Identification of Secondary Crashes in Large Scale Highway Networks

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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, 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 network. The static approach is based on pre-specified temporal and spatial thresholds while the dynamic is based on shockwave principles. The procedure is applied in the State of Tennessee and results show that the dynamic approach can identify secondary crashes with better accuracy and consistency.

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) *(1)*. Earlier studies suggest that up to 15% of reported crashes have occurred partly or entirely as the result of a PC *(2)*. Though a relatively small percentage of all crashes are secondary, it is important to identify contributing factors and characteristics, and mitigate their effect on congestion, delay, fuel consumption and emission. SCs are non-recurring in nature and contribute up to 50% of congestion in urban areas *(3–5)*. 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] *(6, 7)*. U.S. DOT estimates that 18% of freeway traffic related fatalities are attributed to SCs *(8)*. 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 *(9)*. 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 such benefits 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 freeways with a large portion on short segments in small regional scales for easier delineation of direction, and spatial and temporal thresholds. The most challenging task was identification of SCs in terms of temporal and spatial thresholds, and directional criteria *(10)*. The latter, often a complex process, is the task of attaching the precise location of the crash to a specific lane. Often precise lane and direction identification is relatively easier for freeways, but poses a challenge for undivided medians. Therefore, arterials were excluded in most of the published research studies. In contrast, arterials encounter a significant number of SCs and their identification warrants further research.

The purpose of this paper is to develop a procedure to identify SCs in a relatively large transportation network with multiple roadway facility types using a static and a dynamic approach. The former approach assumes pre-specified temporal and spatial thresholds, based on past experience or engineering judgment, while the latter determines these thresholds based on real-time traffic conditions. This paper has two major contributions in the area of identification of SCs: a) development of a procedure to identify SCs in large networks with limited data and within acceptable computational times, and b) development of a dynamic queue length based approach to identify SCs in a large scale multi-facility type highway network using crash, traffic, incident management, and roadway network data.

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 from the static and dynamic approach. The final section concludes the paper, summarizing the findings, and presents future research directions.

LITERATURE REVIEW

In this section, the relevant literature on SCs identification is presented.

Temporal and Spatial Threshold

The first step in defining a SC is selection of temporal and spatial 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 *(11–19)* illustrate the use of static

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

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 *(12, 16)*.

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 *(20–22)*. An Incident Progression Curve (IPC) was proposed in 2007 and 2010 by Sun and Chilukuri *(23, 24)*, 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. Other studies developed queuing models to determine the impact area of a primary incident using estimated queue length and incident duration *(25)*.

The likelihood of SC occurrence is commonly associated with primary incidents by using a certain predefined spatial and temporal criteria. 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 *(26, 27)* identified real time traffic conditions as critical component in the accurate estimation of the influence areas.

SCs Identification Using Recent Techniques

Yang et al. *(28)* 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 *(29)*. 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 happened beyond these frequently used spatio-temporal thresholds. In addition, more than half of the 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 *(29)*. 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 *(16)* 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 temporal and spatial thresholds, independent of facility type, crash severity, clearance time, and flow characteristics; all of which are crucial determinants of SCs as the relevant literature revealed. 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 (types I and II errors respectively). Next, we present the proposed methodology to identify SCs on freeways and arterials in large size networks that eliminates such assumptions and errors.

METHODOLOGY

A pictorial representation of the proposed methodology and a step-by-step workflow is shown in Figure 1 and described in the following subsections. Before we proceed with the methodology description we present the notation used throughout the paper.

Notation	Description
$a_{bf,s}$	Backward-forming shockwave speed in the same direction
$a_{fr,s}$	Forward-recovery shockwave speed in the same direction
$a_{bf,o}$	Backward-forming shockwave speed in the opposite direction
$a_{fr,o}$	Forward-recovery 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	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
$(k_{jam})_s$,$(q_{jam})_s$,$(u_{jam})_s$	Density, flow, and speed of lane in the same direction after primary crash but prior to clearance (jam condition)
$(k_{sat})_s$,$(q_{sat})_s$, $(u_{sat})_s$	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
$(k_{jam})_o$,$(q_{jam})_o$,$(u_{jam})_o$	Density, flow, and speed of lane in the opposite direction after primary crash but prior to clearance (jam condition)
$(k_{sat})_o$,$(q_{sat})_o$, $(u_{sat})_o$	Density, flow, and speed of lane in the opposite direction representing optimal (saturated) condition
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

Static Approach

Identification of SCs using a static approach requires selection of pre-specified temporal and spatial 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 (graphically depicted in figure 2), capturing all possible types of SCs. These five cases are defined as follows:

- Case-1: Same Direction-Upstream: 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.

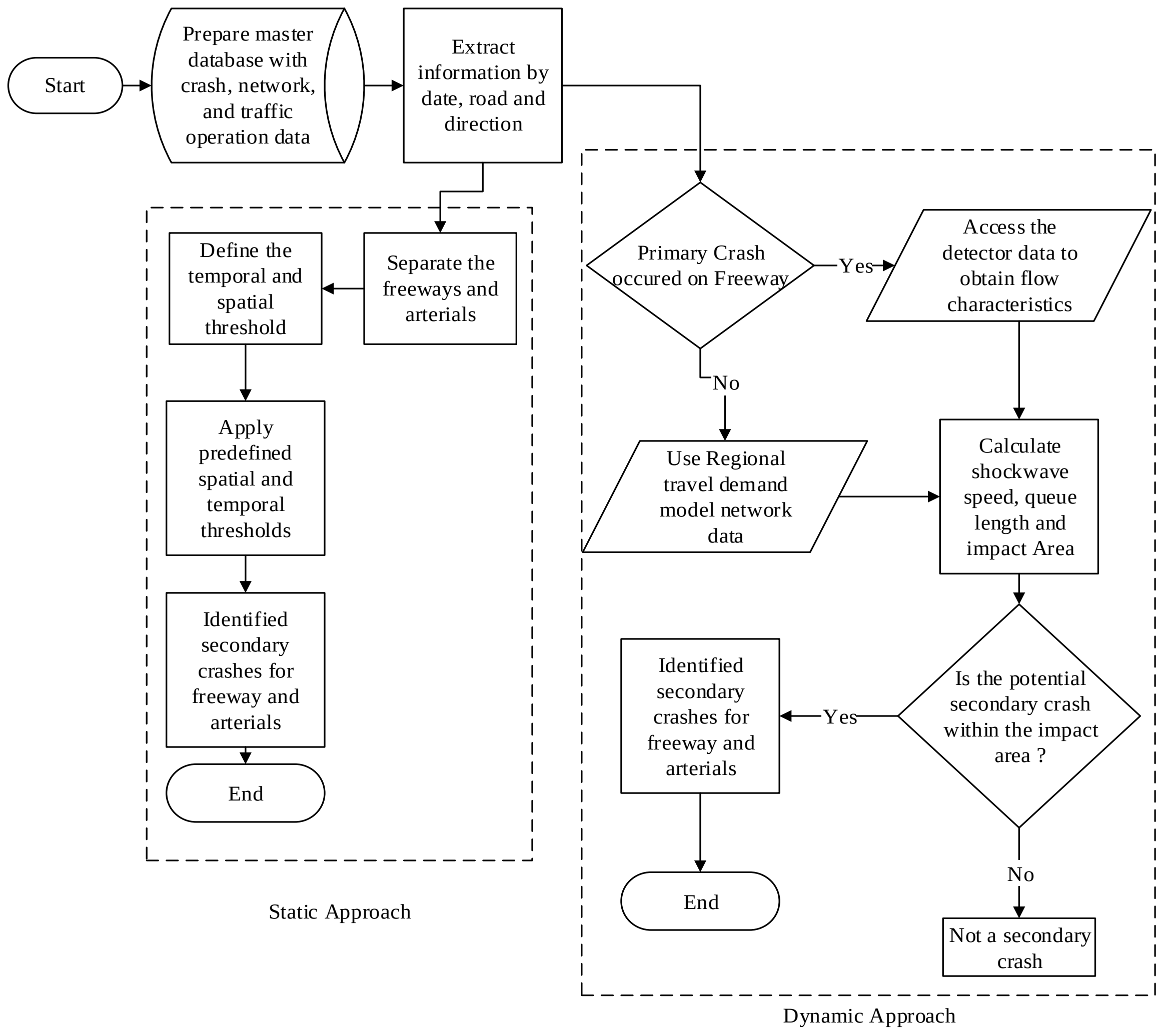


FIGURE 1 Flow chart showing the methodology.

For the static approach, in all five cases, temporal and spatial thresholds are predefined by the user. As an example, one can consider a one mile/one hour space and time threshold. For Cases-2 and 3, spatial threshold is applied in the opposite direction to account for ‘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 *(30)*. 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 *(30)*.

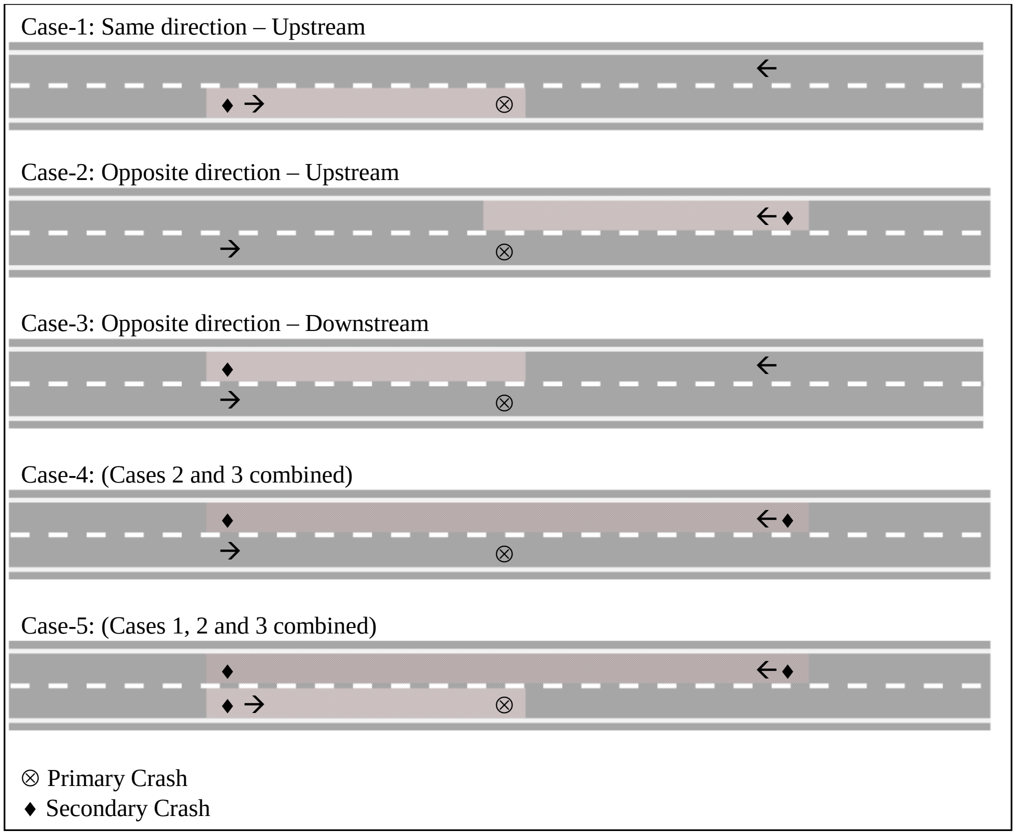


FIGURE 2 Pictorial representation of directionality and locations of SCs.

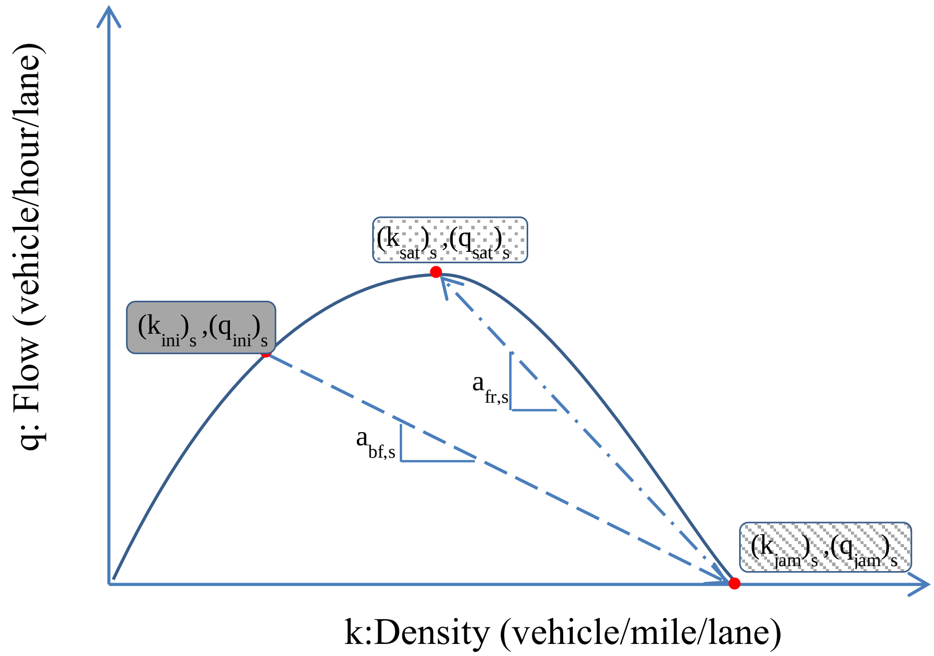
Dynamic Approach

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 queue formation after a PC occurrence. With a given traffic state and lane specific traffic flow parameters, continuously monitored by closely spaced 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 *(31)*. In this subsection we present a dynamic threshold SC incident identification approach to estimate the impact area of a PC created by a backward-forming and forward-recovery shockwave. Backward-forming shockwave affects the growth rate of the queue formed by the PC. Once the PC is cleared, a forward-recovery shockwave is set in motion and eventually catches up with the backward-forming shockwave resulting in dissipation of the queue. Next we discuss the steps required to estimate the impact area using the shockwave principle.

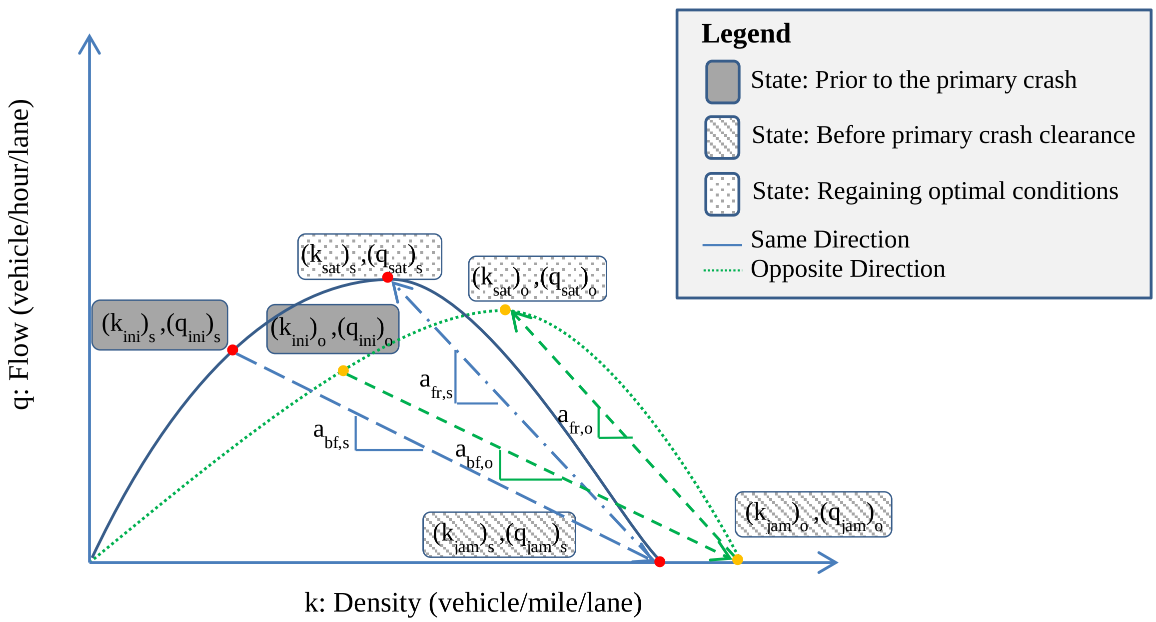
Estimation of backward- forming and forward-recovery shockwaves

Figure 3(a) shows a generalized density-flow plot where $(k_{ini})_s$ and $(q_{ini})_s$ are initial conditions of density and flow. Slope at this point will be the initial speed, $(u_{ini})_s$. If one or more lanes are completely closed (often the case) due to a PC, then the traffic state is represented by $(k_{jam})_s$, and $(q_{jam})_s$ (until the clearance period),where $(k_{jam})_s$ represents jam density and both flow ($(q_{jam})_s$) and speed ($(u_{jam})_s$) are zero. However, if density at this state is not equal to $(k_{jam})_s$, any another flow/density state, represented by the parabola, can be used. Speed of the backward-forming shockwave, is equal to:

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



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



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

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

Once the PC is cleared, the queued traffic state will try to reach optimal conditions ($(k_{sat})_s$, $(q_{sat})_s$ and $(u_{sat})_s$) forming a forward-recovery shockwave with a speed of:

$$a_{fr,s} = \frac{(q_{jam})_s - (q_{sat})_s}{(k_{jam})_s - (k_{sat})_s}.$$

A similar approach can be adopted to analyze shockwaves in the opposite direction. Figure 3(b) demonstrates traffic states for bi-directional traffic where $(k_{ini})_o$, $(k_{jam})_o$ and $(k_{sat})_o$ represent current, jam and optimal density states for the opposite direction, and $(q_{ini})_o$, $(q_{jam})_o$, and $(q_{sat})_o$ are the respective flow states.

Impact Area Estimation

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

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

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

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

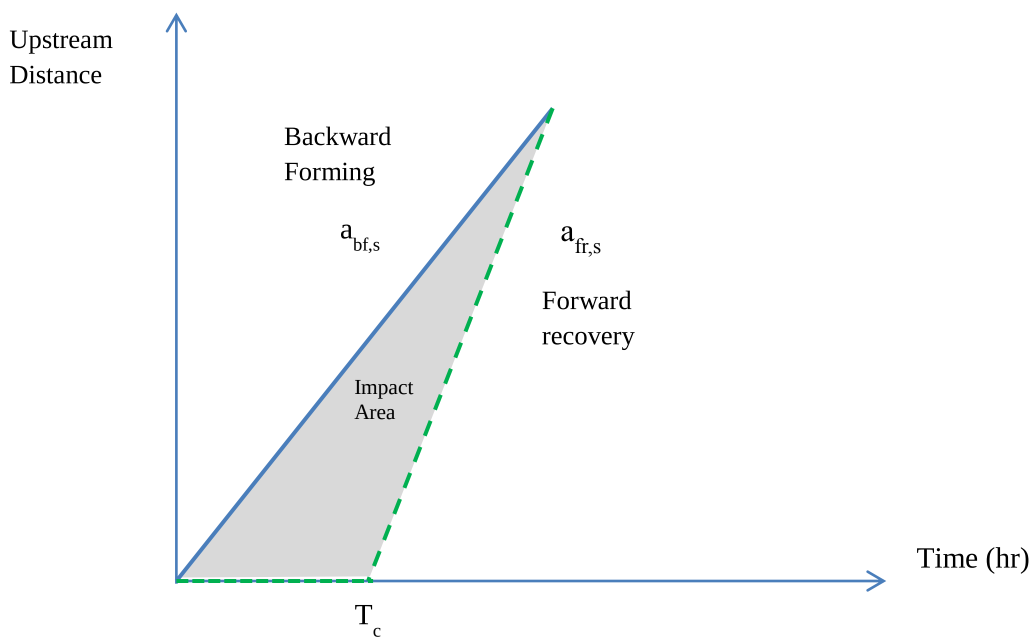


FIGURE 4 Graphical representation of impact area.

CASE STUDY

The transportation network of Shelby County, Tennessee (TN), in the United States (U.S.) is considered as the case study area to apply and evaluate the proposed methodology. Shelby County is the most populous county in the state of TN, home to one 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 the various 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 using 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.

Secondary Crash Identification Algorithm (SCIA)

The algorithm developed to identify SC (SCIA) involves two major steps: a) crash pairing, and b) SC identification and is described in detail next.

Step 1: Crash Pairing

The first step of SCIA involves crash pairing using various criteria such as day of occurrence, route, and a temporal and spatial threshold. Pairing accuracy is crucial in reducing the complexity of the remaining steps of the algorithm. During the first step, any crash (i) is considered as primary and an identification process is performed by querying crash (i) against all the remaining crashes in the database (j) to obtain a list of potential SCs (j). Each crash is associated with a day and time of occurrence, and the associated log mile. Distance between crashes was determined using the absolute difference in Beginning Log Mile (BLM) (as a reference point). The position of the paired crashes, with respect to each other, was determined using their direction, BLM and their respective coordinates.

Step 2: SC Identification

Once crash pairing is complete, SCs are identified using both the static and dynamic approach. For the static approach, only spatial and temporal thresholds were considered as criteria for identifying a SC. These thresholds for static approach can be set by the user. For the dynamic approach, traffic flow characteristics before the occurrence of a PC were required to estimate the impact area. These data were obtained either from detector datasets (for freeway) or the regional MPO travel demand model (for arterials). After the PC occurrence, one or more lanes are completely closed for the duration of the clearance time (T_c) and hence, jam condition is assumed. For this condition, we considered [$(q_{jam})_s$, $(u_{jam})_s$]=0 (i.e. there is no flow of traffic), and $(k_{jam})_s$ = 5280/25 = 211 veh/mi/lane assuming average vehicle length of 25 ft. including 5 ft. of safety distance between lead and following vehicle. 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 freeway) or 1800 veh/hr/lane, 45 mph respectively (for arterial). $(k_{sat})_s$ is calculated accordingly using the basic density-flow-speed formula ($(k_{sat})_s = (q_{sat})_s / (u_{sat})_s$).

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 between the two facility types. Additionally, incident management on urban arterial roadways area is considerably different than on freeways and will effect SC occurrence *(9)*. For the static approach different temporal and spatial 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 accommodate freeway queuing during peak periods.

Static Approach

Figure 5 presents SCs for all five directionality/location cases for the different temporal and spatial threshold values by facility type (freeway and arterial). We observe 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 facilities types when compared to Cases-2 and 3.

Dynamic Approach

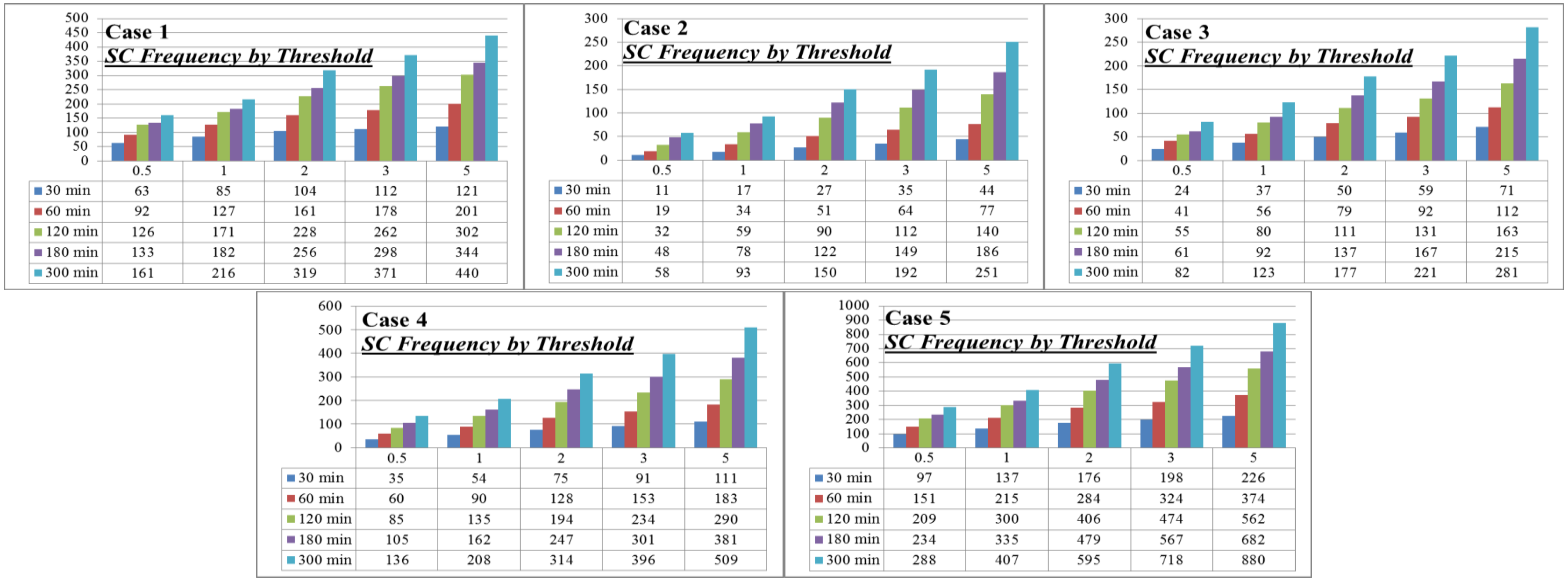
Frequencies of SCs, identified using the dynamic approach, for all five directionality/location cases for freeways and arterials, are shown in Table 1. For freeways, Case-1 exhibits a higher number of SCs when compared to Cases 2 and 3 combined, while SCs for Case-3 results in a higher frequency than Case-2 (142 SCs identified on freeways for Case-1 as compared to 45 and 68 for Cases- 2 and 3 respectively.). The same trend doesn’t apply to arterials as the rubbernecking effect is more prominent. A total of 1,179 SCs (freeways and arterials combined) are identified using the dynamic approach (Figure 6) which is comparable to the 1,095 crashes (Case-5) identified for one mile and one hour of the static threshold (Figure 5).

TABLE 1 Dynamic Threshold Based SCs (Freeways and Arterials)

	Freeways	Arterials	Total
Case-1	142	418	560
Case-2	45	267	312
Case-3	68	256	324
Case-4	112	521	633
Case-5	250	929	1179

Static vs. Dynamic Approach: SC Frequencies

Figure 6 presents the differences between SCs identified by both approaches. Results shown in figures 6a (freeways) and 6b (arterials) reveal that the static approach over-estimates SC frequencies as the thresholds (both spatial and temporal) increase. As expected, for low spatial/temporal thresholds (e.g. 30,60min and 0.5, 1mile) 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.



Case 1

	0.5	1	2	3	5
30 min	63	85	104	112	121
60 min	92	127	161	178	201
120 min	126	171	228	262	302
180 min	133	182	256	298	344
300 min	161	216	319	371	440

Case 2

	0.5	1	2	3	5
30 min	11	17	27	35	44
60 min	19	34	51	64	77
120 min	32	59	90	112	140
180 min	48	78	122	149	186
300 min	58	93	150	192	251

Case 3

	0.5	1	2	3	5
30 min	24	37	50	59	71
60 min	41	56	79	92	112
120 min	55	80	111	131	163
180 min	61	92	137	167	215
300 min	82	123	177	221	281

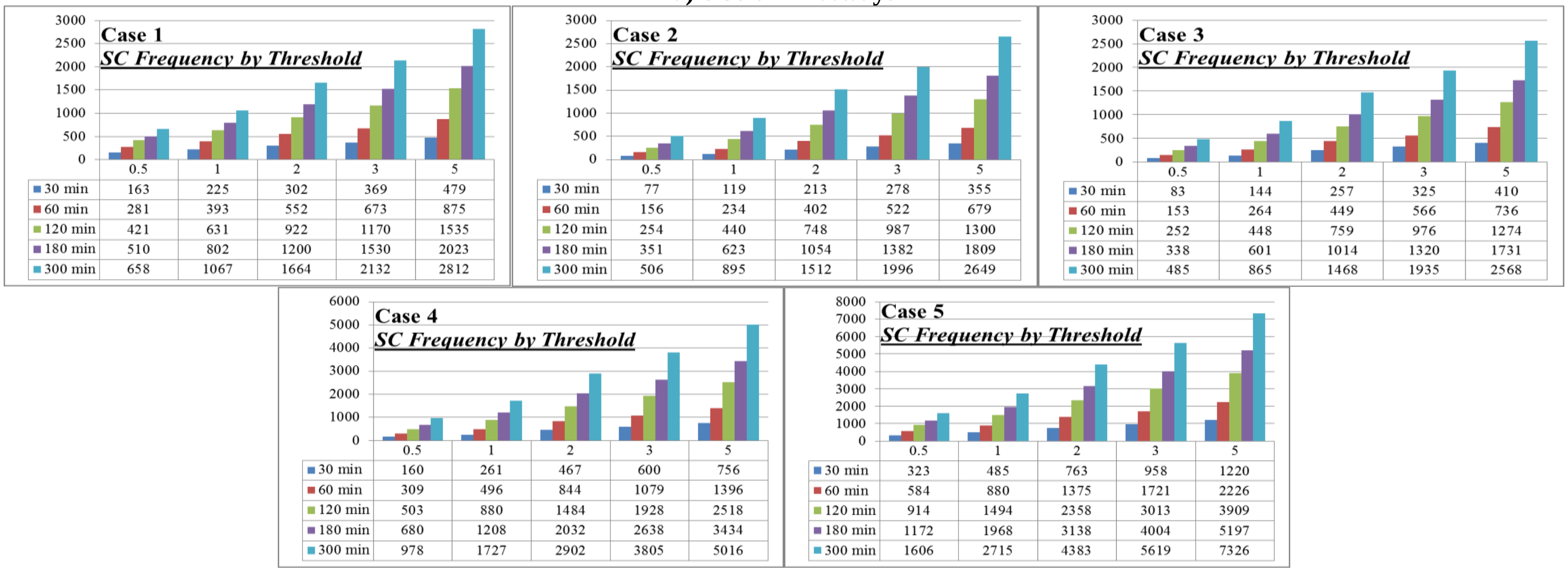
Case 4

	0.5	1	2	3	5
30 min	35	54	75	91	111
60 min	60	90	128	153	183
120 min	85	135	194	234	290
180 min	105	162	247	301	381
300 min	136	208	314	396	509

Case 5

	0.5	1	2	3	5
30 min	97	137	176	198	226
60 min	151	215	284	324	374
120 min	209	300	406	474	562
180 min	234	335	479	567	682
300 min	288	407	595	718	880

a) SCs on Freeways



Case 1

	0.5	1	2	3	5
30 min	163	225	302	369	479
60 min	281	393	552	673	875
120 min	421	631	922	1170	1535
180 min	510	802	1200	1530	2023
300 min	658	1067	1664	2132	2812

Case 2

	0.5	1	2	3	5
30 min	77	119	213	278	355
60 min	156	234	402	522	679
120 min	254	440	748	987	1300
180 min	351	623	1054	1382	1809
300 min	506	895	1512	1996	2649

Case 3

	0.5	1	2	3	5
30 min	83	144	257	325	410
60 min	153	264	449	566	736
120 min	252	448	759	976	1274
180 min	338	601	1014	1320	1731
300 min	485	865	1468	1935	2568

Case 4

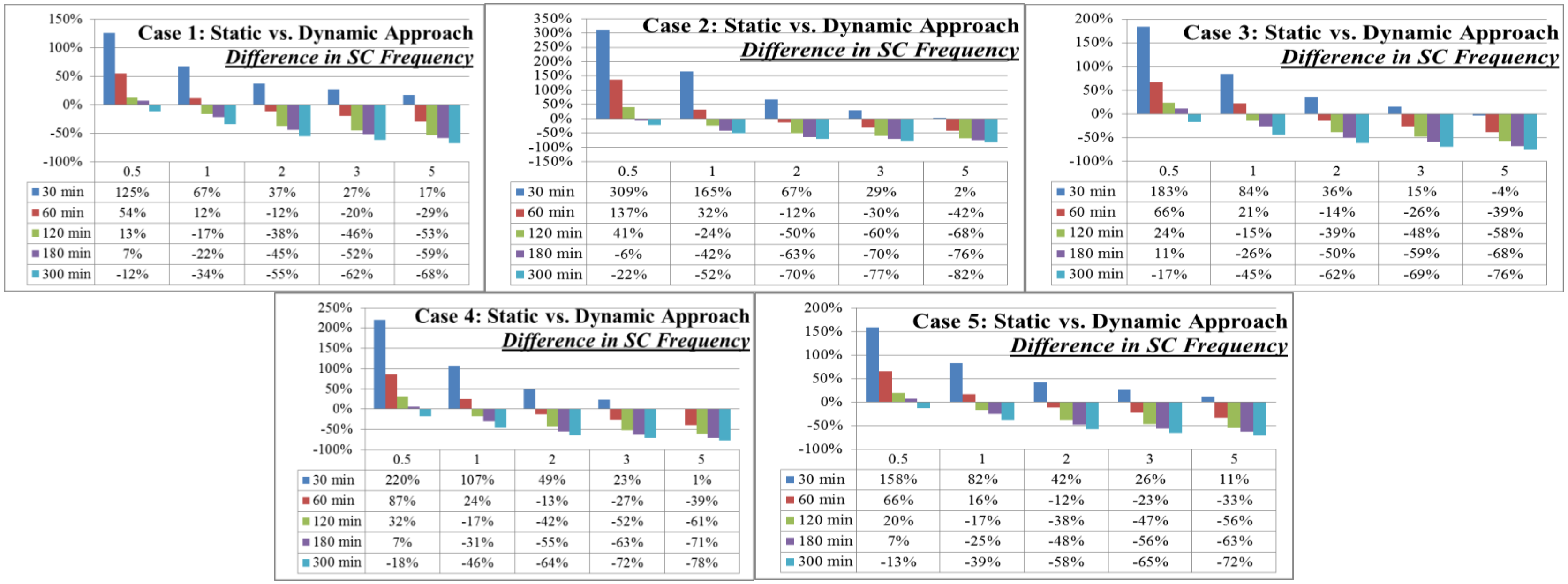
	0.5	1	2	3	5
30 min	160	261	467	600	756
60 min	309	496	844	1079	1396
120 min	503	880	1484	1928	2518
180 min	680	1208	2032	2638	3434
300 min	978	1727	2902	3805	5016

Case 5

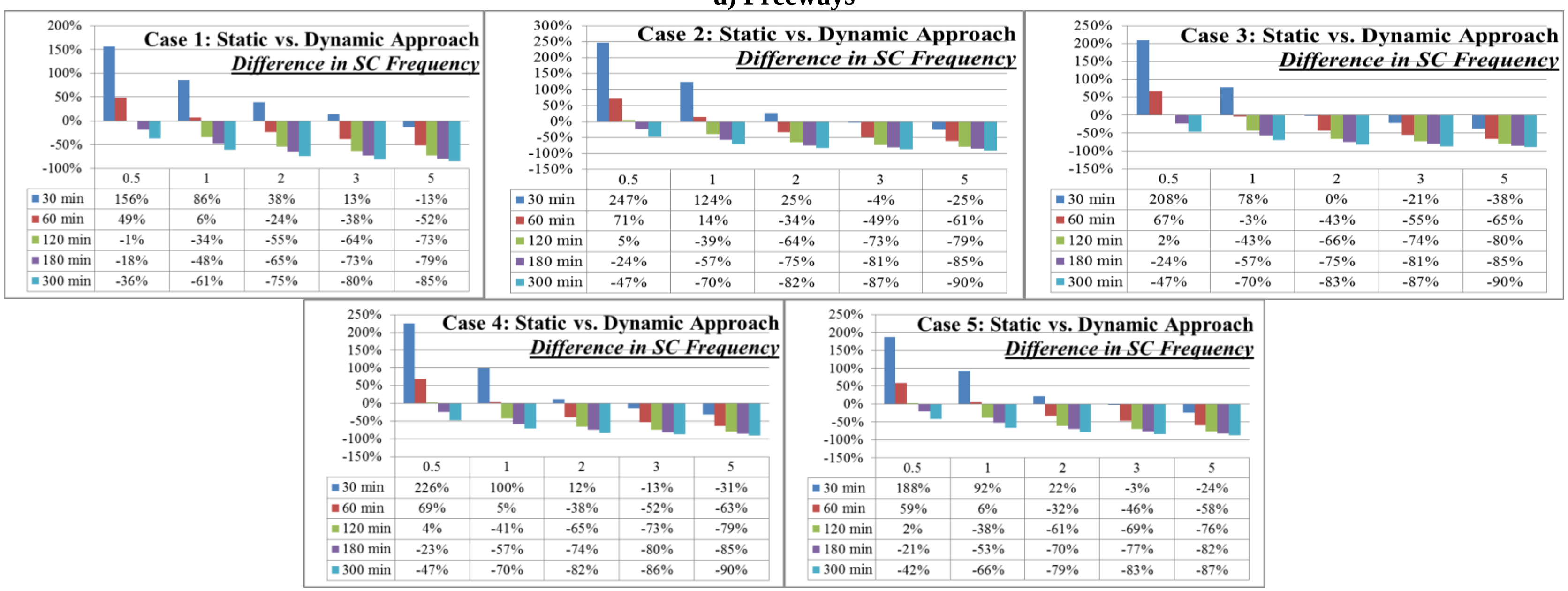
	0.5	1	2	3	5
30 min	323	485	763	958	1220
60 min	584	880	1375	1721	2226
120 min	914	1494	2358	3013	3909
180 min	1172	1968	3138	4004	5197
300 min	1606	2715	4383	5619	7326

b) SCs on Arterials

FIGURE 5 SCs identified using static approach (freeways and arterials).



a) Freeways



b) Arterials

FIGURE 6 Static vs. Dynamic approach SC comparison.

Dynamic Approach: SC Distribution by Time of Day

Figure 7 shows the time of day distribution of SCs obtained from the dynamic case on both freeways and arterials. Due to space limitations, only results for Case-1 are shown. Freeway facilities exhibit two distinct peaks: AM peak (between 8am- 9am), and PM peak (between 5pm-7pm). Both peak periods account for 59% of the total number of identified SCs for Case-1. On the other hand, arterials exhibit a very prominent PM peak (4pm-6pm) when compared to AM peak. SCs identified in the PM peak for arterials account for 48% of all SCs for Case-1. The reason that arterials have only one noticeable peak can be explained by the larger number of PCs occurring in the PM peak as compared to the AM peak. These results are in line with findings from the reviewed literature *(16)*. 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 event (Christmas break, winter weather etc.).

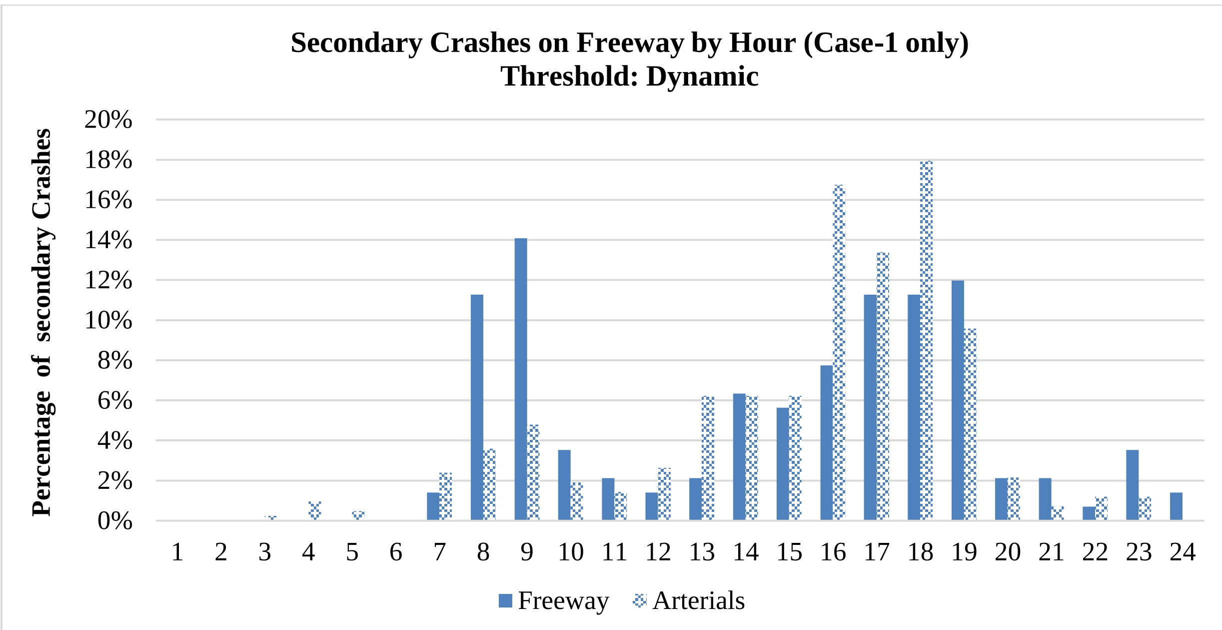


FIGURE 7 SCs (Case-1) by time of day using dynamic approach.

SCs Hotspots Map

SCs hotspots map can be a useful visualization tool for various agencies and can assist in faster identification of problematic facilities as well as dissemination of results and recommendations to a less technical audience. Using the dynamic approach for SC identification, hotspots maps were developed for Shelby County. Due to space limitation only one example (for Case-5) is shown in Figure 8 where the highest SC density occurs on two major arterials. Though traffic volume on those arterials is significantly less than on what usually observed on freeways, flow characteristics along with other primary contributing factors (e.g. geometric design and traffic operations) may have led to the high frequency of SCs. There are also some prominent hotspots on freeways, covering a relatively smaller region.

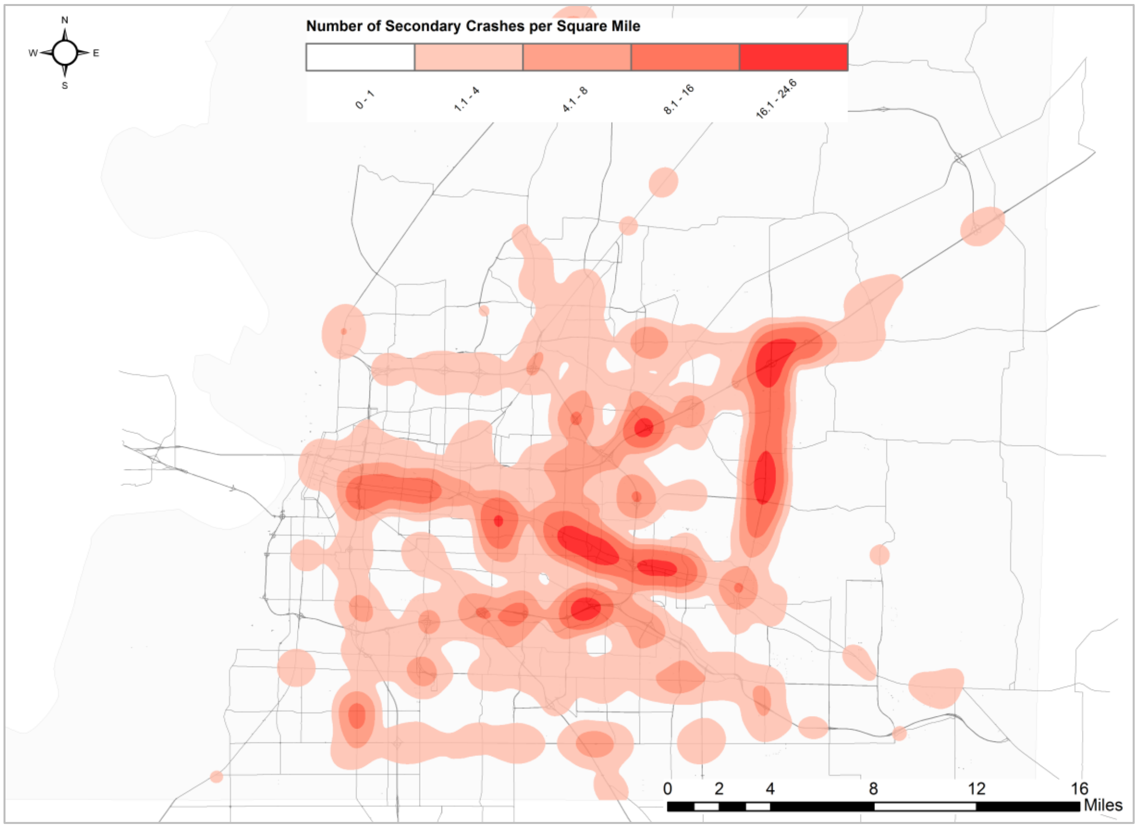


FIGURE 8 SCs hotspot map in Shelby County (Case-5).

CONCLUSIONS

This study proposed a procedure to identify SCs in a large-scale multimodal transportation network using two approaches (static and dynamic). Past studies utilized static and dynamic approaches to identify SCs but a robust methodology had not been proposed to identify SCs with considerable accuracy on large networks. For the static 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. The dynamic approach proposed was based on the shockwave principle and impact area analysis where 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. SCs were identified for two types of facilities: freeway and arterials to account for the different traffic conditions and data availability of each. Analysis revealed that the static approach consistently under- or over-estimates SC frequencies (depending on the spatio-temporal threshold used). Based on the density of SCs a hotspot map was generated for the study area which shows the locations where SCs are more likely to occur and supports identification of problematic facilities. 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.

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