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Modeling secondary accidents identified by traffic shock waves

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ABSTRACT

The high potential for occurrence and the negative consequences of secondary accidents make them an issue of great concern affecting freeway safety. Using accident records from a three-year period together with California interstate freeway loop data, a dynamic method for more accurate classification based on the traffic shock wave detecting method was used to identify secondary accidents. Spatio-temporal gaps between the primary and secondary accident were proven be fit via a mixture of Weibull and normal distribution. A logistic regression model was developed to investigate major factors contributing to secondary accident occurrence. Traffic shock wave speed and volume at the occurrence of a primary accident were explicitly considered in the model, as a secondary accident is defined as an accident that occurs within the spatio-temporal impact scope of the primary accident. Results show that the shock waves originating in the wake of a primary accident have a more significant impact on the likelihood of a secondary accident occurrence than the effects of traffic volume. Primary accidents with long durations can significantly increase the possibility of secondary accidents. Unsafe speed and weather are other factors contributing to secondary crash occurrence. It is strongly suggested that when police or rescue personnel arrive at the scene of an accident, they should not suddenly block, decrease, or unblock the traffic flow, but instead endeavor to control traffic in a smooth and controlled manner. Also it is important to reduce accident processing time to reduce the risk of secondary accident.

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1. Introduction

Freeway accidents not only cause severe travel delays, but can also result in secondary accidents, the risk of which is estimated to be six times greater than that for a primary accident (Tedesco et al., 1994). The high potential for occurrence and the negative consequences of secondary accidents make them an issue of great concern affecting freeway safety. However, secondary accidents and their relationships to primary accidents are usually not specifically mentioned in the accident database. Therefore, in much of the previous research, great effort has been made to identify the secondary accidents as shown in Table 1. Most of the existing research classified secondary accidents by predefining fixed spatio-temporal boundaries—a method that can be very subjective (Raub, 1997; Karlaftis et al., 1999; Moore et al., 2004; Hirunyanitiwattana and Mattingly, 2006). By studying operating traffic data, some study approaches compensated for the static method by proposing a range of dynamic definition methods based on concepts such as queuing theory, speed contour plot of the primary incident, and simulation (Zhan et al., 2009; Sun and Chilukuri, 2010; Green et al., 2012; Chung, 2013; Yang et al., 2013a, 2014b).

Shock wave theory can be used to illustrate how the conversion between two different conditions travels along traffic flow. Moore et al. (2004) applied shock wave filtering using fixed boundaries to identify secondary accidents, which required close manual attention to distinguish shock waves in loop data. However, limited installation of detectors, lack of data, and corrupted records of output data reduced data availability, which resulted in data for only sixteen accidents sufficient to execute this filtering method. Zheng et al. (2014) proved that the shock wave could be a fair tool to identify the secondary accident. He firstly extracted spatially and temporally nearby crash pairs (up to custom static thresholds) from a large network on the basis of a crash-pairing algorithm. In the second phase, two filters are used to select crash pairs that are more likely to be primary–secondary crash pairs. One of the filters uses shockwave theory to evaluate the dynamic traffic impact of the primary incidents. Then the manual review of identified police reports was carried out to confirm actual secondary crashes. Zheng also extended the shockwave filter to a freeway network scale. However Zheng just considered the release shockwave and queuing shockwave. In an incident when the rescue party or the policeman comes

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Table 1
Identification of secondary accident results in previous research.

Author	Spatial Boundaries	Temporal Boundaries	Results	Data
Raub (1997)	1 mile	15 min	More than 15% of the crashes may be secondary	Northern Chicago, metropolitan region (sample size 1796 crashes)
Karlaftis et al. (1999)	1 mile	15 min	34.7% of the crashes may be secondary	Borman Expressway (741 crashes)
Hirunyanitiwattana and Mattingly (2006)	2 miles	60 min	4.35%, more secondary accidents in rural districts	California highway system (sample size: more than 350,000 incidents)
Moore et al. (2004)	2 miles	2 h	1.5% to 3%, lower frequency of secondary accidents	Los Angeles Freeway (sample size 84,684 crashes)
Zhan et al. (2009)	Max queue length 1.09–1.49 miles	Incident recovery time: 33.34–52.6 min. Incident dissipation time: 0–21.76 min	3.23%	Florida District 4 I-595 and I-75. (sample size 7895 crashes)
Sun and Chilukuri (2010)	Incident Progression Curve based		7.14%	I-70 and I-270 in Missouri (sample size 5514 crashes)
Green et al. (2012)	Determine the time and distance relationships between the primary and subsequent-related crashes		3.88% are secondary and able to identify 87% of the secondary crashes that were manual searched	Roadways in Kentucky (sample size 9330 crashes)
Chung (2013)	Speed matrix based		7.5% and 3.8% in 2 directions respectively	California interstate freeways (sample size 6200 crashes)
Yang et al. (2013a)	Binary speed contour plot based		8.4% are secondary (user's defined speed reduction factor 0.7)	A 27-mile segment of a major highway in New Jersey (case study sample size 1188 crashes)
Yang et al. (2014b)	An on-line scalable approach		An automatic detection procedure.	Acquire traffic data from various third-party traffic map services.
Wang et al. (2015)	Shock wave based		1.08% of California interstate freeway accidents were secondary	2012 California interstate freeway accident (10,762 crashes)

to the crash site to manage the traffic, one more shock wave can be created. Moreover, the shock waves can trace each other, and this situation will be more complicated than Zheng's model. These problems could also happen in Chung (2013) and Yang's (2013, 2014) method.

A shock wave boundary filtering (SWBF) method was applied to identify 2012 California interstate freeway secondary accidents, and a lower frequency of 114 (1.08%) was found compared with findings from previous research (Wang et al., 2015). In this paper, SWBF is sequentially used to amplify the secondary accident sample in order to develop a more accurate secondary accident causation model. A total of 49,753 accidents that occurred from 2010 to 2012 on California interstate freeways, along with their corresponding upstream loop data were analyzed by the proposed method to demonstrate its reliability and efficiency. In addition, spatio-temporal gaps between the primary and secondary accident were subsequently studied.

Previous studies have investigated major factors contributing to secondary incident occurrence as shown in Table 2. Most of these studies used logistic regression models to explore the characteristics of secondary crashes (Karlaftis et al., 1999; Latoski et al., 1999; Zhan et al., 2008, 2009; Yang et al., 2013a). Some of the studies used probit models to assess the presence of significant differences between secondary crashes and primary crashes (Hirunyanitiwattana and Mattingly, 2006; Vlahogianni et al., 2012; Yang et al., 2013b, 2014a,c). In addition, other models were applied, including ordinal regression, binary probit regression, and Bayesian network (Khattak et al., 2009; Vlahogianni et al., 2010; Zhang and Khattak, 2010, 2011).

According to the literature, factors such as accident type, weather, duration, AADT, and vehicle involved have significant effects on the likelihood of incident occurrence. However, traffic situations resulting in secondary accidents were not further studied, as the AADT and time period of the incidents could not reflect the real traffic state at the time when the secondary accident occurred. Demonstrating the shock waves of each accident, a logistic regression model was built to compare primary accidents that led to secondary accidents with independent accidents.

2. Method

2.1. Shock wave boundary filtering (SWBF) method

In this study, a shock wave boundary filtering method (SWBF) (Wang et al., 2015) was used for secondary accident classification. Unlike most of the static filtering methods and dynamic methods based on queuing theory, SWBF provides real-time accident impact scope and is equipped with an automatic algorithm to conduct the filtering work circularly.

The SWBF method includes three main steps: (1) calculate traveling speed of primary accident impact through flow and density information; (2) determine a feasible spatio-temporal district for secondary accidents by estimating the real time space-time scope of shock waves generated by every potential primary accident; and

Table 2
Modeling approaches of secondary accidents in previous research.

Author	Method	Test variables	Conclusion
Karlaftis et al. (1999)	Logistic regression	Clearance time, vehicle type, vehicle location, season, day of week	Clearance time, season, type of vehicle involved, and lateral location of the primary crash significantly influence the likelihood of secondary crash occurrence.
Hirunyanitiwattana and Mattingly (2006)	Proportional test	Time of day, roadway classification, primary collision, severity level, type of accident	Secondary incidents are more likely to occur on urban freeways with more than four lanes and during peak periods, and are associated with exceedance of posted speed limits.
Zhan et al. (2008)	Logistic regression	Incident duration, time, environmental condition, incident type, location and traffic condition, lane closure, injuries, vehicle type	The number of vehicles involved in the primary incident, the number of lanes at the primary incident site, the primary incident duration, the time of day, and if vehicle rollover occurred during the primary incident impact secondary accident occurrence.
Zhan et al. (2009)	Logistic regression	Incident duration, time, environmental condition, incident type, location, traffic condition, lane closure, injury condition, vehicle type	Primary incident type, primary incident lane-blockage duration, time of day, and whether the incident occurred on northbound I-95 are significant. Accidents occurring during the day and with long lane-blockage durations can significantly increase the possibility of secondary crashes.
Khattak et al. (2009)	Binary probit regression models	Detection source, incident type, response vehicles, AADT, whether left shoulder affected, whether ramp affected, whether during peak hours, vehicle involved, observed duration, residual for duration, number of observations	Factors associated with higher secondary incident occurrence are longer duration, accidents, peak hours, more vehicles involved in incident, and higher AADT.
Zhang and Khattak (2010)	Ordinal regression	Incident duration, whether truck involved, number of vehicles, out of state vehicle, lane blockage, segment length, number of lanes, curve, AADT	Longer duration crashes, shorter segments, and heavy traffic are associated with higher propensity increase secondary incident risk. Multiple-vehicle involvement and lane blockage are associated with multiple secondary incidents.
Vlahogianni et al. (2010)	Bayesian network	Time, number of vehicles, distance, duration, type of vehicle, location, maximum queue length, duration of queue observed upstream	Traffic conditions at the time of an incident, as well as the time needed to respond to and clear the crash scene, are the most significant determinants in defining the upstream influence area of a crash.
Zhang and Khattak (2011)	Ordinary least squares (OLS) regression	The characteristics of primary incidents, road geometry, traffic	Longer time gaps are associated with crashes and disablements. Longer duration and detection by safety service patrol, phone calls, and cameras are associated with longer time gaps. Crashes and fires are associated with secondary incidents that occur at longer distances. Longer duration is related to larger distances.
Vlahogianni et al. (2012)	Probit models	Duration, collision type, number of lanes, number of vehicles, heavy vehicle, travel speed, hourly volume, rainfall, alignment, downstream geometry, upstream geometry	Traffic speed, duration of the primary accident, hourly volume, rainfall intensity, and number of vehicles involved in the primary accident are the top five factors associated with secondary accident likelihood. Blocked lanes, percentage of trucks, and upstream geometry also significantly influence the probability of a secondary accident.
Yang et al. (2013a)	Logistic regression	Time period, rear end, severity, duration, work zone, weekend, winter, lane closure, truck involved	Explanatory variables including time periods, crash type, crash duration, number of lanes closed, and season were found to significantly affect the likelihood of secondary crash occurrence.
Yang et al. (2013b, 2014a,c)	Probit model	The frequency of secondary crashes, spatio-temporal distributions, clearance time, crash type, severity	Almost half of the secondary crashes were found to occur within two miles upstream and two hours of primary crashes. Secondary crashes were more likely to involve two or more vehicles and to be rear-end crashes. Following too closely and improper lane change were the major reported contributing circumstances for secondary crashes.

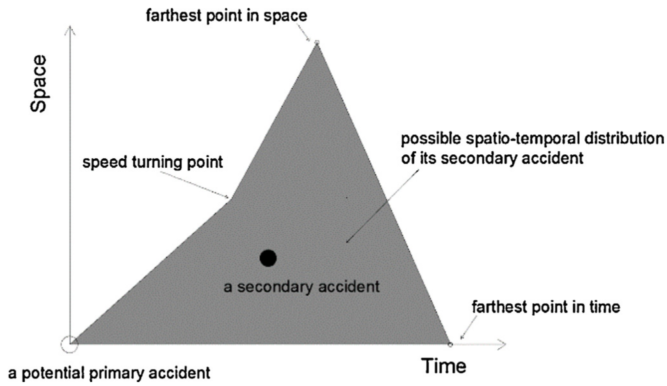

Fig. 1. Spatio-temporal secondary accident matching.

(3) match the primary accident with the corresponding the loop data to calculate the spatio-temporal district for secondary accidents.

The filtering process can be demonstrated as shown in Fig. 1. A primary accident can generate three shock waves with different speeds respectively, two different upstream forming shock waves, and one upstream dispersing shock wave. Shock wave 1 is generated when the accident takes place and causes a speed-reducing and density-increasing bottleneck until the treatment reaction begins. Shock wave 2 is generated, after tow trucks or police arrive, and the aftermath traffic status commences, causing a further worsening of the traffic flow condition. Shock wave 1 and shock wave 2 continue to spread upward until dispersal. Shock wave 3 is generated, after the accident bottleneck is relieved, and the traffic congestion begins to dissipate. The slopes in Fig. 1 represent the shock wave speed. A secondary accident is identified if it falls within the primary accident impact range, represented by the gray area in Fig. 1.

2.2. Data

Interstate freeway accidents that occurred in California from January 2010 to December 2012, collected from the California Statewide Integrated Traffic Records System (SWITRS), were used in this study. A total of 49,753 accidents that took place on interstate freeways across eight Caltrans districts were collected, since historic loop data is only available for these eight districts in the Caltrans Performance Measurement System (PeMS). In PeMS, average speed, traffic volume, and average occupancy for every 5 min of all loops located in the upstream of the corresponding accident were collected. Accident data and relevant traffic flow information from the loops were linked according to the time indicator and the location indicator, which is post mile. SWITRS and PeMS have different post mile fields—absolute post mile and California post mile, which renews by counties. A computer program was composed to match them.

Accident duration was not recorded in SWITRS, while PeMS (DOT database) have all the incident records which include all the accidents happened in California highways. Therefore a computer program was composed to match them according to the longitude, latitude, date, time, road name. Thus the accident processing duration could be got according to the corresponding incident duration.

Since the loop detector data are enormous, it is unnecessary to calculate all the shock waves generated by the 49,753 accidents. A pre-selection process was conducted according to previous research. The largest time gap between the primary and secondary accident in the previous research is about 200 min (Chung, 2013), and the largest distance gap in the previous research about 20 miles (Chima and Kutela, 2014). Boundaries of 3 h and 40 km were determined for pre-selection to confidently include the potential primary and secondary accident pairs. This resulted in the pre-selection of 1183 accident pairs from the original 49,753 accident records. The SWBF method for the identification of secondary crashes was then implemented as a filter. Finally, 204 primary accidents were found to induce 209 secondary accidents (one primary crash may cause multiple secondary crashes).

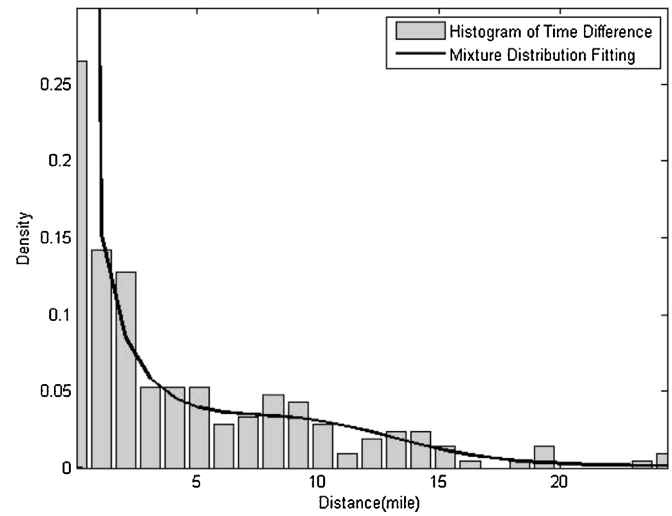

Fig. 2. Frequency distribution histogram of distance difference.

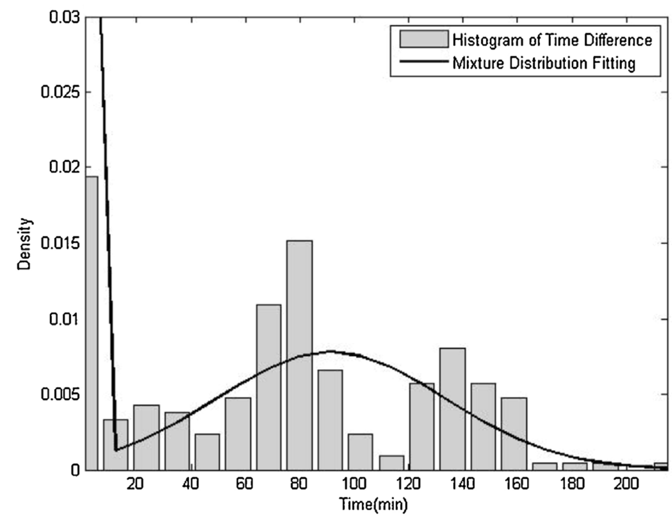

Fig. 3. Frequency distribution histogram of time gap.

2.3. Spatio-temporal distribution of secondary accidents

Figs. 2 and 3 show the frequency distribution histogram of the distance difference between the primary and secondary accidents. The distance difference less than one mile and the time gap less than 10 min account for a high percentage of secondary accidents in that spatio-temporal scope (19.4% and 26.5% respectively). A mixture of Weibull and normal distribution can describe the spatio-temporal distribution of secondary accidents. Parameters and values in Kolmogorov Smirnov (K–S) test are listed in Table 3.

2.4. Variables

Accident data from SWITRS include the detailed crash information as shown in Table 4. In addition, data from five

Table 3
Estimated parameters of time and distance difference distribution.

	Distribution		Position	Scale	Weight coefficient	K–S test	
						Stat	P value
Distance gap	Mixture	Weibull	2.041	0.573	0.785	0.073	0.199
		Normal	9.459	3.964	0.215		
Time gap	Mixture	Weibull	2.339	1.528	0.181	0.112	0.010
		Normal	91.417	41.850	0.819		

Table 4
Specification of variables in SWITRS.

Fields	Type of variables	Variable explanations (percentage in secondary accidents)
Crash severity	Discrete	1 Fatal (4%), 2 severe (3.9%), 3 minor (92.1%)
Violation category	Discrete	1 Alcohol or drug (4.6%), 2 unsafe speed (65.3%), 3 following too closely (1.4%), 4 improper turning (13.7%), 5 improper driving (13.6%), 6 other (1.4%)
Weather	Discrete	1 Clear and cloudy (90.5%), 2 raining (9.2%), 3 snowing (0.3%)
Tow away	Discrete	1 Yes (73.7%), 2 No (26.3%)
Road surface	Discrete	1 Dry (83.1%), 2 wet (16.7%), 3 snowy or icy (0.2%)
Lighting	Discrete	1 Daylight (78.4%), 2 dusk (2.4%), 3 dark-streetlights (12.1%), 4 no street lights or street lights not functioning (7.1%)

Fields	Type of variables		Mean	Variance	Std. Dev.	Min	Max
Parties involved	Continuous	Counts total parties in the collision	2.310	0.902	0.950	1	7
Shock Wave1 (km/h)	Continuous	Shockwave generated by the accident	125.155	23,681.390	153.887	0.085	502.683
Shock Wave2 (km/h)	Continuous	Shockwave generated when rescue personnel or police arrive (positive value: make traffic jam worse)	36.184	3726.956	61.049	0.000	500.000
Shock Wave3 (km/h)	Continuous	Dissipation shockwave after accident has been transacted	135.912	24,427.713	156.294	0.056	500.988
Volume (Veh/5 min)	Continuous	Traffic volume 5 minutes before accident	273.296	3.07E+04	175.267	2.042	807.458
Duration (h)	Continuous	Duration of the accident processing	0.89	0.695	0.834	0	18

minutes prior to the accident in the upstream loop were collected and shock wave speed was calculated using the SWBF method.

2.5. Statistical analysis

A logit model was built to compare primary accidents resulting in secondary accidents with independent accidents. The 204 primary accidents were counted as the case group with dependent value 1, while the 979 independent accidents were counted as the control group with value 0.

R software was used to conduct the logistic regression. The general form of secondary leading accident occurrence probability in a logistics model is as follows:

$$P(y_i = 1/x_i) = p_i = \frac{e^{\alpha+\beta x_i}}{1 + e^{\alpha+\beta x_i}} \quad (1)$$

The odds of an event occurring (odds ratio) is defined as follows (Wang and Guo):

$$\frac{p_i}{1 - p_i} = e^{\alpha+\beta x_i} \quad (2)$$

where p_i, probability that an instance i will occur; α, constant; β, vector of coefficients for independent variables; x_i, vector of independent variables.

3. Results and discussion

The regression results in R software are shown in Table 5. When the coefficients of the identified variables are positive or the odds ratio is greater than 1, then these variables can increase the likelihood of secondary accidents.

The model revealed the following:

The three shock wave speeds all significantly affect the occurrence of secondary accidents. Wave1, the shockwave that occurs at the time of the accident, has a negative coefficient. A possible explanation for this is that the high speed of Wave1 results in low density being abruptly transformed into high density. It is possible that secondary accidents are more likely happens under higher traffic volume conditions, when the primary accident increases the high density to even higher density, although low volume may cause chain-reaction accidents.

Wave2 is the shock wave generated when police or rescue personnel arrive at the site to control traffic. This wave intensifies the negative impact on secondary accident likelihood. The higher the wave speed, the greater the accident risk of the impact of traffic flow. Therefore, it is suggested that when police or rescue personnel arrive at the accident site, they should not block or suddenly decrease traffic flow—instead they should endeavor to control traffic in a smooth and controlled manner.

Wave3 is the dissipation shockwave, when the primary accident has been transacted and the bottleneck is recovered. Although the coefficient in the model is low, the sudden change of traffic capacity

Table 5
Logistic model result.

Deviance residuals				
Min	1Q	Median	3Q	Max
−2.9983	−0.5680	−0.3960	−0.0296	3.2425

Coefficients					
Variable	Estimate	Std. Error	*z* value	*P* value (>|z|)	Odds ratio
Intercept	2.101	1.974	1.065	0.287	–
Unsafe Speed	−0.366	0.185	−1.975	0.048	0.694
Clear and Cloudy	−4.055	1.963	−2.066	0.039	0.017
Raining	−3.680	1.978	−1.861	0.063	0.025
Wave1	−0.014	0.002	−7.358	1.86E−13	0.986
Wave2	0.010	0.002	5.943	2.81E−09	1.010
Wave3	0.006	0.002	3.177	0.001	1.006
Duration	0.715	0.096	7.420	1.17E−13	2.044
Null deviance: 1087.74 on 1182 degrees of freedom					
Residual deviance: 799.16 on 1175 degrees of freedom					
AIC: 815.16					

in the bottleneck also increases the probability of a secondary accident, when the shock wave attains high speed. It is also suggested that when the accident site has been transacted, police or rescue personnel should open the bottleneck for the waiting traffic in a smooth and controlled manner also. For example, stepwise speed control is necessary in the downstream section of the bottleneck to slow down the traffic wave.

As expected, accident processing duration significantly affect the occurrence of secondary accidents, which is similar to the results reported in most of the studies (Karlaftis et al., 1999; Zhan et al., 2008, 2009; Khattak et al., 2009; Vlahogianni et al., 2010, 2012; Zhang and Khattak, 2010, 2011; Yang et al., 2013a). Therefore, it is important to reduce accident response time and processing time to reduce the risk of secondary accident.

It is unexpected that unsafe speed of the primary accident is a negative factor relating to secondary accident occurrence. A possible explanation for this result is that drivers tend to travel at high speeds when the traffic flow is low. Although the traffic volume is not significant in the model, lower traffic volume may reduce the possibility of secondary accidents. This is consistent with the results reported in Vlahogianni et al. (2012). In their study, decreases in speed and increases in lane volume were shown to possibly lead to an increase in the probability of the occurrence of a secondary accident.

It is expected that rain has a negative influence on secondary accident occurrence. The absolute coefficient value of the clear and cloudy factor is higher than that of the rain factor. This finding differs from the results reported in some studies (Karlaftis et al., 1999; Yang et al., 2014a,c), in. which the winter factor was significant and had a negative coefficient.

Unlike the significant variables reported in previous research (Karlaftis et al., 1999; Zhan et al., 2009; Vlahogianni et al., 2012; Yang et al., 2013a), variables including tow away, involved parties, and road surface condition were not found to be significant in the present research. This could be due to the lower sample size for the secondary accident identification method.

4. Summary and conclusions

This research aimed to study the factors involving primary accidents resulting in secondary accidents. Shock waves are used identify secondary accidents. The findings indicate that secondary accident frequency is low (209 of 49,753 accidents over a three-year period) on California interstate freeways. Spatio-temporal gaps between the primary and secondary accident were proven be fit a mixture of Weibull and normal distribution. Time gaps of less than 10 min and distance gaps of less than one mile comprise a high percentage of the spatio-temporal gaps. The one-mile upstream and 10-min duration of the accident warrant further investigation. The proposed logistic regression model described in this paper shows the high significance of shock waves generated by the primary accident. This also suggests that when police or rescue personnel arrive at the accident site, they should not block or suddenly decrease traffic flow—instead they should endeavor to control traffic in a smooth and controlled manner.

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