC, using various criteria such as day of occurrence, route, and spatiotemporal thresholds. Accuracy of this procedure is crucial in reducing the complexity of the remaining steps of the algorithm. In the "Crash Pairing" step, two crashes are paired only if they occur on the same route and within a pre-specified spatiotemporal threshold. The threshold used in the crash pairing step can be specified by the user. The primary purpose of crash pairing is to minimize computational time. At this stage, any crash available in the database is considered as PC with all other crashes considered as a candidate SCs to that particular crash. Since each crash *i* is checked against all other crashes *j* in the database, reducing the number of total crashes in the database (using a certain spatiotemporal threshold) will improve SCIA runtime efficiency. A crash *j* is then considered as a SC and paired with its PC *i*, upon satisfying the above-mentioned criterions. For each crash *i*, a set of crashes P_i is created that contains all the crashes which are paired with *i*. Later in the identification process, the static and dynamic approach uses P_i instead of the entire dataset. Distance between crashes was determined using the absolute difference in Beginning Log Mile (BLM). The position of the paired crashes, with respect to each other, was determined using their direction, BLM and their respective spatial coordinates.

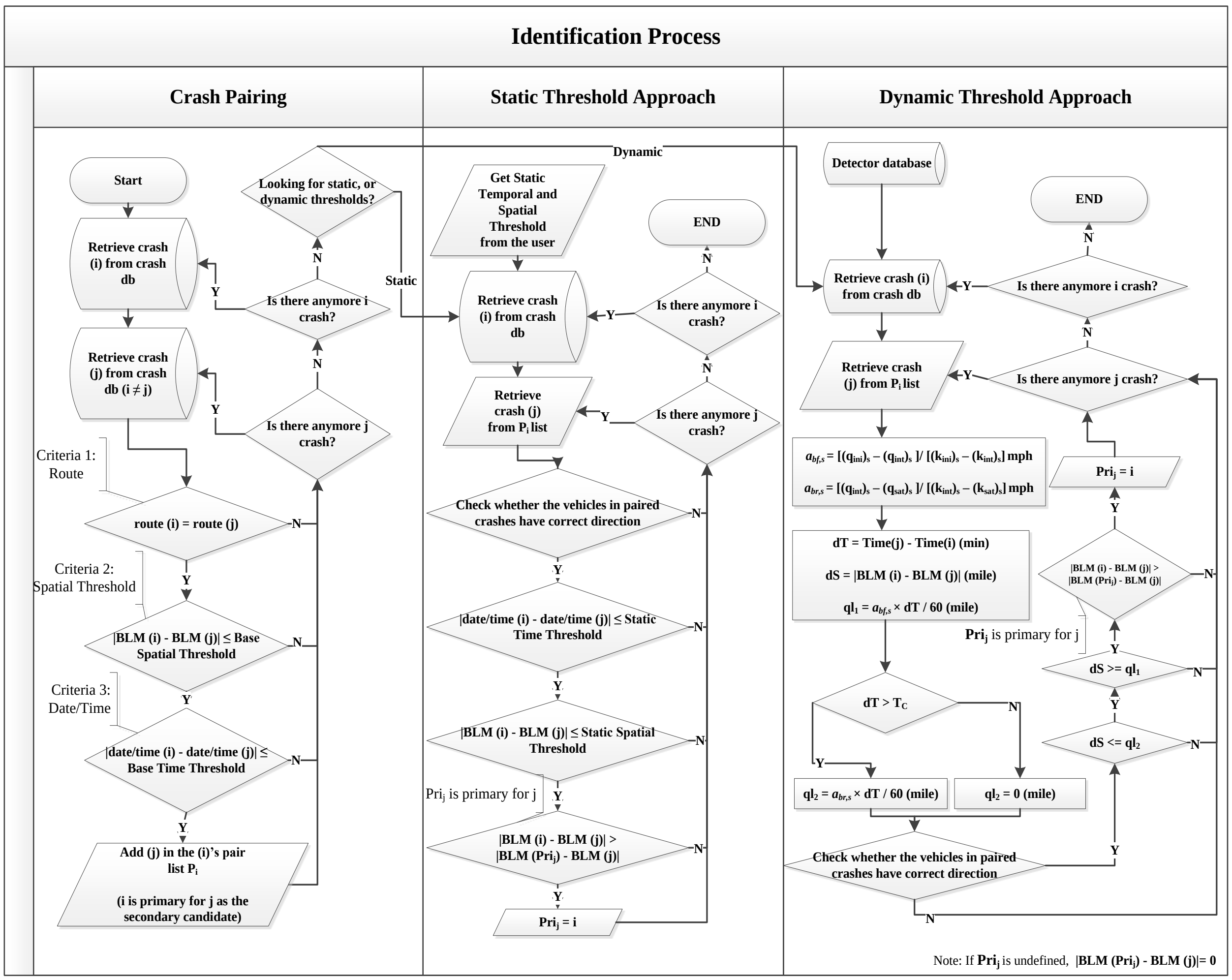


Fig. 5. Flowchart representing the algorithms.

4.1.2. Step 2: SC Identification

For the static approach, only spatiotemporal thresholds were considered as criteria for identifying a SC. These thresholds can be set by the user. For the dynamic approach, traffic flow characteristics before and after the occurrence of a PC were required to estimate the impact area. These data were obtained from the detector datasets. After the primary incident is cleared, flow conditions will eventually reach saturated condition where $(q_{sat})_s$, $(u_{sat})_s$ are assumed to be 1900 veh/hr/lane, 65 mph for freeways. $(k_{sat})_s$ is calculated accordingly using the basic density-flow-speed formula ($(k_{sat})_s=(q_{sat})_s/(u_{sat})_s$). The pseudocode for SC identification is presented next.

Static Approach pseudocode (Case-1)*

Let $\boldsymbol{R_i}$ = Route on which crash ***i*** is located $\boldsymbol{D_i}$ = Direction of the route for crash ***i***
$\boldsymbol{t_i}$ = Time of occurrence of crash ***I*** $\boldsymbol{S_i}$ = Set of secondary crashes for ***i*** and set $\boldsymbol{S_i} = \emptyset$

For each crash ***i***, $\forall\, \boldsymbol{i} \in \boldsymbol{I}$
For each other crash ***j***, $\forall\, \boldsymbol{j} \in \boldsymbol{I}$ and $(i \neq j)$

Step 1: Check the route and direction for both crashes
If $R_i = R_j$ & $D_i = D_j$ & crash ***j*** is in the upstream of crash ***i***
Go to **Step 2,**
Else Skip crash ***j*** and **Step 2** and continue with **Step 1**

Step 2: Check if spatiotemporal threshold is satisfied
If $|t_i - t_j| \leq$ Time Threshold & $|BLM_i - BLM_j| \leq$ Spatial Threshold
i is the primary crash and ***j*** is the secondary crash
$\boldsymbol{S_i = S_i \cup j}$

*Note: This pseudocode is for Case-1(static approach) only. For other cases, only direction criteria will be modified in Step 1.

Dynamic Approach pseudocode (Case-1)*

Let $\boldsymbol{R_i}$ = Route on which crash ***i*** is located $\boldsymbol{D_i}$ = Direction of the route for crash ***i***
$\boldsymbol{t_i}$ = Time of occurrence of crash ***i*** $\boldsymbol{dT} = |t_i - t_j|$
$\boldsymbol{dS} = |BLM_i - BLM_j|$ $\boldsymbol{S_i}$ = Set of secondary crashes for ***i*** and set $\boldsymbol{S_i} = \emptyset$

Step 0: Set the default parameters for freeway: q_{sat} , u_{sat} , k_{sat}

For each crash ***i***, $\forall\, \boldsymbol{i} \in \boldsymbol{I}$
For each other crash ***j***, $\forall\, \boldsymbol{j} \in \boldsymbol{I}$ and $(i \neq j)$

Step 1: Check the route and direction for both crashes
If $R_i = R_j$ & $D_i = D_j$ & crash ***j*** is in the upstream of crash ***i***
Go to **Step 2,**
Else Skip crash ***j*** and continue with **Step 1**

Step 2: Obtain traffic volume (q_{ini}) and speed (u_{ini}) before PC and calculate density $\boldsymbol{k_{ini}}$,

Step 3: Determine $(k_{int})_s$, $(u_{int})_s$ and $(q_{int})_s$ to calculate $\boldsymbol{a_{bf,s}}$ and $\boldsymbol{a_{br,s}}$

Step 4: Calculate

$\boldsymbol{ql_1} = a_{bf,s} \times dT/60$

If (dT > T_c)

$\boldsymbol{ql_2} = a_{br,s} \times (dT-T_c)/60$

Else $\boldsymbol{ql_2} = 0$

Step 5: Check if the crash ***j*** is within the impact area

If $ql_2 \leq$ dS $\leq ql_1$

i is the primary crash and ***j*** is the secondary crash

$\boldsymbol{S_i = S_i \cup j}$

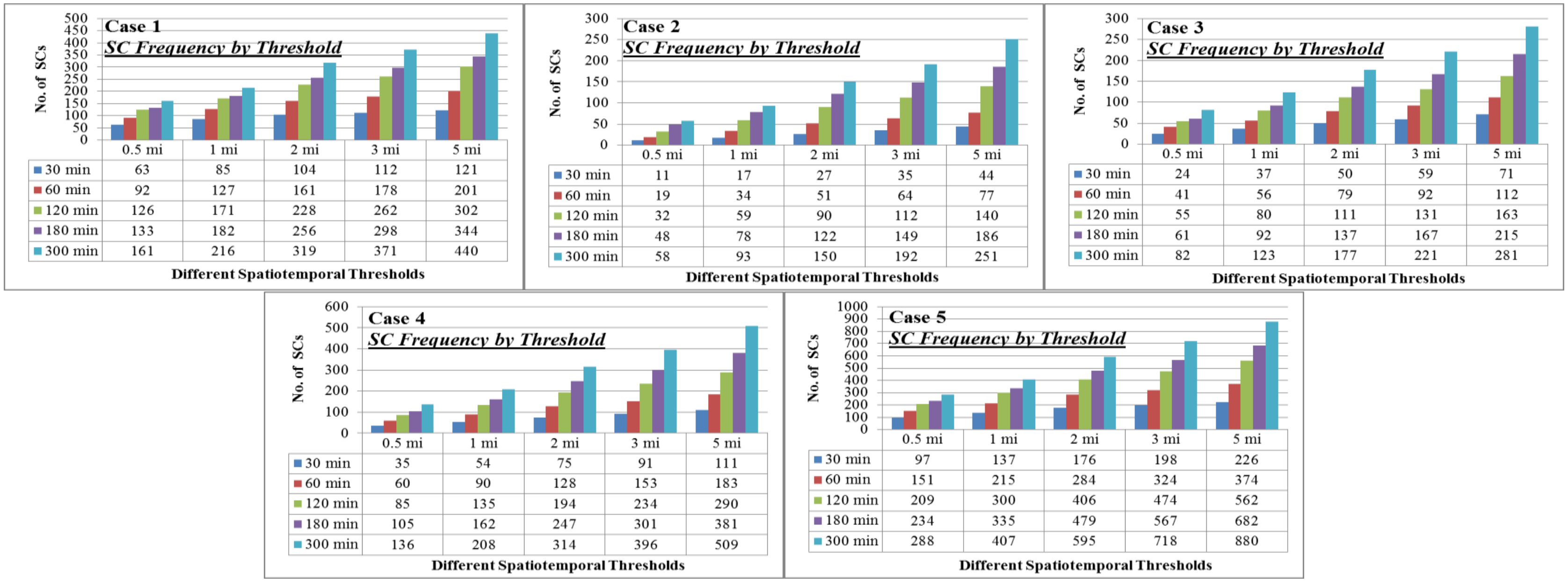
*Note: This pseudocode is for Case-1(dynamic approach) only. For other cases, only direction criteria will be modified in Step 1 and shockwave speed will be calculated for that particular direction in Step 3.

5. Results

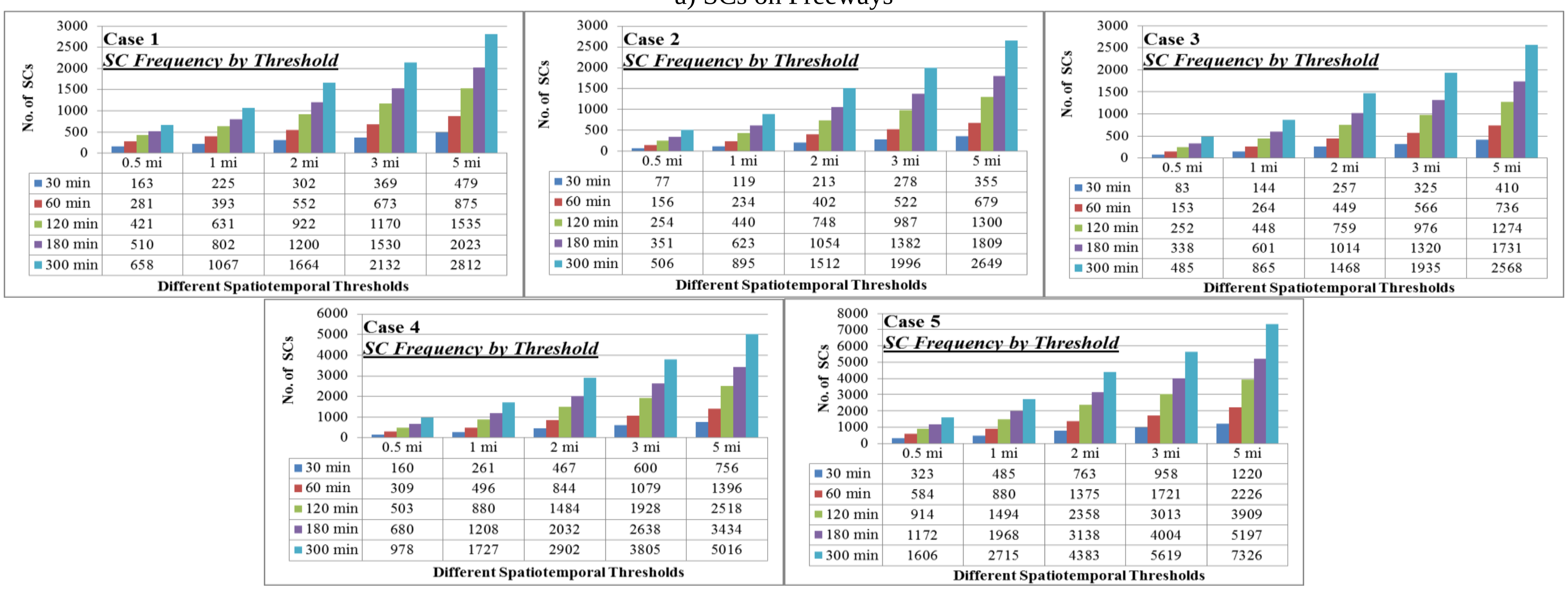
SCs were classified into two categories based on facility type (i.e. SCs on freeways or arterials) to account for the significant differences in flow, speed and density characteristics of the two facility types. Additionally, incident management on urban arterial roadways area is considerably different than on freeways and will effect SC occurrence (Raub and Schofer, 1997). For the static approach different spatiotemporal thresholds were used to determine sensitivity and to assess over/under estimation of SC identification when compared to the dynamic approach. Temporal thresholds of 30, 60, 120, 180 and 300 minutes were used along with spatial thresholds of 0.5, 1, 2, 3 and 5 miles. Larger thresholds (e.g. over 120 minutes and 2 miles) were used to account for freeway queuing during peak periods.

5.1. Static approach

SCs identified for all five cases using different spatiotemporal threshold values by facility type (freeway and arterial) are presented in Fig. 6. It is observed that SC occurrences increase as the spatial threshold increases (for all cases and facility types). In general, higher number of SCs and higher rates are observed on arterials than freeways, which can be explained by the larger number of lane-miles covered by arterials. Note that Case-1 (same direction-upstream) has a significantly larger number of SCs for both facility types when compared to Cases-2 and 3 as a PC is more likely to cause congestion upstream in the same direction than the opposite which in turn may lead to SCs.



a) SCs on Freeways



b) SCs on Arterials

Fig. 6. SCs identified using the static approach (freeways and arterials).

5.2. Dynamic approach

Frequencies of SCs, identified using the dynamic approach, for all five directionality/location cases for freeways, are shown in Fig. 7. Case-1 exhibits a higher number of SCs when compared to Cases-2 and 3 combined, while SCs for Case-3 results in a higher frequency than Case-2 (142 SCs identified on freeways for Case-1 as compared to 30 and 68 for Case-2 and 3 respectively). A total of 235 SCs are identified on freeways using the dynamic approach (Fig.7) which is comparable to the 215 crashes (Case-5) identified for one mile and one hour static threshold (Fig. 6a).

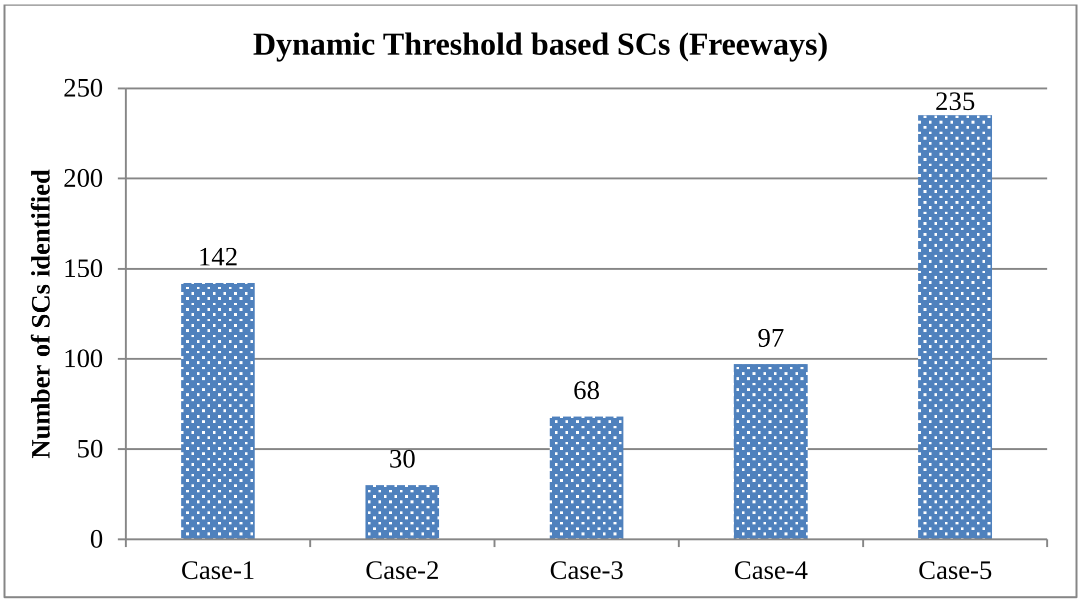


Fig. 7. Secondary crashes identified on freeways using the dynamic approach

5.3. Static vs. Dynamic approach: SC frequencies

Comparison of both approaches in terms of SCs identification is presented in Fig. 8. Results shown in Fig. 8 reveal that the static approach over-estimates SC frequencies as spatiotemporal thresholds increase. As expected, for low spatiotemporal thresholds (e.g. 30, 60 min and 0.5, 1 mile) the static approach underestimates SC frequencies. Overall, when comparing results from the static and dynamic approach, the number of SCs identified using the latter are significantly less when compared to SCs for larger thresholds used by the static approach. Fig. 9 shows the comparison of SC frequencies for Case-1 on freeways by time of day. For the AM and PM peak, the static 1 hour/2 mile spatiotemporal threshold differs by up to 5% from the dynamic approach, but for the midday period, the 1hour/1mile spatiotemporal threshold shows more congruity. Similarly for the off-peak, the 2 hour/0.5 mile spatiotemporal threshold shows no difference to the dynamic approach. In cases where the dynamic approach cannot be implemented, results shown in Fig. 9 can be helpful to agencies to determine suitable static spatiotemporal thresholds for a given facility type and time of day and also provide a basis for comparison with the dynamic approach.

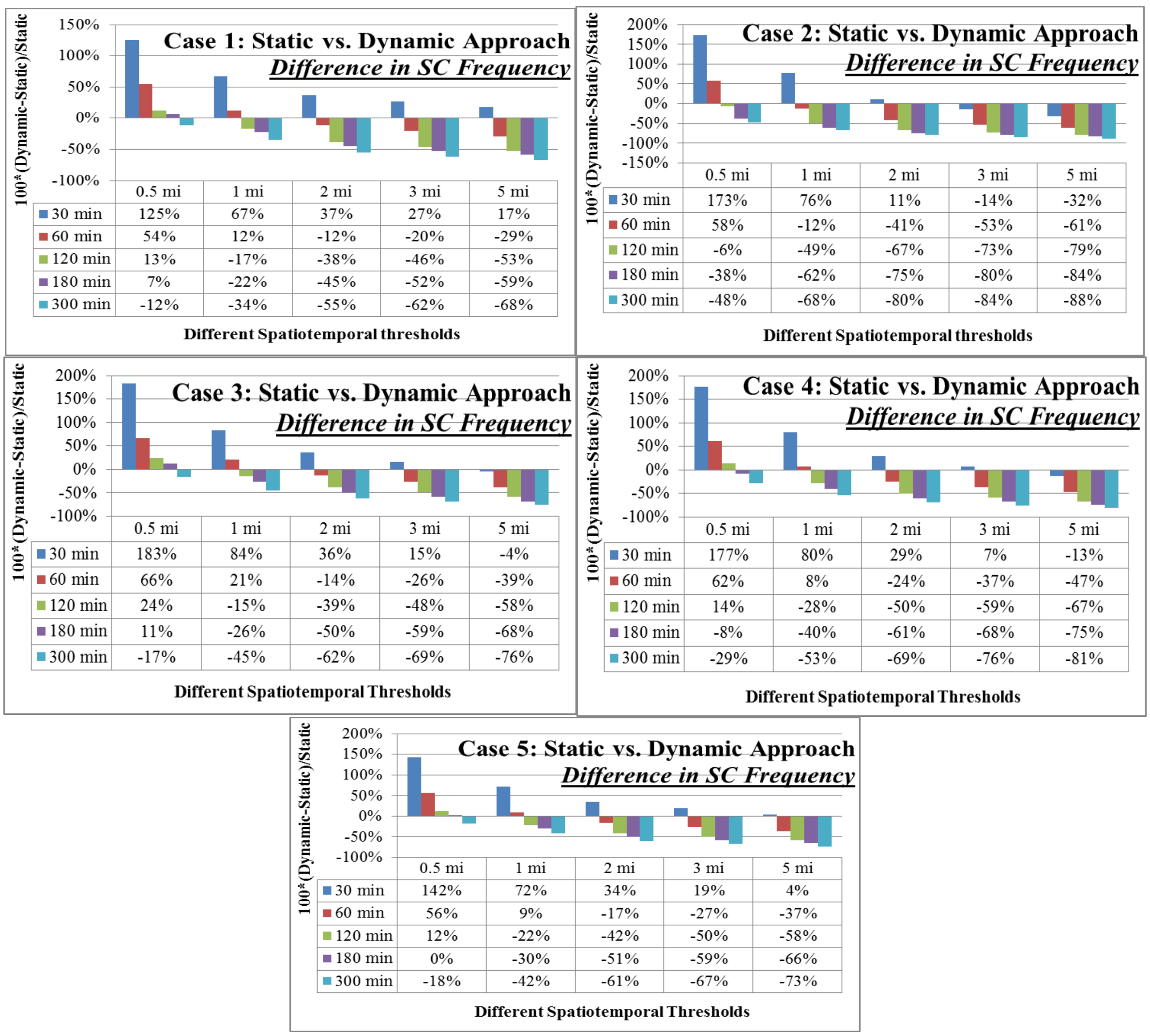
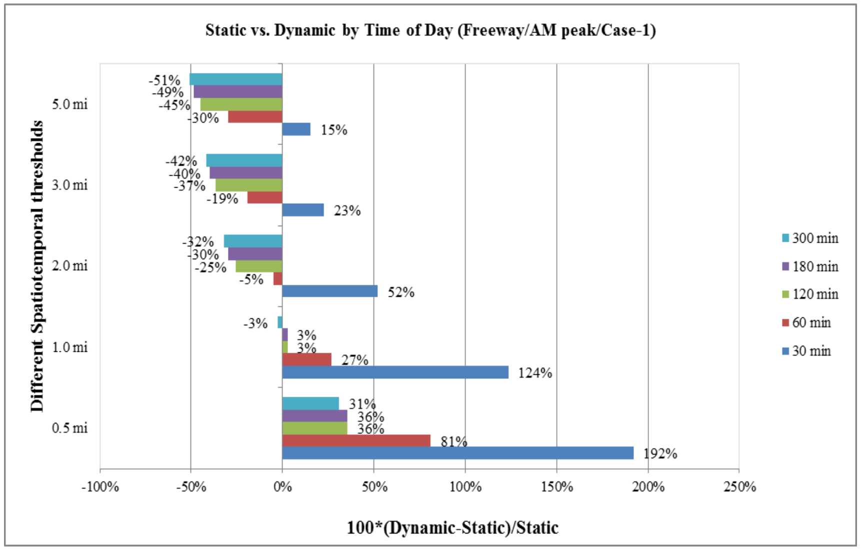
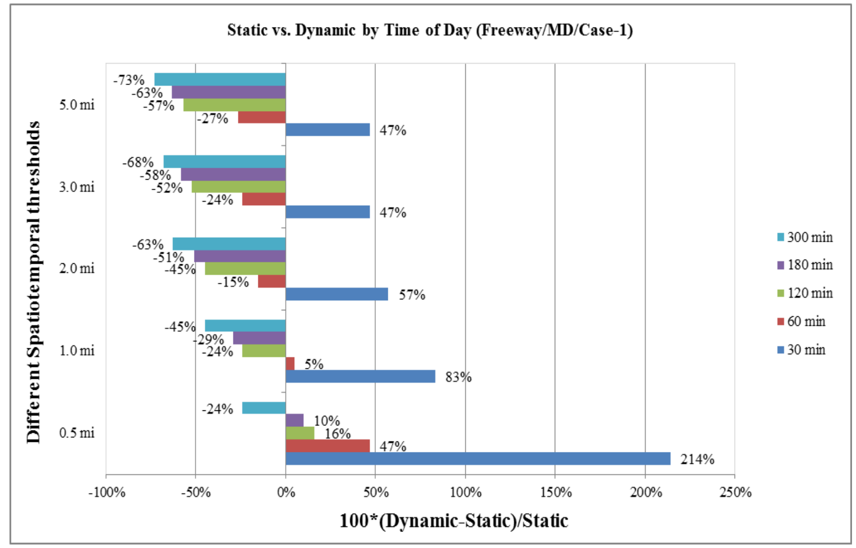


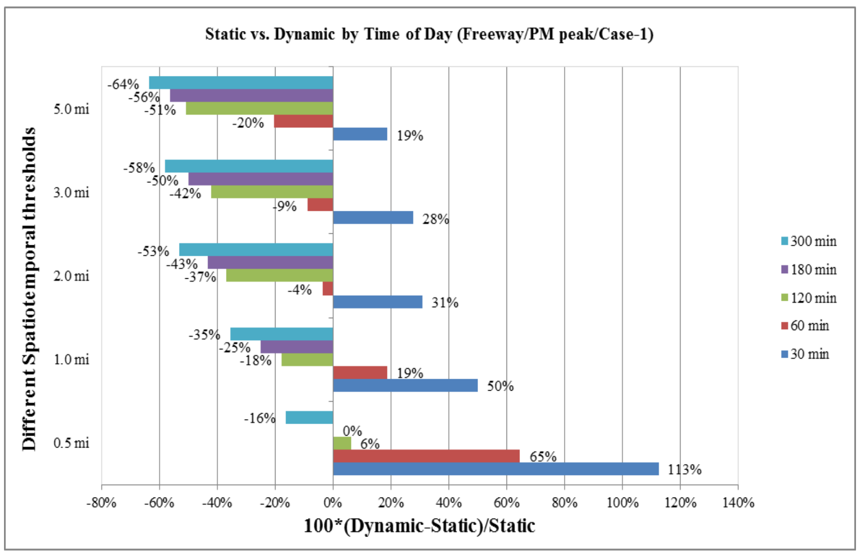
Fig. 8. Static vs. Dynamic approach SC comparison (Freeways).



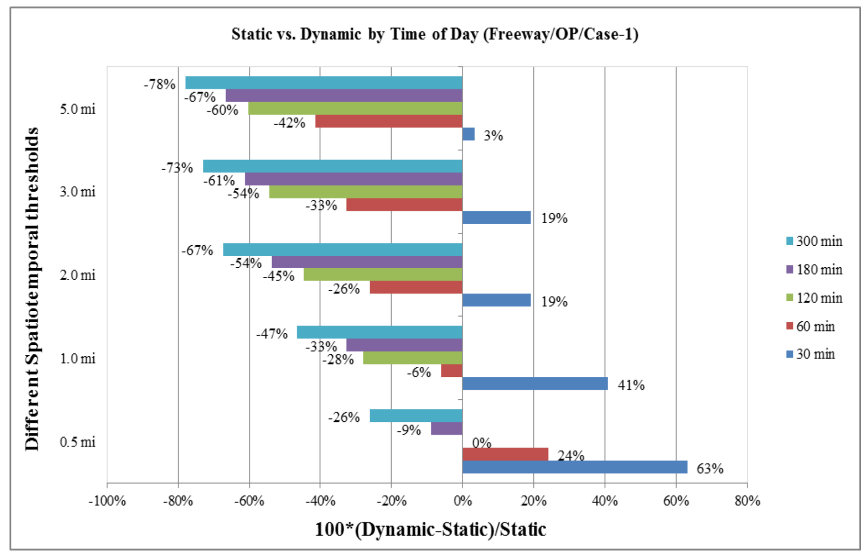
a) AM Peak



b) Midday



c) PM Peak



d) Off-peak

Fig. 9. Static vs. Dynamic approach SC comparison (Freeways) by time of day.

5.4. Dynamic Approach: SC Distribution by Time of Day

Fig. 10 shows the time of day distribution of SCs identified using the dynamic approach on both freeways and arterials. Freeway facilities exhibit two distinct peaks: AM peak (between 8am- 9am), and PM peak (between 3pm-7pm). Both peak periods account for 57% of the total number of identified SCs for Case-1. It can also be noticed that the "rubbernecking effect", portrayed by Case-2, is more prominent during the peak hours (8am-9am and 3pm-5pm) which account for 69% of the total number of identified SCs for Case-2. Case-3 exhibits trends similar to Case-1.These results are in line with findings from the reviewed literature (Hirunyanitiwattana and Mattingly, 2006). Note that the majority of SCs observed late at night (10pm-3am) occurred during the last week of December and might be the results of high traffic from special events (Christmas break etc.) or due to the adverse winter weather.

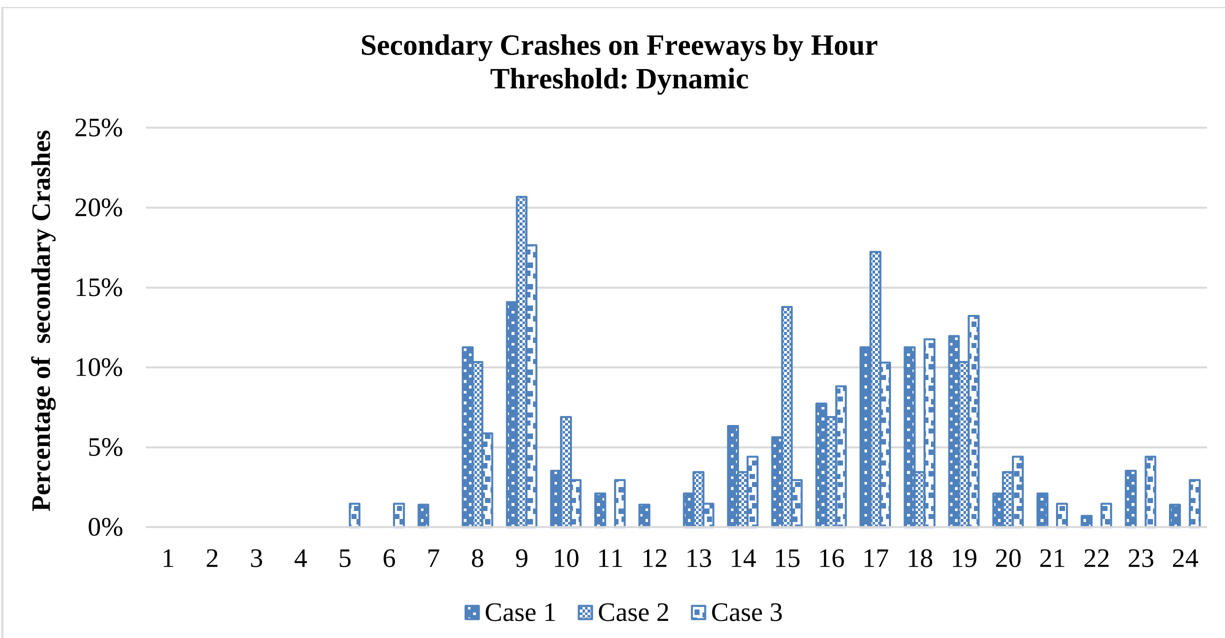
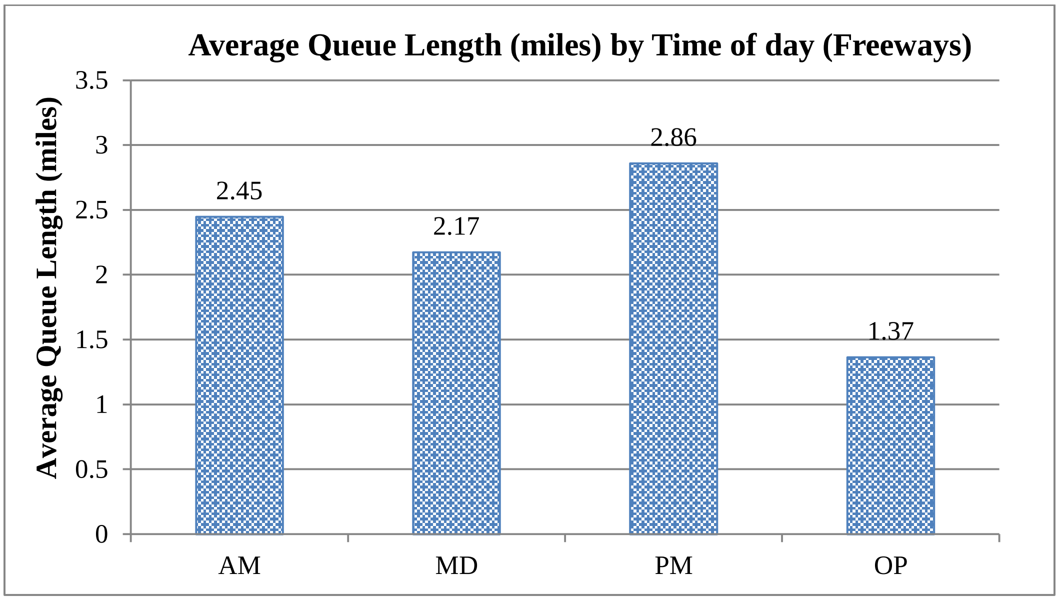


Fig. 10. SCs (Case-1) by time of day using the dynamic approach.

5.5. Dynamic Approach: Average Queue Length by Time of Day

It is preordained that queue length varies by time of day and facility type which, in this paper, is quantified from the perspective of SCs. Fig. 11 shows the variation in average queue length in Freeways due to PCs (that resulted in SCs). During the PM peak average queue length is the highest, suggesting that any crash occurring on freeways during PM peak is expected to cause a longer period of congestion compared to any other time of day. During midday period, 11% to 24% smaller queue lengths are observed as compared to the AM and PM peak. These results may help agencies in determining suitable spatial thresholds for given time of day and a particular facility type to identify SCs in the absence of dynamic approach.

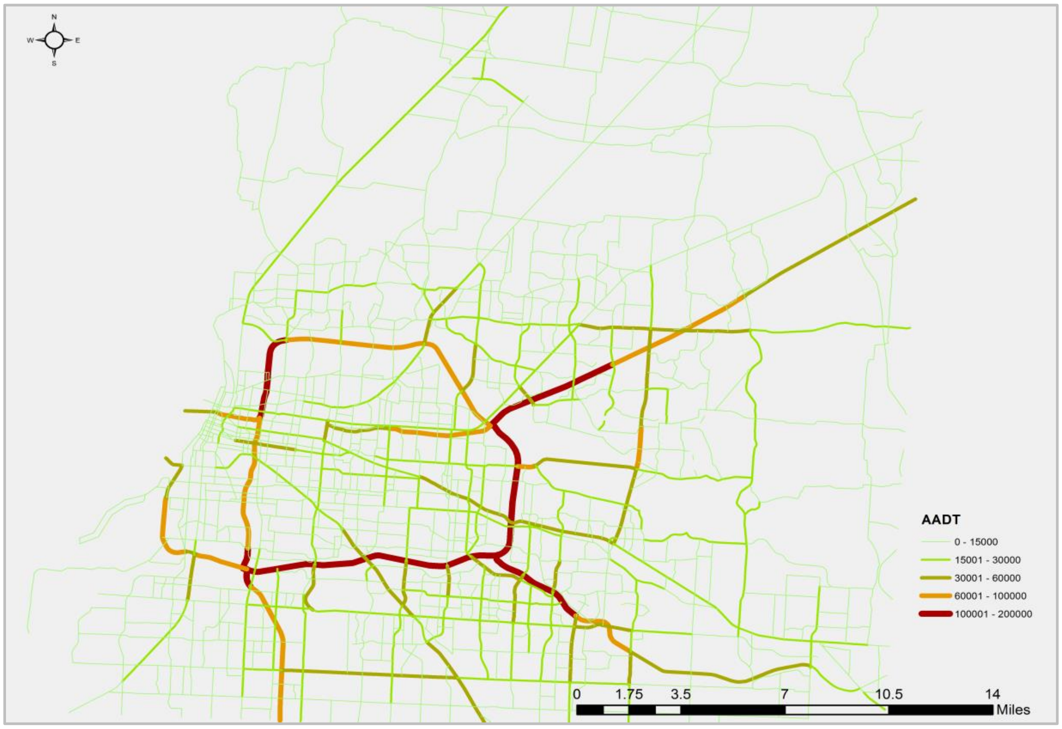


Note: AM 6:00-9:00, MD 9:00-14:00, PM 14:00-18:00, OP 18:00-6:00 next day

Fig. 11. Variation in average queue length by time of day.

5.6. Traffic Volume and SC Occurrence

Fig. 12(a) shows AADT for the case study roadway network with moderate (orange) to high (red) volumes observed on freeways and interstates. Fig 12(b) presents SCs identified in the study area. Results shown in Fig.12 indicates that several roadway facilities with moderate AADT experienced large number of SCs while a large portion of interstates encountered small number of SCs. It is found that moderately congested freeway segments (as opposed to heavily congested segments) experienced very high occurrence of SCs. A possible explanation could be lower speeds and higher alertness of drivers for highly congested roadways; whereas on facilities with moderate congestion higher speeds, and lower alertness increase the probability of PC and also the induced effect of a SC. These findings are similar to previous studies in the literature (Dixit et al., 2011; Schefer and Rietveld, 1994).



a) Roadway network with AADT

b) Identified SCs (Case-5)

Fig. 12. Comparing AADT and SCs.

6. Validation

To assess the accuracy of SCIA additional observed data was collected from four Traffic Management Centers (TMCs) in TN, USA for the years of 2011 to 2014. The geographic location and roadway coverage of each TMC is shown in Fig. 13. Four TMCs maintain their own database on each and every incident in their respective region encompassing 400 miles of urban freeway segments. SC occurrences are noted in TMC database, and verified by TMC officials with video detection technologies.

Fig. 13. Validation Study Areas in Four Regions of Tennessee[2]

For validation purposes, each individual observed SC is verified against the respective modeled SCs to determine whether that particular crash is accurately simulated according to SCIA. We then aggregated the result by each region and each quarter of 2011-2014**,** resulting in 64 observations (4 regions×4

[2] Secondary incident data available from Transportation Management Centers for red highlighted links in the zoomed-in network

years×4 quarters). Each observation in the validation graph (Fig. 14) represents number of observed SCs and number of modeled SCs for a particular quarter of a given year in a specific region. For example, the observation, marked with red triangle suggests that 23 SCs were observed by TMC and out of 23, 20 SCs are correctly simulated according to SCIA (the red triangle presents observed and simulated SCs for first quarter of 2012). For simplicity, region and quarter information is not shown in Fig. 14. The R^2 value of 0.9492 shows a reasonable fitness suggesting SCIA replicated the observed SC data well. The validation plot displays a tendency of underestimation because some of the non-crash incidents (overturned vehicle, disabled vehicle, vehicle fire) were misclassified as SCs by TMC personnel in the observed SC database. Also the proposed methodology does not consider SC occurrence on arterials and/or ramp because of queues extending from freeways and vice versa. These limitations may have caused type I errors resulting in underestimation.

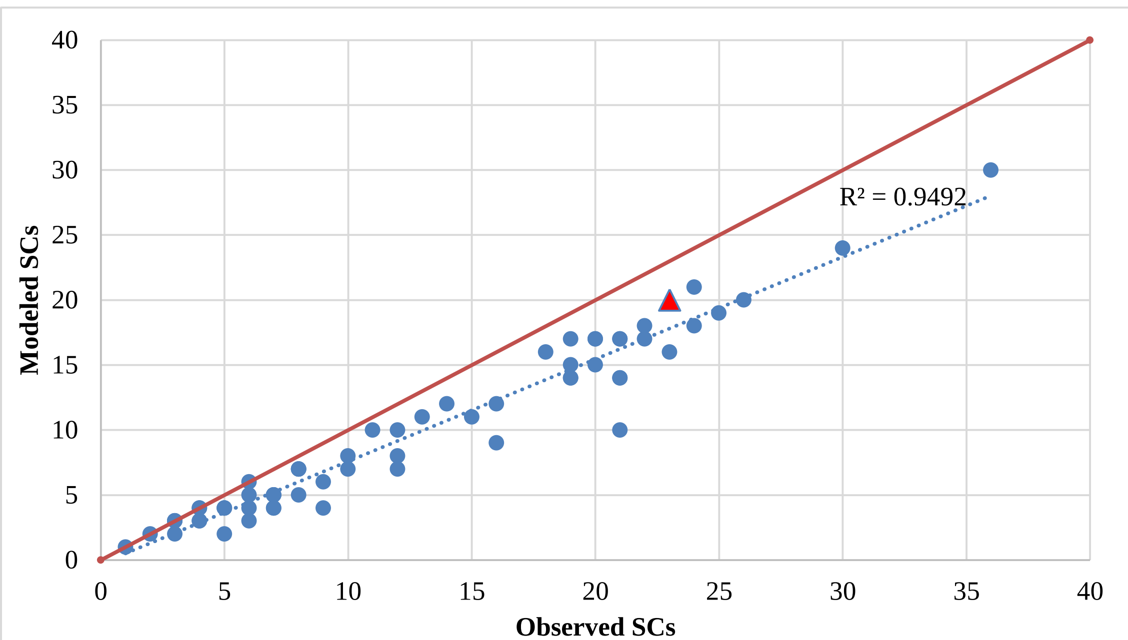


Fig. 14. Validation of SCIA

For robustness, the validation process was disaggregated by Cases (Case-1, 2 and 3) to determine if the accuracy changes because of directionality. After each observed SC is verified against the modeled SCs, the results are aggregated by year as shown in Table 1. The result shows that SCIA can accurately identify SCs at a minimum accuracy level of 72.50% in all the case scenarios and can go up to about 91%. Also, percentage of correctly identified SCs varies depending on the directionality of the PC while Case-1 scenario exhibits relatively higher accuracy compared to Case-2 and 3.

Table 1
Validation of SCIA

Year	Observed			Simulated			% Correct		
	Case-1	*Case-2*	*Case-3*	*Case-1*	*Case-2*	*Case-3*	*Case-1*	*Case-2*	*Case-3*
2011	108	42	24	92	33	18	85.19%	78.57%	75.00%
2012	126	54	40	111	40	29	88.10%	74.07%	72.50%
2013	141	46	46	116	34	35	82.27%	73.91%	76.09%
2014	111	48	36	101	36	29	90.99%	75.00%	80.56%
Grand Total	**486**	**190**	**146**	**420**	**143**	**111**	**86.42%**	**75.26%**	**76.03%**

The validation shown in Table 1 displays percentage of SCs correctly identified. False negative errors can be obtained by subtracting the percentage correct from one hundred percent. False negative errors are arising from the fact that non-crash incidents (overturned vehicle, disabled vehicle, vehicle fire) were misclassified as SCs by Traffic Management Center (TMC) personnel in the observed SC database. Also, the proposed methodology does not consider SC occurrence on arterials and/or ramp because of queues extending from freeways and vice versa. These limitations may have caused false negative error resulting in underestimation.

On the other hand, false positive errors were the result of misidentification of a SC by SCIA, however, that particular SC is not present in the observed data. False positive errors are not reported in this paper because of several reasons. *First,* the observed SC database in the case study area is at its infancy stage, and the SCs reported are only a fraction of total occurred in reality. Shelby county TMC have started gathering data on SCs only in last four years, and the traffic crash reporting database has not fully grown to record each and every SC. Currently, the traffic enforcement officers use their observation and TMC staff use traffic cameras to record SCs only on freeways. *Second*, because of lack of technology (communication gap between traffic enforcement officers dealing with PC and SC, and lack of personnel in the TMC) it is possible that a number of SCs are not reported or recorded. *Third*, the impact area identified by SCIA can be erroneous due to several reasons: **i)** faulty detectors which were providing unreliable traffic flow characteristics, **ii)** inaccurate clearance time for the PC which can lead to overestimation of impact area. With more awareness of SC occurrence on roadways and its importance for reporting the observed data, in the future it will be possible to also include the percentage of false positives in the validation result.

7. Study Limitations

The proposed algorithm identifies SCs on large scale transportation networks but limitations still exist as a result of insufficient data which are discussed next.

- Unavailability of disaggregate traffic flow data on arterials: For a realistic implementation of SCIA it is imperative to have traffic flow data for the exact time of PC and SC occurrence. Such data allows SCIA to adequately estimate the potential queue length and impact area using kinematic wave theory. Many public agencies maintain real-time and archived data on freeways and arterials using detectors. However, all planning agencies may not have access to such detailed data for arterials. Therefore, in its absence, agencies can utilize traffic flow data from planning models which are for a typical week day and cross classified by time of day distributions. However, typical week day diurnal distribution of traffic volume may not represent the flow conditions during the occurrence of PC and SC. If researchers and practitioners use typical week day diurnal distribution of traffic volume in SCIA, then some error will be present in the identification process.

- Queue length extending to multiple facility types: The proposed methodology only considers queue length for one facility type (e.g. freeway or arterial) and does not consider spill over to other connecting facilities. For example if a PC occurs in the close location of a ramp then the queue may extend to adjacent arterials causing a SC. More research is needed to determine queue length extending to multiple facility types.

- Adequate capacity reduction in intermediate state for arterials: For the case study, data on the number of lanes closed was not available for arterials. A distribution, approximating the number of lanes closed, was developed as a function of severity of the crash and the number of vehicles involved. Availability of more accurate crash data could allow the determination of the exact capacity reduction on arterials and improve the accuracy of SCIA.

- Clearance time: In the process of SC identification, clearance time is a crucial component and hence its accuracy is essential. Any sort of discrepancy will lead to type I and II error when identifying SCs. In this research, reasonably accurate clearance time is used as incident detection and its clearance are verified by video detection cameras on freeway segments by TMC. For the arterials, clearance time is reported by law enforcement officials. Overall, data on clearance time were comparable with past studies."

8. Conclusions

This study identified SCs for freeways using both a static and a dynamic approach. Past studies have proposed static and dynamic approaches to identify SCs but, to date no robust methodology had been proposed that can identify SCs with considerable accuracy on large networks within an acceptable computation time. Most of the past studies were conducted on short segments of freeways in a small regional scale and the dynamic approach was used only where detailed data were available. High resolution data to capture the dynamic variation in traffic flow characteristics as a result of a primary incident are rarely available for arterials. These data limitations restricted the application of dynamic approaches to SCs identification on arterials.

For the static approach this paper proposed five cases in an effort to consider all the different location and directionality combinations available when identifying SCs. The spatial threshold was applied in the opposite direction to capture effects of 'rubbernecking' which causes congestion and reduction in capacity in the opposite direction of the PC and can induce SC on freeways. For the static approach different spatiotemporal thresholds were used to evaluate their effect on the numbers of identified SCs. Temporal thresholds of 30, 60, 120, 180 and 300 minutes were used along with spatial thresholds of 0.5, 1, 2, 3 and 5 miles. The dynamic approach was based on shockwave principles and impact area analysis. A crash was identified as secondary if it occurred within the impact area of the PC. The proposed methodology was implemented in Shelby County, TN, USA where SCs were identified for freeways.

The analysis of the results revealed that the static approach consistently under and overestimated SC frequencies for small and large spatiotemporal threshold respectively. This phenomenon is expected as most SCs have a high probability of occurrence within the 30-60 min and 0.5-1 miles spatiotemporal thresholds and a low probability of occurrence within the 300 min and 5 miles spatiotemporal thresholds. It was observed that time of day play a crucial role in inducing SCs. Results also revealed that facilities with moderate AADT are quite likely to encounter large number of SCs. The validation of SCIA shows that the dynamic approach performs well in terms of replicating the observed SCs. The proposed methodology can identify SCs and network wide hotspots to assist transportation agencies in the decision making process to mitigate such incidents. Future research could focus on identifying primary contributing factors of SCs and development of prediction models for incident duration, probability of SC occurrence, associated delays and queue lengths.

Acknowledgment

This research was partially funded by WisDOT, TDOT, and USDOT. Also, computational facilities at Intermodal Freight Transportation Institute (IFTI) at University of Memphis are greatly acknowledged. Any opinions, findings, and conclusions or recommendations expressed are those of the authors and do not necessarily reflect the views of the above-mentioned agencies.

References

Chang, G.-L., Rochon, S., 2003. Performance Evaluation of CHART–Coordinated Highways Action Response Team–Year 2002.URL: www.chart.state.md.us/CHART/Final_Evaluation_Report_03-04.doc (accessed 1.15.15).

Chimba, D., Kutela, B., Ogletree, G., Horne, F., Tugwell, M., 2014. Impact of Abandoned and Disabled Vehicles on Freeway Incident Duration. Journal of Transportation Engineering 140, 04013013. doi:10.1061/(ASCE)TE.1943-5436.0000635

Chung, Y., 2010. Development of an accident duration prediction model on the Korean Freeway Systems. Accident Analysis & Prevention 42, 282–289. doi:10.1016/j.aap.2009.08.005

Chung, Y., Recker, W.W., 2013. Spatiotemporal Analysis of Traffic Congestion Caused by Rubbernecking at Freeway Accidents. Intelligent Transportation Systems, IEEE Transactions on 14, 1416–1422.

Colon, N.P., Rupp, M.A., Mouloua, M., 2013. Temporary Barriers to Reduce the Effects of Rubbernecking, in: Proceedings of the Human Factors and Ergonomics Society Annual Meeting. SAGE Publications, pp. 1810–1814.

Dixit, V.V., Pande, A., Abdel-Aty, M., Das, A., Radwan, E., 2011. Quality of traffic flow on urban arterial streets and its relationship with safety. Accident Analysis & Prevention 43, 1610–1616. doi:10.1016/j.aap.2011.01.006

Dunn, W.M., Latoski, S.P., 2003. Safe and quick clearance of traffic incidents. NCHRP Synthesis of Highway Practice 318.

Hagen, L.T., 2005. Best Practices for Traffic Incident Management in Florida (CUTR Report No. 21170543, HS-043 799). University of South Florida, Tampa and Florida Department of Transportation. URL: http://www.dot.state.fl.us/research-center/Completed_Proj/Summary_TE/FDOT_BC353_47_rpt.pdf (accessed 1.10.15)

Hirunyanitiwattana, W., Mattingly, S.P., 2006. Identifying Secondary Crash Characteristics for California Highway System. Presented at the Transportation Research Board 85th Annual Meeting.

Imprialou, M.-I.M., Orfanou, F.P., Vlahogianni, E.I., Karlaftis, M.G., 2014. Methods for Defining Spatiotemporal Influence Areas and Secondary Incident Detection in Freeways. Journal of Transportation Engineering 140, 70–80. doi:10.1061/(ASCE)TE.1943-5436.0000612

Jones, B., Janssen, L., Mannering, F., 1991. Analysis of the frequency and duration of freeway accidents in Seattle. Accident Analysis & Prevention 23, 239–255. doi:10.1016/0001-4575(91)90003-N

Karlaftis, M.G., Latoski, S.P., Richards, N.J., Sinha, K.C., 1999. ITS impacts on safety and traffic management: an investigation of secondary crash causes. Journal of Intelligent Transportation Systems 5, 39–52.

Khattak, A.J., Wang, X., Zhang, H., 2010. Spatial Analysis and Modeling of Traffic Incidents for Proactive Incident Management and Strategic Planning. Transportation Research Record: Journal of the Transportation Research Board 2178, 128–137. doi:10.3141/2178-14

Khattak, A.J., Wang, X., Zhang, H., Cetin, M., 2011. Primary and Secondary Incident Management: Predicting Durations in Real Time (No. VCTIR 11-R11, Project No. 87648). Old Dominion University and Virginia Center for Transportation Innovation and Research. URL: www.virginiadot.org/vtrc/main/online_reports/pdf/11-r11.pdf (accessed 7.20.14)

Kwon, J., Mauch, M., Varaiya, P., 2006. Components of congestion: delay from incidents, special events, lane closures, weather, potential ramp metering gain, and excess demand. Transportation Research Record: Journal of the Transportation Research Board 1959, 84–91.

Lighthill, M.J., Whitham, G.B., 1955. On kinematic waves. II. A theory of traffic flow on long crowded roads. Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences 229, 317–345.

Margiotta, R., Dowling, R., Paracha, J., 2012. Analysis, Modeling, and Simulation for Traffic Incident Management Applications (No. FHWA-HOP-12-045). URL: http://www.ops.fhwa.dot.gov/ publications/fhwahop12045 /fhwahop12045.pdf (accessed 7.3.14)

Masinick, J.P., Teng, H., 2004. An analysis on the impact of rubbernecking on urban freeway traffic (No. UVACTS-15-0-62). University of Virginia, Charlottesville. URL: www.scirp.org/journal/PaperDownload.aspx?paperID=42488 (accessed 3.7.15)

Moore, J.E., Giuliano, G., Cho, S., 2004. Secondary accident rates on Los Angeles freeways. Journal of Transportation Engineering 130, 280–285.

Owens, N., Armstrong, A., Sullivan, P., Mitchell, C., Newton, D., Brewster, R., Trego, T., 2010. Traffic incident management handbook (No. FHWA-HOP-10-013). URL: http://www.ops.fhwa.dot.gov/eto_tim_pse/publications/timhandbook/tim_handbook.pdf (accessed 1.10.15).

Ozbay, K., Kachroo, P., 1999. Incident management in intelligent transportation systems. URL: http://digitalscholarship.unlv.edu/ece_fac_articles/103 (accessed 3.7.15)

Pigman, J.G., Green, E.R., Walton, J.R., 2011. Identification of Secondary Crashes and Recommended Countermeasures (No. KTC-11-06/SPR402-10-1F). URL: http://www.ktc.uky.edu/files/2012/06/KTC_11_06_SPR_402_10_1F.pdf (accessed 1.7.15)

Raub, R.A., 1997a. Secondary crashes: An important component of roadway incident management. Transportation Quarterly 51 (3), 93-104

Raub, R.A., 1997b. Occurrence of secondary crashes on urban arterial roadways. Transportation Research Record: Journal of the Transportation Research Board 1581, 53–58.

Raub, R., Schofer, J., 1997. Managing Incidents on Urban Arterial Roadways. Transportation Research Record 1603, 12–19. doi:10.3141/1603-02

Saddi, R.R., 2009. Studying the impacts of primary incidents on freeways to identify secondary incidents. URL: http://digitalscholarship.unlv.edu/thesesdissertations/165 (accessed 1.10.15)

Schefer, D., Rietveld, P., 1994. Congestion and Safety on Highways; Towards an Analytical Model. Presented at the Proceedings of The Third International Conference on Safety and the Environment in the 21st Century: Lessons From The Past Shaping The Future, November 7-10, 1994, Tel Aviv, Israel.

Shah, S.R., Knoop, V.L., Hoogendoorn, S.P., 2015. Driver Heterogeneity in Rubbernecking Behaviour at an Incident Site, in: Traffic and Granular Flow'13. Springer, pp. 533–539.

Skabardonis, A., Petty, K., Varaiya, P., Bertini, R., 1998. Evaluation of the freeway service patrol (FSP) in Los Angeles. California Partners for Advanced Transit and Highways (PATH). URL: http://escholarship.org/uc/item/3920p806.pdf (accessed 1.5.15)

Sun, C.C., Chilukuri, V., 2010. Dynamic incident progression curve for classifying secondary traffic crashes. Journal of Transportation Engineering 136, 1153–1158.

Sun, C., Chilukuri, V., 2007. Secondary accident data fusion for assessing long-term performance of transportation systems. Midwest Trasportation Consortium, c/o Iowa State University. URL: http://www.ctre.iastate.edu/PUBS/midcon2005/SunFusion.pdf (accessed 1.10.15)

Vlahogianni, E.I., Karlaftis, M.G., Golias, J.C., Halkias, B.M., 2010. Freeway Operations, Spatiotemporal-Incident Characteristics, and Secondary-Crash Occurrence. Transportation Research Record: Journal of the Transportation Research Board 2178, 1–9.

Yang, H., Bartin, B., Ozbay, K., 2014a. Mining the Characteristics of Secondary Crashes on Highways. Journal of Transportation Engineering 140, 04013024. doi:10.1061/(ASCE)TE.1943-5436.0000646

Yang, H., Ozbay, K., Morgul, E.F., Bartin, B., Xie, K., 2014b. Development of an On-line Scalable Approach for Identifying Secondary Crashes. Presented at the Transportation Research Board 93rd Annual Meeting.

Zhan, C., Gan, A., Hadi, M., 2009. Identifying Secondary Crashes and Their Contributing Factors. Transportation Research Record: Journal of the Transportation Research Board 2102, 68–75. doi:10.3141/2102-09

Zhan, C., Shen, L., Hadi, M.A., Gan, A., 2008. Understanding the Characteristics of Secondary Crashes on Freeways. Presented at the Transportation Research Board 87th Annual Meeting.

Zhang, H., Khattak, A., 2011. Spatiotemporal patterns of primary and secondary incidents on urban freeways. Transportation Research Record: Journal of the Transportation Research Board 2229, 19–27.

Zhang, H., Khattak, A., 2010. What is the role of multiple secondary incidents in traffic operations? Journal of Transportation Engineering 136, 986–997.

Zheng, D., Chitturi, M.V., Bill, A.R., Noyce, D.A., 2014. Secondary Crash Identification on a Large-Scale Highway System. Presented at the Transportation Research Board 93rd Annual Meeting.