

Fall 11-2015

Identifying Secondary Crashes by Using Geographic Information System (GIS) and Determining the Secondary Crashes Characteristics

Yuan Tian
Embry-Riddle Aeronautical University

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IDENTIFYING SECONDARY CRASHES BY USING GEOGRAPHIC
INFORMATION SYSTEM (GIS) AND DETERMINING THE SECONDARY
CRASHES CHARACTERISTICS

by

Yuan Tian

A Thesis Submitted to the College of Engineering Department of Mechanical
Engineering in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Mechanical Engineering

Embry-Riddle Aeronautical University
Daytona Beach, Florida
November 2015

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This thesis was prepared under the direction of the candidate's Thesis Committee Chair, Dr. Hongyun Chen, Assistant Professor, Daytona Beach Campus, and Thesis Committee Members Dr. Christopher Grant, Professor, Daytona Beach Campus, and Dr. Darris L. White, Professor, Daytona Beach Campus, and has been approved by the Thesis Committee. It was submitted to the Department of Mechanical Engineering in partial fulfillment of the requirements for the degree of Master of Science in Mechanical Engineering

Thesis Review Committee:



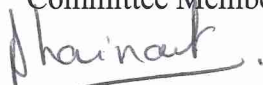
Hongyun Chen, Ph.D.
Committee Chair




Christopher Grant, Ph.D.
Committee Member



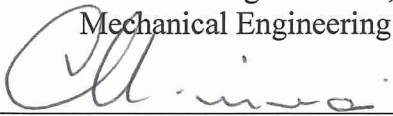
Darris L. White, Ph.D.
Committee Member



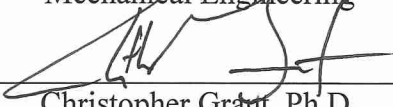
Jean-Michel Dhainaut, Ph.D.
Graduate Program Chair,
Mechanical Engineering



Charles F. Reinholtz, Ph.D.
Department Chair,
Mechanical Engineering



Maj Mirmirani, Ph.D.
Dean, College of Engineering



Christopher Grant, Ph.D.
Associate Vice President of Academics

11/13/15
Date

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor Dr. Chen for the continuous support of my master study and related research, for her patience, motivation, and immense knowledge. Her guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my master study.

Besides my advisor, I would like to thank the rest of my thesis committee: Dr. Grant and Dr. White, for their insightful comments and encouragement, but also for the hard question which incited me to widen my research from various perspectives.

Last but not the least, I would like to thank my family and friends for supporting me spiritually throughout writing this thesis and my life in general.

Abstract

Researcher: Yuan Tian

Title: Identifying Secondary Crashes by Using Geographic Information Systems (GIS) and Determining the Secondary Crashes Characteristics

Institution: Embry-Riddle Aeronautical University

Degree: Master of Science in Mechanical Engineering

Year: 2015

As the nation's transportation infrastructure expands, traffic incidents led to more than 25% of traffic congestion in the United States (FHWA, 2014). The risk of the occurrence of secondary crashes can be six times higher in the presence of a primary crash than that at a normal traffic condition (Yang et al., 2013 and Tedesco, 1994). The purpose of this study is 1) to develop a method to identify the secondary crashes with the primary incidents in Geographic Information Systems (GIS) under different spatial-temporal criteria, and 2) to determine the impacts of spatial-temporal criteria on the secondary crash characteristics in terms of crash injury severity, crash types and contributing factors.

ArcGIS is a powerful software package providing users with ease of processing large databases while linking crash data with geometric information. A logic-processing diagram that feasibly links the secondary crashes with the primary incidents under different temporal and spatial criteria was developed in this study. T-tests were used to determine whether the spatial-temporal criteria significantly affected the secondary crashes with different crash characteristics. The results are expected to help traffic agencies to select effective countermeasures to reduce secondary crashes and injury severity levels.

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List of Acronyms

GIS	Geographic Information System
NHTSA	National Highway Traffic Safety Administration
FHWA	Federal Highway Administration
GPS	Geographic Positioning System
WisDOT	Wisconsin Department of Transportation
FDOT	Florida Department of Transportation
CAR	Crash Annual Report
AADT	Average Annual Daily Traffic

Chapter I

Introduction

In the past decade, motor vehicle crashes remain one of the leading causes of death nationwide (NHTSA, 2012). In 2012, there were 33,561 fatalities in motor vehicle crashes in the United States, which rose from the 32,479 fatalities in 2011 (NHTSA, 2012). Primary incidents occur due to different contributing factors including vehicle characteristics, roadway features, and human factors, such as fatigue driving, low visibility speeding, etc. According to the Federal Highway Administration (FHWA, 2014), approximately 25% of traffic congestions were caused by traffic incidents. These facts indicate that it is imperative to improve roadway safety and reduce congestion in an effective manner.

Besides the traffic delays caused by the primary incidents, the occurrence of secondary crashes creates additional delays and safety issues. The definitions of secondary crashes vary, but the most commonly accepted one is that the crashes occur at least in part by a primary incident within the congested spatial-temporal region (Imprialou et al., 2013 and Pigman et al., 2011). The risk of the occurrence of secondary crashes can be six times higher in the presence of a primary crash than that at a normal traffic condition (Yang et al., 2013 and Tedesco, 1994). The reduction and prevention of secondary crash occurrence require a full understanding of their characteristics, contributing factors with respect to traffic, geometric conditions, and incident details. However, research on secondary crashes is limited; the spatial and temporal boundary definitions also vary by states and locations. No thorough comparison or definition has been used so far.

The existing research on freeway incidents focuses on incident duration and its relation to formation and duration of traffic congestion, whereas secondary incident research has focused on induced delay (Zhan et al., 2008). Identifying secondary incidents requires completed data resources to accurately link the secondary crashes to the primary incidents. The larger-scale the data set, the more complicated the procedure becomes. It used to be very tedious work and complex in the process no matter which method was used. This study proposes a method to link the secondary crashes with primary incidents under different spatial and temporal criteria in ArcGIS, which is expected to reduce the amount of work in the previous studies to identify and link the secondary crashes with the primary incidents.

ArcGIS is a widely applicable software package that allows users to analyze data by collecting, storing, controlling and geographically displaying it. It provides users with the ease of processing large databases to link crash data with geometric information and temporal criteria, and the flexibility to query the datasets under different criteria. Large amounts of information can be processed quickly due to the visual and tabular format of the GIS data. Using GIS in the crash analysis has been of great interest recently in analyzing highway crashes (Emaasit et al., 2013, Kim et al., 2000 and FHWA, 1999). The time and effort required to analyze crash data can be significantly reduced while an increasing number of scenarios and alternatives can be evaluated. It is a tool to assist engineers, administration, policy makers, law enforcement, and emergency personnel to make informed decisions on traffic safety related problems (Roche et al., 2000).

The main purpose of this study is to 1) identify a method to link the primary incidents with secondary crashes in ArcGIS, and 2) determine the impacts of spatial-

temporal criteria on the secondary crash characteristics in terms of crash injury severity levels, crash types and contributing factors.

Chapter II

Review of the Relevant Literature

The static method and dynamic method are the two methods that have been used to identify secondary crashes. The static method uses fixed spatial and temporal thresholds. The dynamic method uses changing spatial and/or temporal boundaries depending on queue lengths, roadway types, and other relevant factors.

Static Method

Many studies have used the static method as listed in Table 2.1. These spatial and temporal boundaries are determined. Some studies use a fixed duration or the clearance time plus selected additional recovery time as the temporal boundary.

Carlos Sun and Venkat Chilikuri (Sun et al., 2010) extracted a total of 480 incidents reports from I-70 and I-270. They selected 3.62 miles and 42 minutes spatial-temporal criteria. Another study in Kentucky (Pigman, 2011) chose the boundaries to be 80 minutes and 1000 ft. The Kentucky study used 236 vehicles from the database, and confirmed secondary incidents only after a duplicate removal process. They filtered out crashes that did not also correspond with the criteria set in “Secondary Collision” code that was developed to examine whether the crashes meet the requirement to be the secondary crashes or not. This additional process further refined the accuracy of the identification.

Raub (1997) defined the secondary incident to be any crash that happened during the clearance period of a primary incident plus an additional recovery time of 15 minutes and a fixed spatial boundary of one mile upstream. Zhan, C., L. Shen, M. A. Hadi, and A.

Gan(2008) selected the similar temporal criterion; however, the spatial criterion was assumed to be two miles upstream of the primary incidents in the same direction.

Table 2.1 Summary of Spatial-Temporal Criteria of Static Methods

Method	Spatial	Temporal	Location
Fixed Criteria (Pigman et al., 2011)	3.62 Miles	42 Minutes	Major Freeways
GPS (Raub et al., 1997)	1000 Feet	80 Minutes	State Highways
Fixed Criteria (Mattingly et al., 2006)	3 Miles	Clearance Time + 15 Minutes	I-65,I-80,I-94
Programming (Raub.A.A et al.,1997)	2 Miles	Clearance Time + 15 Minutes	I-95, I-75, I-595
Fixed Criteria (Zhang et al., 2010)	2 Miles in Both Directions	2 Hours in Both Directions	I-5 from Mexican border to Orange County
Programming (Khattak et al., 2009)	2 Miles	1 Hour	32 California Interstate Highways, 7 US highways, 218 state routes
Fixed Criteria (Kopitch et al. , 2011)	1 Mile	Actual Incident Duration + 15 Minutes	Freeways in Hampton Roads Area
Existing Database (Zhan et al., 2009)	2 Miles in the Same Direction, 0.5 Mile in the Opposite Direction	2 Hours in the Same Direction, 0.5 Hour in the Opposite Direction	Statewide Ops Center (SOC) TOC 3, near Capital Beltway, and TOC 4 near Baltimore Beltway

One study investigated secondary incidents in Los Angeles (Mattingly, 2006) and determined a 2-hour and 2-mile in each direction boundary standard at first, but then they resolved that downstream crashes are not secondary incidents and eliminated such crashes from the results. Another one selected 2 -mile and 1-hour as the criteria in Northern California.

Dynamic Method

Different from the static method, the dynamic method uses different spatial and temporal criteria based on different primary incidents. The maximum queue length was commonly used as the spatial boundary, and most of the existing dynamic methods developed models and/or algorithms to describe it. The other methods preferred using computer software with Geographic Positioning System (GPS) technology that allows finding out the actual point-to-point distance between crashes rather than modeling. As for the temporal threshold, the incident duration was used in the most studies. Table 2.2 summarizes the methods and criteria used to identify secondary crashes.

A master incident progression curve developed by Chilikuri and Sun (2010) based on a third order polynomial was a typical modeling research. In that study, the spatial threshold was 3.09 miles, and the temporal threshold was 80.5 minutes. However, this research was limited by the fact that only traffic queues in the downstream direction were used in setting the spatial boundaries. Data from police crash records have the potential to mislead as police officers physical ability to observe is limited.

Another study conducted by Zhan, Gan, and Hadi (2009) utilized a combination of deterministic queuing methods and shockwave analysis to create a cumulative arrival and departure curve. This study took place on I-95 in Fort Lauderdale, Florida and resulted in

1.14 miles and 33.34 minutes for the spatial and temporal criteria. Another modeling study developed a Bayesian mathematical model (Vlahogianni et al., 2010) to help identify the thresholds, and the maximum queue length and duration of the queue were selected as the criteria.

Table 2.2 Summary of Spatial-Temporal Criteria of Dynamic Methods

Method	Spatial	Temporal	Location
Queue Based Model (D/D/1) (Emaasit, 2013)	Queue length	Incident Duration	Hampton Roads
3rd Order Polynomial Models (Pigman, 2011)	Result of Master ICP = 3.09 miles	Result of Master ICP = 80.5 minutes	I-70
Cumulative Arrival and Departure Curve (Zhan, 2009)	Arrival & Depart Curve, Ex: 1.14 miles	Arrival & Depart Curve Ex: 33.34 min	I-95 Fort Lauderdale
Bayesian Model (Vlahogianni et al., 2010)	Max queue Length Observed Upstream	Duration of Queue Observed Upstream	Attica Tollway
Queue based software (Secondary Identification Tool) (SiT) (Khattakl et al., 2009)	Queue Caused by Primary Traffic Incident, including Opposite Traffic	Actual Duration of Primary Incident Plus Incident Clearance time	Hampton Roads
Speed Contour Maps, Line Algorithms (Yang et al., 2013)	Queue length	Incident Duration	Turnpike
Linear Referencing System, Crash Pairing Algorithm (Zheng et al., 2013)	Queue length	Incident Duration	WI freeways

Other studies chose GPS technology to find out needed spatial and temporal criteria according to diverse requirements. A graphic user interface program called Secondary Identification Tool was developed (Khattakl et al., 2009). This program allowed the users to determine the temporal criteria by their own needs. The minimum temporal boundary was the clearance time of the primary incidents, and then the users can add extra time to it according to different conditions or studies.

Another program using Application Programming Interface (Yang et al., 2013) extracted real-time traffic information from private third parties such as MapQuest and Google Maps. The traffic information was converted into a series of maps from which an algorithm determines the spatial and temporal boundaries of the primary incidents. Wisconsin Department of Transportation (2013) used a linear referencing system in their STN, from which any point can be located based on its coordinates and be validated accordingly with a map. A crash-pairing algorithm was developed along with two filters that weeded out crashes that occurred on ramps and primary secondary pairs with illogical spatial-temporal thresholds.

For the static methods, even the spatial-temporal criteria are fixed at each location; the selecting criteria were varied. The average value of temporal threshold was about 2 hours. The spatial threshold varies from 1000 feet to 3.62 miles. For the dynamic methods, most studies used the queue length and the incident duration as the spatial and temporal criteria. Thus, an effective processing method is needed to be flexible and practical to link secondary crashes with primary incidents for both static and dynamic methods.

Chapter III

Methodology

Data Selecting Criteria

As a pilot study, the primary incidents and the secondary crashes were selected from Florida's interstate highways (I). The data on the primary incidents of 2010 were obtained from the incident database. Only incidents categorized as *crash* were selected. In this case, 296 primary incidents were found. The crash data were obtained from the Crash Annual Report (CAR) system maintained by the Florida Department of Transportation (FDOT).

Before developing the logic process in ArcGIS, the appropriate spatial and temporal criteria were established. The static method that was used set the fixed spatial and temporal criteria. The developed logic process should be able to identify the secondary crashes under various temporal and spatial criteria.

Based on the previous studies, the fixed spatial boundary was set as 2 miles in the same direction of the primary incidents and as 2 miles upstream of the primary incidents. The static temporal threshold was set as two hours. Different types of crashes influence traffic delays in different ways. For instance, a fatal crash will lead to a longer disposing time and blocking distance than a property damage only (PDO) crash. The temporal threshold should vary based on the traffic conditions, the geometric information, and the incident characteristics. The clearance time is one factor that can remain constant in different situations. The clearance time is the gap between the first response time and the last response time of the FDOT. However, an incident usually occurs before the first notice

time. Extra time is always required to reach the FDOT. Therefore, the clearance time plus 15 minutes and the clearance time plus 30 minutes were selected as additional temporal criteria in this study.

For the spatial boundary, the third order polynomial model was selected to determine the queue length that is based on the incident duration. Chilikuri and Sun's study verified that the third order polynomial model was appropriate to find the queue length for each incident (2010). Therefore, in this study, the queue lengths and the incident durations from the existing database were used to develop a third order polynomial model. The queue lengths can be calculated from the following equation,

$$Q = -0.0000060958 * t^3 - 0.000266 * t^2 + 0.067784 * t + 0.02046 \quad (1)$$

Where:

Q = Calculated queue length per mile.

t = Incident duration per minute.

For the purposes of this study, incident duration was defined as the time gap between the first notice time and the last response time. Figure 3.1 and Figure 3.2 list the spatial-temporal criteria distributions of all the primary incidents that were selected. The temporal criteria were 2 hours, the clearance time plus 15 minutes, and the clearance time plus 30 minutes. The clearance time plus 15 minutes ranges from 0.25 to 1.82 hours, with an average value of 52.2 minutes. The average values of the clearance time plus 30 minutes and the clearance time plus 15 minutes are much lower than the fixed temporal criteria of 2 hours.

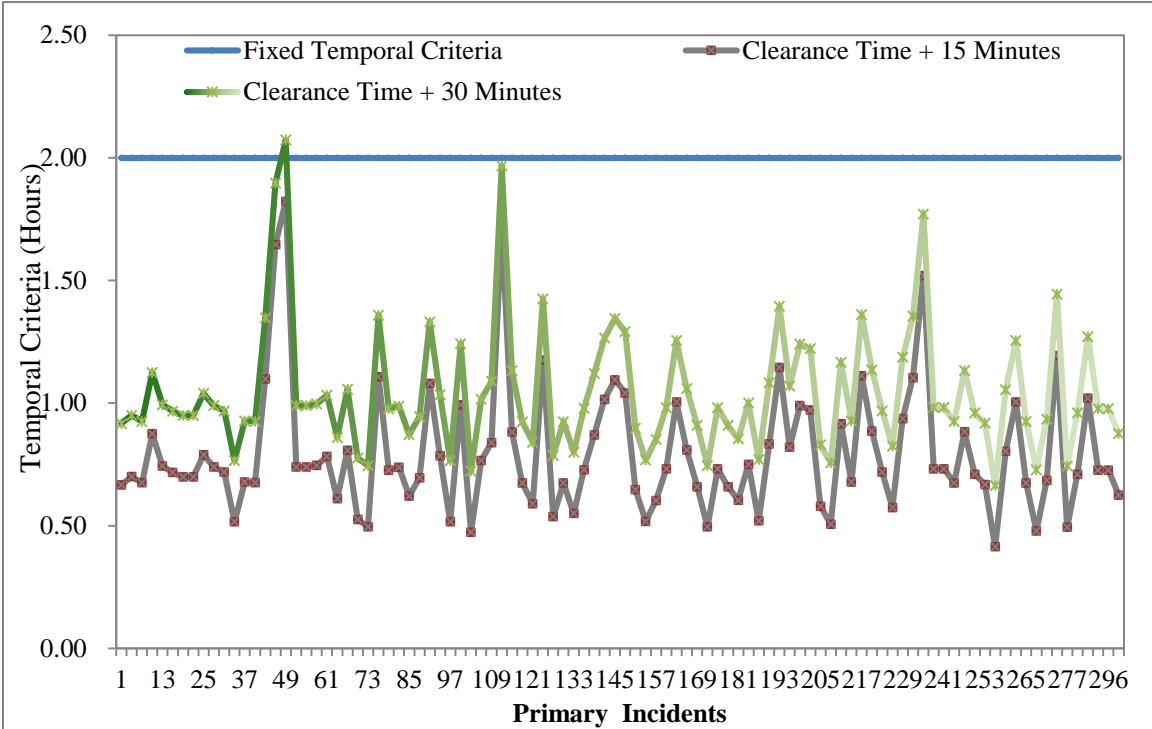


Figure 3.1 Temporal Threshold Distributions

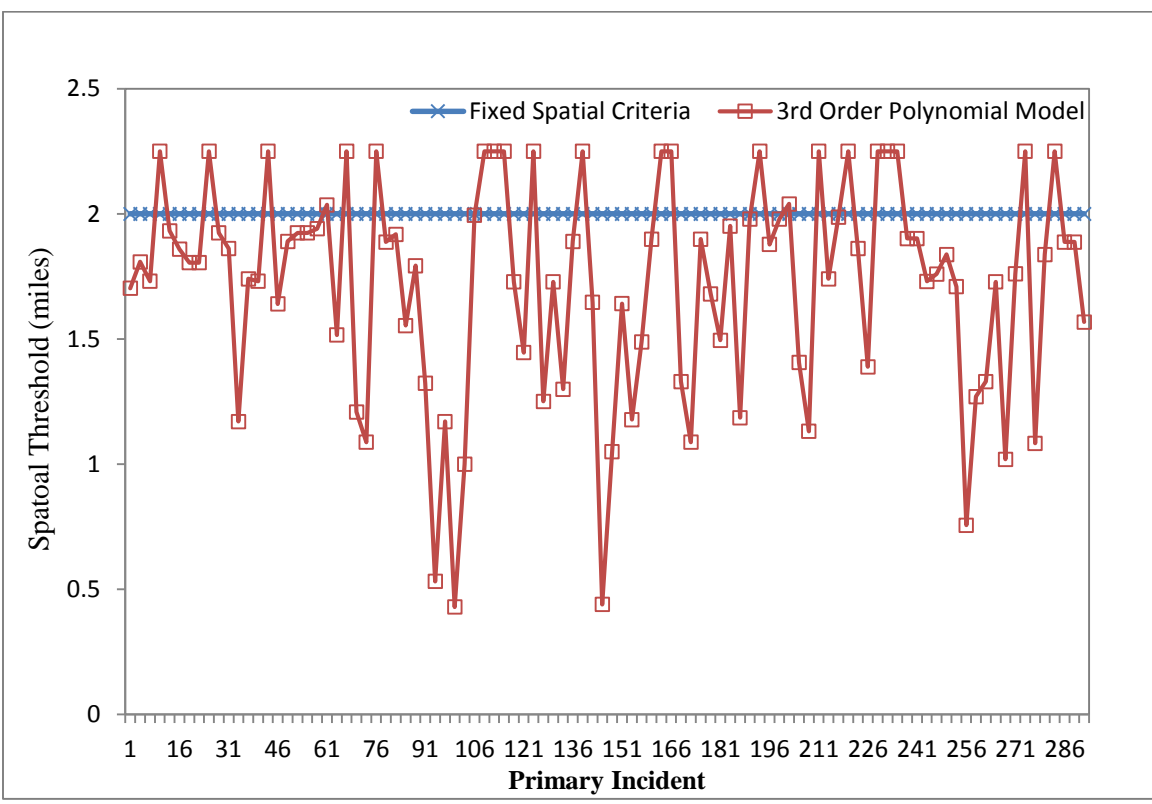


Figure 3.2 Spatial Threshold Distributions

Regarding the spatial criteria, the fixed spatial threshold, of two miles and the calculated queue lengths are plotted in Figure 3.2. In terms of the spatial criteria, the queue lengths range from 0.24 to 2.25 miles. The average value of the calculated spatial criteria is 1.77 miles, which is relatively close to the fixed spatial criteria.

In this study, the secondary crashes were those that occurred within the determined spatial and temporal boundaries. The combinations of the selected spatial-temporal criteria were categorized into six groups:

- Group 1: 2 miles, 2 hours
- Group 2: 2 miles, Clearance Time + 15 minutes
- Group 3: 2 miles, Clearance Time + 30 minutes
- Group 4: Calculated Queue Length, 2 hours
- Group 5: Calculated Queue Length, Clearance Time + 15 Minutes
- Group 6: Calculated Queue Length, Clearance Time + 30 Minutes

Data Processing

Figure 3.3 shows the algorithm and the data resources used to build the secondary crash database with the primary incidents by using ArcGIS. First, incident data were collected and analyzed to identify the incident durations, clearance times, as well as any other relevant factors.

After the primary incidents were selected, the crashes were extracted from the CAR system. ArcGIS was then used to join the incident data with the crash data using *spatial join*, a function that allows the user to link different crashes based on the geometric information in the GIS. After enough information was obtained regarding the incidents, *buffer* was used to draw circles, with the primary incidents as the centers. The function

buffer is able to create circles with user-determined diameters. In the present study, the diameters were determined based on three different spatial criteria. Then, the crashes were spatial join occurred within the buffered circles with the primary incidents.

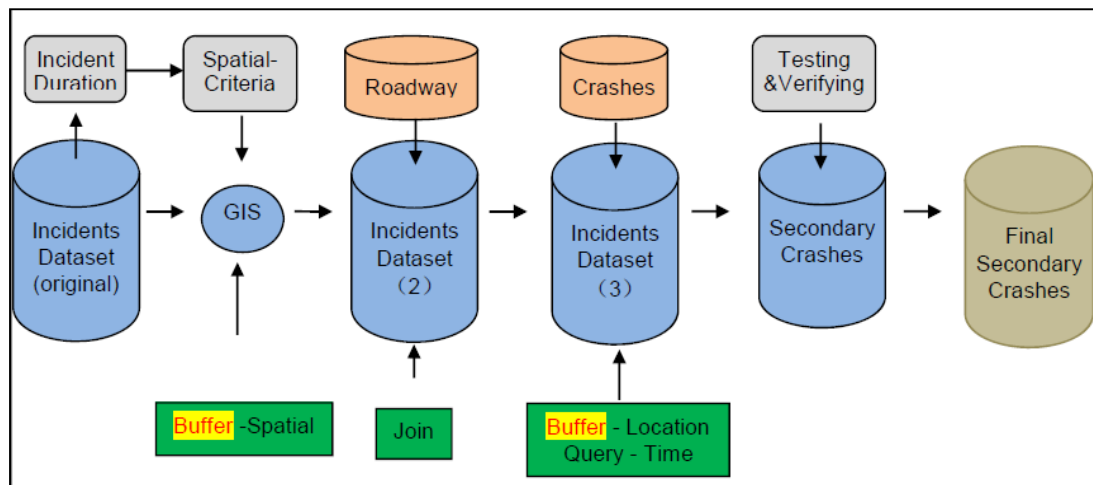


Figure 3.3 Process of Creating Secondary Incident Database

This study assumed that only the upstream primary incidents led to the secondary crashes that occurred in the same direction. In order to remove the crashes that failed to meet these requirements, the database was divided into two catalogs: the primary incidents and the secondary crashes with the same roadway IDs and those with the different roadway IDs. In the first condition, the secondary crashes with mileage that were lower than the primary incidents were kept if the traffic flowed in the same direction as the mileage increment. Otherwise, the crashes were filtered. In the secondary condition, the secondary crashes caused by the primary incidents with mileages that were lower than the determined spatial criteria were kept if the direction of traffic flow and the mileage increments were the same. The secondary crashes were filtered if they occurred in the opposite direction.

Figure 3.4 shows the examples of how to filter the downstream primary incidents using the fixed spatial criteria of two miles. The blue circle represents the primary incident and the orange circle represents the secondary crash. The assumption is that the mileage increases from left to right and the traffic flows in the same direction as the arrow. Figure 3.4-a and 3.4-b show the cases in which the primary incident and the secondary crash have the same roadway ID. When the traffic flows from left to right, the secondary crash with a mileage that is higher than that of the primary incident occurs upstream of the primary incident and should be filtered. In the opposite direction, the mileage decreases. The secondary crash is filtered when its mileage is lower than the primary incident.

Figure 3.4-c and 3.4-d indicate that when the roadway IDs of the primary incident and secondary crash are different, if the mileage of the primary incident is within 2 miles, all the secondary crashes connected using *spatial joined* by two miles with different roadway IDs must occur downstream and should be kept. In the opposite direction, if the primary incident takes place within the last two miles of a roadway, all the *spatial joined* crashes with different roadway IDs occur downstream and could be considered potential secondary crashes.

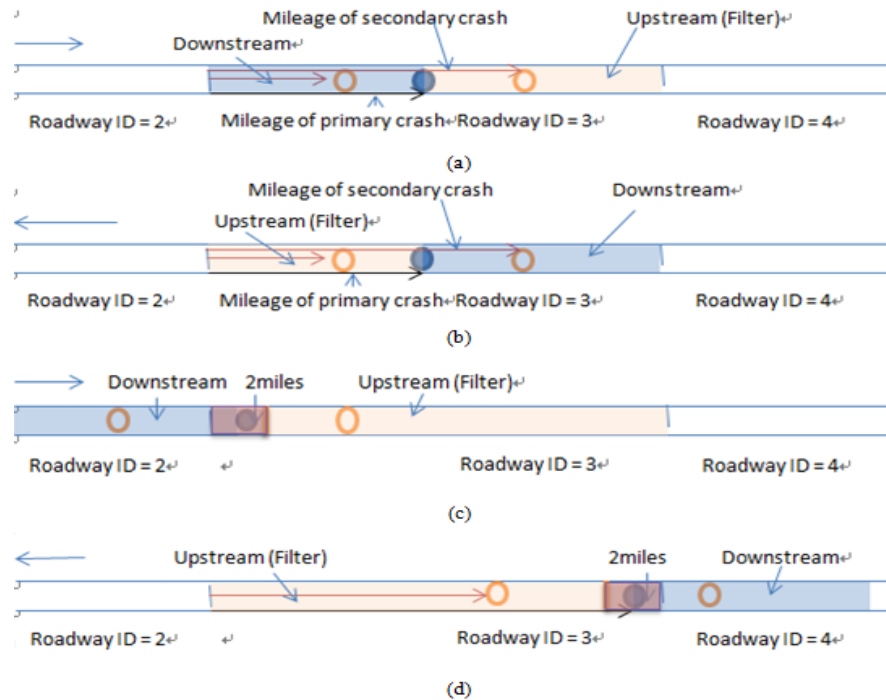


Figure 3.4 An Example of Major Steps to Filter Upstream Secondary Crashes

To identify the secondary crashes within the selected temporal criteria, Microsoft Excel was used to transfer the time information of the crashes into decimals. Crashes with time gaps between the primary incidents were longer than the determined queries were deleted. The results of this step produced the secondary crash database.

As a pilot test to prove the feasibility of the developed method, Figure 3.5 illustrates the steps taken to build the Group 1 database according to the spatial-temporal criteria, two miles and two hours. First, the incident and crash data were input into ArcGIS. The function *spatial join* was used to join the incidents with crashes that occurred within two miles. Next, the time format of the incident and crash data were transferred into decimal, and the crashes that had time gaps between the primary incidents that were longer than two hours were filtered. Following this procedure, the potential secondary incident database was built for Group 1. Databases for Group 2 to 6 were built using the same method.

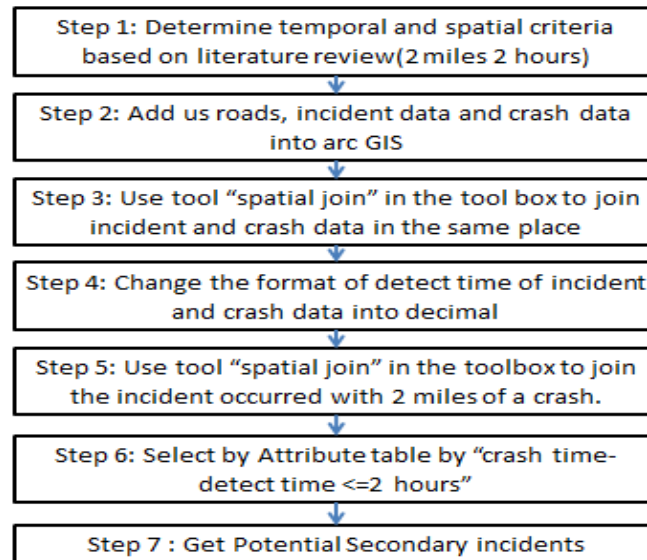


Figure 3.5 An Example of Major Steps to Identify Secondary Crashes by Using ArcGIS

Crash Predictive Model

In this research, crash predictive models were developed to establish the relationships between crash counts and the explanatory variables. Nowadays, the two most commonly used generalized linear models in transportation safety are Poisson and negative binomial (NB) regression models. However, one important assumption of the Poisson distribution is that the variance and the mean of the crash count should be equal. In this study, some sample variances exceed the sample means. As a result, the observations are overdispersed with respect to a Poisson distribution. NB model is estimated using STATA followed Gamma distribution as follows:

$$\Pr(Y = y) = \frac{\Gamma(\alpha+y)}{\Gamma(\alpha)y!} \left(\frac{\beta}{1+\beta}\right)^y \left(\frac{1}{1+\beta}\right)^\alpha, y = 0, 1 \dots \quad (2)$$

Where $y|\lambda \sim \text{Poisson}(\lambda)$, $\lambda \sim \text{Gamma}(\alpha, \beta)$, but λ itself is a random variable with a gamma distribution. Where Gamma (α, β) is the gamma distribution with mean $\alpha\beta$ and variance $\alpha\beta^2$. This study aims to use NB model to solve with the possibility of secondary crash occurrence. The frequency of secondary crashes can be predicted in regression format as follows:

$$Y = \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik}) \quad (3)$$

Where $\beta_0, \beta_1, \dots, \beta_k$ are coefficients and $x_{i1}, x_{i2}, \dots, x_{ik}$ are explanatory variables including dummy variables, continuous variables and categorical variables as shown in Table 3.1. Table 3.1 shows the summary of the variables with respect to geometric conditions (road shoulder width, road median width, etc.), traffic conditions (AADT on the major street, Posted Speed on Major Approach, etc.), and other parameters (weather condition, invisibility condition, etc.). The data is gained from FDOT and can be applied in ArcGIS.

Table 3.1 Collected Field Data and Values for the Static Method

Variables	Type	Codes/Ranges	
Primary Incident Crash Type	Dummy	0	Rear End Crash
		1	
		0	Angle Crash
		1	
		0	Sideswipe Crash
		1	
		0	Possible Injury
		1	
Primary Incident Injury Severity Level		0	Non-incapacitating Injury
		1	
		0	Incapacitating Injury
		1	
		0	Fatality
		1	
RCISLDTYP		0	Paved
		1	Unpaved
ROADWAY CONDITION	0	No Defects	
	1	Defect	
VISIBILITY	0	Vision not Obscured	
	1	Inclement Weather	
ROADSURFACE CONDITION	0	Dry	
	1	Not Dry	
DIV_UNDIV	0	Divided	
	1	Undivided	
WEATHER CONDITION	Category	0	Clear
		1	Cloudy
		2	Rain
		3	Fog

Table 3.1 (Continued)

LIGHT CONDITION		0	Daylight
		1	Dusk/Dawn
		2	Dark(Street Light)
		3	Dark(No Street Light)
Number of Lane(s) of Major Approach		2	
		3	
		4	
		5	
RDSURFTYPE		0	Not Coded
		1	Blacktop
		2	Concrete
RCISLDWTH(Width of Shoulder in Feet)		Continuous	3 ~ 13
RCISURFWTH (The Total Width of the	15 ~ 48		
Median Width (in feet)	0 ~ 250		
Major Street AADT	2600 ~ 164000		
Posted Speed on Major Approach (mph)	50~70		

Chapter IV

Data Analysis

Crash Frequency

Based on the spatial-temporal criteria, the secondary crashes were identified by six groups as listed in Table 4.1. Group 1 (2 miles and 2 hours) had the highest secondary crash frequency, 326 crashes in total, which was about 50% more (107 crashes) than that of group 4 (the calculated queue length and 2 hours). The secondary crashes of Group 2 and 3 were 124 and 137 respectively, which were about one-third more than that of Group 5 and 6.

Table 4.1 Summary of Secondary Crash Criteria and Frequency

Group	Temporal Criteria		Spatial Criteria		Secondary Crash Frequency
1	2 Hours		2 Miles		326
2	Clearance Time + 15 Minutes	0.25 to 1.82 Hours	2 Miles		124
3	Clearance Time + 30 Minutes	0.75 to 2.32 Hours	2 Miles		137
4	2 Hours		Queue Length	0.24 to 2.05 Miles	216
5	Clearance Time + 15 Minutes	0.25 to 1.82 Hours	Queue Length	0.26 to 2.05 Miles	90
6	Clearance Time + 30 Minutes	0.75 to 2.32 Hours	Queue Length	0.24 to 2.05 Miles	103

Crash Types

Crash types are defined as the first harmful event in the FDOT CAR system. Table 4.2 lists the percentages of different secondary crash types for six groups. Overall, rear-end crashes were the most common crashes, accounting for about 30% in all the groups, followed by angle crashes and sideswipe crashes. The results obtained using the fixed spatial criteria had fewer angle crashes, sideswipe crashes, and collisions with MV on the roadway than those using the calculated queue length as the spatial threshold. When the spatial boundary was selected as 2 miles, the angle crashes were relatively consistent at 8%; even the temporal criteria varied from 2 hours, the clearance time plus 15 minutes, and the clearance time plus 30 minutes.

Table 4.2 Selected Secondary Crash Types for Six Groups in 2010

Group	1	2	3	4	5	6
Rear-end Crash	26.23%	30.43%	34.94%	34.33%	28.38%	30.93%
Angle Crash	8.28%	8.35%	8.61%	13.43%	20.27%	18.56%
Sideswipe Crash	9.37%	10.80%	11.02%	16.42%	14.86%	13.40%
Collision with MV on Roadway	0.55%	1.45%	1.20%	5.97%	9.46%	8.25%
MV Hit Guardrail	2.07%	3.623%	3.253%	2.99%	2.70%	4.12%
All Other	1.64%	2.90%	2.41%	13.43%	8.11%	7.22%

The findings also show that the influence of different time criteria is limited if the spatial criteria was constant. The same result also can be found for sideswipe crashes, collisions with MV on the roadway, and other crash types. There was only 1% for collisions with MV on roadway for group 1 to 3; however the percentages increased to 10% for collisions with MV on roadway for group 4 to 6. Overall, using different spatial criteria, about 62.19%, 142.75%, and 115.56% more angle crashes were observed for group 1 vs. 4, group 2 vs. 5, group 3 vs. 6 respectively under the same temporal criteria. Similarly, there were about 75.24%, 52.03%, and 21.60% more sideswipe crashes, and 985.45%, 552.41%, and 587.5% more collision with MV on the roadway between group 1 vs. 4, group 2 vs. 5, group 3 vs. 6. The results indicate that secondary crashes determined by the 3rd order polynomial model have a higher percentage of angle crashes, sideswipe crashes, and collisions with MV on the roadway.

Crash Severity Level

Injury severity level is one of the major concerns in improving the safety performance of transportation systems. In the FDOT CAR system, injury severity is categorized into five levels: Property Damage Only (PDO), possible injury, non-incapacitating injury, incapacitating injury, and fatal crash.

Figure 4.1 shows the results of injury severity levels for each group. Most secondary crashes have low injury severity levels. Over 50% of the crashes among all the groups were Property Damage Only (PDO), while only about 1% of crashes were fatal crashes. In addition, the results show that under the same temporal thresholds, using calculated queue lengths yields fewer possible injuries and fewer non-incapacitating injuries than using 2 miles. The percentages of possible injury for group 1-3 (2 miles under

different temporal criteria) are 18.12%, 18.57%, and 15.48% respectively. These percentages are much higher than those for the last three groups. Similarly, the percentages of non-incapacitating injuries for the first three groups are about twice those of the last three groups.

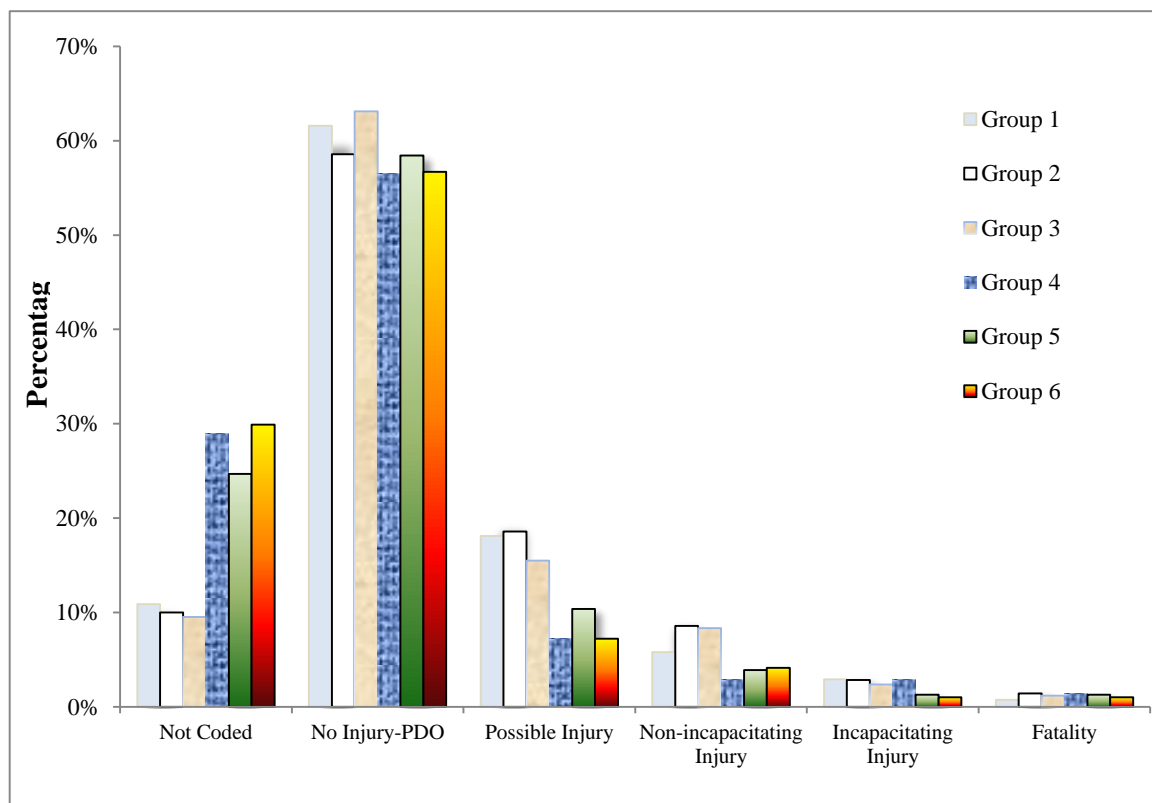


Figure 4.1 Crash Severity Level in 2010 for Six Groups

Contributing Factors

Figure 4.2 lists the top six contributing factors. Careless driving is the leading factor. Careless driving caused more than half of the secondary crashes, which seems reasonable. There are relatively slight differences among the six groups. The results show that using a fixed spatial criterion (2 miles with different temporal thresholds) yields much fewer crashes caused by following too closely and improper backing than those using

calculated queue lengths. The percentage of crashes of vehicles that followed too closely drops from 15% for the last three groups to about 6% for the first three groups. The percentage of improper backing doubles when using the calculated queue length instead of a fixed 2 miles.

The result is opposite for crashes exceeding the safe speed limit. Using 2 miles as the spatial criterion produces more secondary crashes exceeding the speed limit. Even though the average queue length, 1.87 miles, is close to the fixed spatial criterion, 2 miles, the results using calculated queue lengths are more likely to accurately link the secondary crashes caused by careless driving, improper backing, and following too closely.

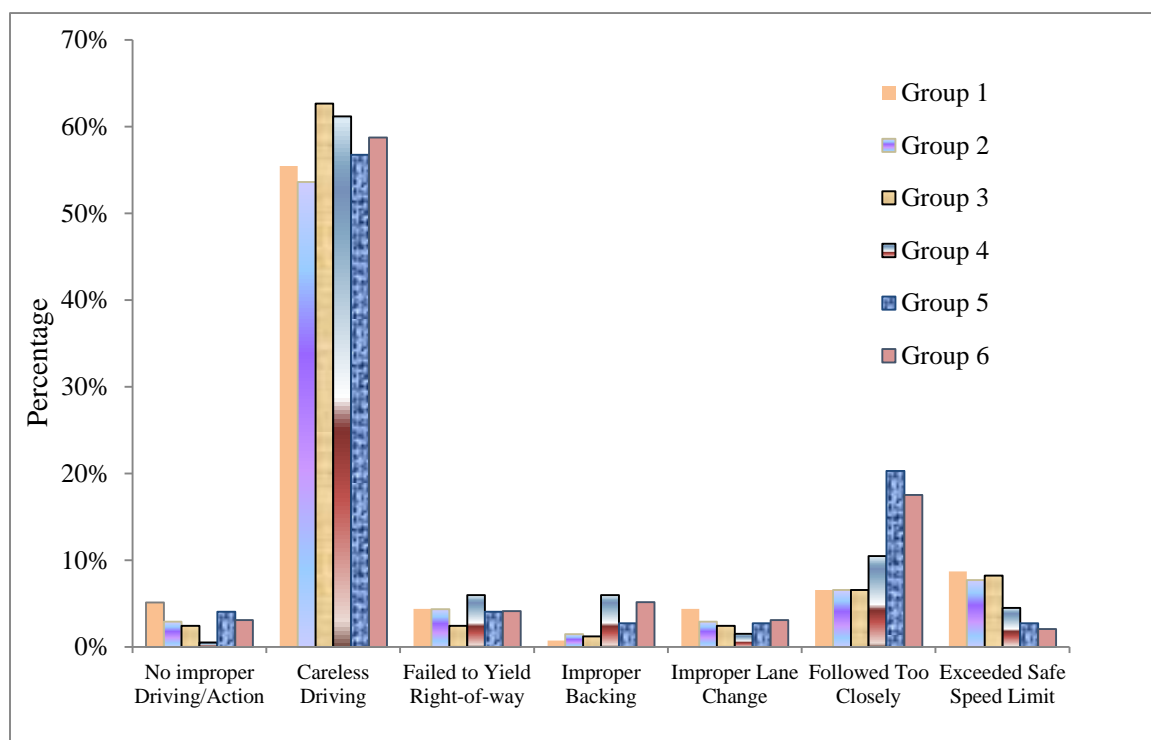


Figure 4.2 Primary Incidents Contributing Factors in 2010 for Six Groups

Statistical Analysis

A 95% confidence level was selected to determine whether there is a statistically-significant difference among the six groups in injury severity levels, primary crash types, and crash contributing factors. The calculated t-values are listed in Table 4.3.

There is no significant difference in incapacitating injury or fatality among the six groups. The results for group 4 vs. group 5 and group 4 vs. group 6 indicate that the number of secondary crashes leading to possible injury and non-incapacitating injury is significantly decreased.

In terms of crash types, using different temporal and spatial criteria has a slight influence on rear-end crashes, collisions with MV on the roadway and crashes of moving vehicles that hit guardrails. Comparing the results of group 1 vs. 4, group 2 vs. 5, and group 3 vs. 6, the number of secondary crashes that are angle crashes and sideswipe crashes is significantly higher when using the calculated queue length versus the spatial criterion, even though the average calculated queue length is relatively close to 2 miles. There is no significant difference found between group 1 vs. 2 and 3, group 2 vs. 3 and 4, and group 4 vs. 5; This indicates that compared with spatial criteria, the impact of the temporal criteria is limited.

As for contributing factors, the results show that using the calculated queue length significantly leads to more above-speed crashes and crashes of vehicles that followed too closely. The results are consistent with the previous conclusion that dynamic methods yield a significantly-higher percentage of those two crash types using calculated queue lengths is more likely to accurately link secondary crashes. However, using different criteria does

not have a significant difference on careless driving and crashes due to failure to yield the right-of-way.

Table 4.3 Statistical Test Results of Crash Injury Severity Levels, Crash Types, and Contributing Factors among Six Groups

Group	1vs.2	1vs.3	1vs.4	1vs.5	1vs.6	2vs.3	2vs.4	2vs.5	2vs.6	3vs.4	3vs.5	3vs.6	4vs.5	4vs.6	5vs.6
Injury Severity Levels															
No Injury	0.49	-0.26	-1.18	-0.57	-0.92	-0.64	-0.35	-0.02	-0.28	-1.18	-0.72	-1.00	-0.37	-0.04	0.28
Possible Injury	0.85	1.12	-2.96	-0.44	-0.91	0.21	-2.01	0.45	0.08	-1.73	0.69	0.32	-3.65	-2.27	0.42
Non-incapacitating Injury	-0.89	-0.85	-1.68	-0.77	-0.70	0.06	-2.39	-1.44	1.45	-2.39	-1.41	-1.37	-0.54	-0.07	-0.09
Incapacitating Injury	0.02	0.27	0.00	-0.95	-1.18	0.21	0.02	-0.81	-1.03	0.28	-0.61	-0.82	0.98	1.22	0.20
Fatality	1.16	-0.41	0.77	0.53	0.30	0.15	0.01	-0.08	-0.27	0.20	0.07	-0.12	0.12	0.36	0.20
Crash Types															
Rear End Crash	-0.75	-1.61	2.00	0.43	0.96	-0.67	0.69	-0.33	0.08	-0.11	-1.06	-0.66	0.01	0.71	-0.45
Angle Crash	-0.02	-0.10	1.86	3.21	2.88	-0.06	1.30	2.39	2.14	1.30	2.45	2.18	-0.02	-1.41	0.35
Sideswipe Crash	0.03	0.03	-3.20	3.82	3.24	0.03	1.11	2.81	2.39	1.17	2.96	2.51	-2.75	-2.10	0.57
Collision with MV on Roadway	-0.38	-0.46	2.35	1.54	1.19	-0.05	1.31	0.87	0.58	1.33	0.85	0.55	0.40	0.82	0.34
MV Hit Guardrail	-0.79	-0.64	0.66	0.37	1.13	0.14	-0.30	-0.38	0.19	-0.13	-0.24	0.35	0.16	-0.62	-0.63
All Other	-0.80	-0.63	3.25	4.16	3.84	0.15	1.74	2.42	2.19	1.97	2.67	2.43	-0.01	-0.90	0.34

Table 4.3 (Continued)

Contributing Factors															
No improper Driving/Action	-0.72	-0.47	4.79	2.95	2.68	0.21	2.81	1.59	1.40	3.14	1.87	1.67	0.02	1.91	0.27
Careless Driving	0.30	-1.22	1.03	0.23	0.61	-1.27	1.30	0.46	0.76	-0.27	-0.90	-0.61	0.86	0.49	-0.33
Failed to Yield Right-of-way	0.01	0.87	0.99	-0.15	-0.12	0.75	0.59	-0.11	-0.08	1.43	0.69	0.72	0.80	0.49	-0.03
Improper Backing	-0.57	-0.42	1.78	1.47	2.63	0.15	1.74	0.62	1.45	0.22	0.80	1.66	1.41	0.35	-1.01
Improper Lane Change	0.61	0.87	-1.05	-0.78	-0.61	0.21	2.24	-0.09	0.08	1.17	0.14	0.32	-0.09	-1.13	-0.19
Followed Too Closely	0.23	0.37	5.03	3.36	4.53	0.11	3.69	2.73	3.54	4.02	2.97	3.83	0.36	-0.20	-0.94
Exceeded Safe Speed Limit	0.03	0.03	1.07	-2.16	-2.54	0.03	-1.57	-1.95	-2.31	-1.64	2.43	-2.36	0.86	1.22	0.34
All Other	-0.50	0.08	1.54	-2.08	-2.25	0.50	-1.54	-2.27	-2.42	-0.92	-1.79	-1.94	1.24	1.39	0.09

T-test is also used to test whether primary incidents have a strong effect on secondary crashes. Table 4.4 and Table 4.5 illustrate the relationships between primary incidents and secondary crashes. The results demonstrate that there are significant differences between them on crash types, especially when using 2 miles and 2 hours as the spatial and temporal criteria respectively. Secondary crashes are more likely to have the same crash types with the primary incidents under fixed criteria. As for groups 2 and 3, the other two groups that used a fixed spatial threshold, more secondary crashes were found to be angle crashes when the primary incidents were also angle crashes. Similar results were seen for collisions with vehicles on the roadway. Also, secondary crashes were found to be correlated with primary incidents in crashes involving moving vehicles hitting guardrails when calculated queue lengths were chosen as the threshold.

Low injury severity levels for primary incidents are more likely to result in secondary crashes that are not severe. If a primary incident leads to possible injuries, the probability of a secondary crash with possible injury significantly increases. In addition, for group 1 and 3, the secondary crash has a significantly-lower probability of the same injury severity level when the primary incident was PDO. However, if the primary incident was serious, such as a fatality or incapacitating injury, there was no significant difference between the primary incidents and secondary crashes.

Table 4.4 Statistical Test Results of Crash Types between Primary Incidents and Secondary Crashes for Six Groups

Group	Crash Type	T test result
1	Rear End Crash	2.29388
	Angle Crash	3.87578
	Sideswipe Crash	3.4151
	Collision with MV on Roadway	2.53608
	MV Hit Guardrail	6.7822
	All Other	2.9098
2	Rear End Crash	-0.37047
	Angle Crash	2.30108
	Sideswipe Crash	1.275122
	Collision with MV on Roadway	2.65147
	MV Hit Guardrail	1.524055
	All Other	4.16995
3	Rear End Crash	-0.6376
	Angle Crash	2.41323
	Sideswipe Crash	0.625528
	Collision with MV on Roadway	2.75623
	MV Hit Guardrail	0.395392
	All Other	5.24386
4	Rear End Crash	-2.2353
	Angle Crash	0.916775
	Sideswipe Crash	-0.87365
	Collision with MV on Roadway	0.941814
	MV Hit Guardrail	5.37192
	All Other	1.300916
5	Rear End Crash	-1.72568
	Angle Crash	-1.56721

Table 4.4 (Continued)

	Sideswipe Crash	-0.77129
	Collision with MV on Roadway	-1.57904
	MV Hit Guardrail	5.81852
	All Other	2.10245
6	Rear End Crash	-1.41376
	Angle Crash	-1.02333
	Sideswipe Crash	-1.13673
	Collision with MV on Roadway	-1.50425
	MV Hit Guardrail	4.52959
	All Other	3.56398

Table 4.5 Statistical Test Results of Crash Injury Severity Levels between Primary Incidents and Secondary Crashes for Six Groups

Group	Injury Severity Level	T test result
1	Not Coded	-1.17381
	No Injury	-1.6873
	Possible Injury	2.73866
	Non-incapacitating Injury	4.1178
	Incapacitating Injury	1.001059
	Fatality	0.713095
2	Not Coded	-0.16424
	No Injury	-1.59657
	Possible Injury	0.718031
	Non-incapacitating Injury	1.373179
	Incapacitating Injury	0.969263
	Fatality	-0.71604
3	Not Coded	-0.88947
	No Injury	-2.5121
	Possible Injury	2.38161
	Non-incapacitating Injury	0.885216
	Incapacitating Injury	1.229839
	Fatality	0.151303
4	Not Coded	-6.2928
	No Injury	-0.65831
	Possible Injury	4.45998
	Non-incapacitating Injury	4.14122
	Incapacitating Injury	0.753149
	Fatality	-1.32139
5	Not Coded	-2.5474
	No Injury	0.390229

Table 4.5 (Continued)

	Possible Injury	0.666072
	Non-incapacitating Injury	1.624679
	Incapacitating Injury	1.016296
	Fatality	0.0011
	Not Coded	-3.7248
6	No Injury	0.954236
	Possible Injury	1.96284
	Non-incapacitating Injury	0.668542
	Incapacitating Injury	1.443824
	Fatality	0.19285

Crash Predictive Model

Crash predictive models were developed for total crashes. For the total crashes models, 16 variables were initially selected as described in Table 3.1. The variables included 7 dummy variables, 4 categorical variables, and 5 continuous variables. The geometric variables included the number of lanes on major streets, posted speed limits on the major approach, roadway surface and shoulder types, roadway surface shoulder width, and median width. The traffic feature includes AADT on major streets and roadway condition. The other variable associated with the crash is the primary incident type.

During modeling, 10 of the 16 variables were found to be statistically insignificant. The Negative Binominal models indicated to be adequate fitting, as the goodness-of-fit statistics are close to 1. However, better results for groups 1 to 3 were found using a fixed spatial criterion than using calculated queue lengths. Different combinations of variables and variable formats were tested to find the best-fitted models. During the test, insignificant

variables were filtered one by one, to see whether or not they had a strong influence on other variables. Among all six groups, no strong correlations were found between the variables. However, there was a slight positive correlation among light condition, weather condition, and visibility. Table 4.6 to Table 4.11 list the final fitted NB models for all six groups with different temporal and spatial criteria using a 95% confidence level.

Table 4.6 Negative Binomial Model Results for Total Crashes for Group 1

Fixed Spatial and Temporal Criteria				
Goodness of Fit for Total Crash Model				
Number of Observations	326	Log Likelihood	-173.6221	
Deviance	312.7328	Pearson χ^2	328.6799	
Deviance/DF	0.9622	Pearson χ^2/DF	1.0113	
Analysis of Parameter				
Parameter	Coefficient	Standard Error	Chi ²	Prob > Chi ²
Intercept	-294.3524	2.3623	80.6865	0.0036
Roadway Condition	1.5777	1.2191	21.6065	0.0450
Rear End	2.3458	1.9235	3.7965	0.0475
Possible Injury	7.2842	3.9807	4.9965	0.0211
Number of Lane(s) of Major Approach	3.2396	2.2188	1.7765	0.0494
LN Major Roadway AADT in Thousand	3.7414	1.385	30.1965	0.0031
Posted Speed Limit on Major Roadway	3.2743	0.6881	2.2065	<0.002
Dispersion	0.7537	0.0574		

Table 4.7 Negative Binomial Model Results for Total Crashes for Group 2

Fixed Spatial and Clearance Time+ 15 Minutes				
Goodness of Fit for Total Crash Model				
Number of Observations	124	Log Likelihood	-113.2352	
Deviance	117.6563	Pearson χ^2	125.2645	
Deviance/DF	0.9887	Pearson χ^2/DF	1.0526	
Analysis of Parameter				
Parameter	Coefficient	Standard Error	Chi ²	Prob > Chi ²
Intercept	-98.6484	2.9947	78.143	0.0013
Roadway Condition	3.2423	1.8515	19.063	0.0499
Rear End	11.4243	2.5559	1.253	0.029
Possible Injury	6.3532	4.6131	2.453	0.0211
Number of Lane(s) of Major Approach	3.9463	2.8512	0.767	0.0450
LN Major Roadway AADT in Thousand	2.6643	2.0174	27.653	0.0074
Posted Speed Limit on Major Roadway	1.6362	1.3205	0.337	<0.002
Dispersion	0.7657	0.0600		

Table 4.8 Negative Binomial Model Results for Total Crashes for Group 3

Fixed Spatial and Clearance Time+ 30 Minutes				
Goodness of Fit for Total Crash Model				
Number of Observations	137	Log Likelihood	-117.4505	
Deviance	131.2352	Pearson χ^2	151.5645	
Deviance/DF	0.9646	Pearson χ^2/DF	1.1144	
Analysis of Parameter				
Parameter	Coefficient	Standard Error	Chi ²	Prob > Chi ²
Intercept	-102.4753	1.787	83.9375	0.0022
Roadway Condition	4.3572	0.6438	24.8575	0.0463
Rear End	7.3856	1.3482	7.0475	0.0355
Possible Injury	8.5624	3.4054	8.2475	0.0132
LN Major Roadway AADT in Thousand	4.2476	1.6435	5.0275	0.0075
Posted Speed Limit on Major Roadway	1.1033	0.8097	33.4475	0.0038
Dispersion	0.7930	0.0634		

The results for the first three groups indicate that increasing the LN of AADT in thousand on major roads, and/or the posted speed limit on major roads results in a statistically-significant increase in secondary crash rates. These findings seem reasonable. When there are more vehicles on the roadway or the vehicles traveling at high speed, drivers have less time to make decisions and take appropriate actions. As a result, the risk of the secondary crash rises. In addition, if the primary incident was a rear-end crash; or if the injury severity level of the primary incident was possible injury, the probability of occurrence of secondary crashes will be significantly higher. This result for rear-end crash

rates is consistent with the previous analysis. Most of the primary incidents with secondary crashes were rear-end crashes, which means the rear-end crash is more likely than other crash types to cause secondary crashes. Furthermore, the geometric factor, roadway condition, is found to have a significant relationship with secondary crash counts for groups using a fixed spatial criterion. The danger of secondary crashes for these groups increases with defective roadways. This result also reveals that increasing the number of lanes for a major approach will significantly raise the probability of secondary crash for all groups except group 3.

Table 4.9 Negative Binomial Model Results for Total Crashes for Group 4

IPC and Fixed Temporal Criteria				
Goodness of Fit for Total Crash Model				
Number of Observations	219	Log Likelihood	-133.5366	
Deviance	209.4409	Pearson χ^2	227.4419	
Deviance/DF	1.0472	Pearson χ^2/DF	1.1872	
Analysis of Parameter				
Parameter	Coefficient	Standard Error	Chi ²	Prob > Chi ²
Intercept	-188.4735	2.1612	87.0286	0.0147
Rear End	7.4365	1.018	27.9486	0.0439
Possible Injury	5.3572	1.7224	10.1386	0.0322
LN Major Roadway AADT in Thousand	3.4563	3.7796	11.3386	0.0143
Posted Speed Limit on Major Roadway	2.4635	2.0177	8.1186	0.0337
Dispersion	0.6783	0.0544		

Table 4.10 Negative Binomial Model Results for Total Crashes for Group 5

IPC and Clearance Time+ 15 Minutes				
Goodness of Fit for Total Crash Model				
Number of Observations	90	Log Likelihood		-97.5721
Deviance	81.0013	Pearson χ^2		84.3202
Deviance/DF	1.0122	Pearson χ^2/DF		1.0541
Analysis of Parameter				
Parameter	Coefficient	Standard Error	Chi ²	Prob > Chi ²
Intercept	-72.3456	2.5634	91.2286	0.0167
Rear End	13.5763	1.4202	32.1486	0.0464
Possible Injury	8.3532	2.1246	14.3386	0.0198
LN Major Roadway AADT in Thousand	2.8365	4.1818	4.4544	0.0199
Posted Speed Limit on Major Roadway	1.5687	2.4199	1.2344	0.0097
Dispersion	0.7164	0.0454		

Table 4.11 Negative Binomial Model Results for Total Crashes for Group 6

IPC and Clearance Time+ 30 Minutes				
Goodness of Fit for Total Crash Model				
Number of Observations	103	Log Likelihood	-107.7343	
Deviance	114.2432	Pearson χ^2	109.3303	
Deviance/DF	1.2025	Pearson χ^2/DF	1.1501	
Analysis of Parameter				
Parameter	Coefficient	Standard Error	Chi ²	Prob > Chi ²
Intercept	-64.7346	2.6864	70.1444	0.0073
Rear End	5.3563	1.5432	11.0644	0.0399
Possible Injury	7.6735	0.2476	3.7456	0.0206
LN Major Roadway AADT in Thousand	5.3673	4.3048	5.5456	0.0100
Posted Speed Limit on Major Roadway	2.4673	0.5429	8.7656	0.0879
Dispersion	0.6349	0.0555		

As for using the calculated queue length, only 4 variables were found to be significant at a 95% confidence level for total crash models, rear-end crashes, possible injury, LN major roadway AADT and posted speed limit on major roadway. The influences of these significant variables are found to be similar to those in the group 1 to 3 models. However, the influence of the primary incidents on rear-end crash seems to be less significant than the secondary crash rates). The reason for this can be explained by that fewer rear-end crashes for the primary incidents with secondary crashes were found when using dynamic spatial thresholds. For the last three groups, more primary incidents

with secondary crashes were found to be MVs. hit guardrails. The modeling results show that MVs hit guardrails with a value of Prob> Chi2 of 0.0521, which is close to but not sufficient, fails to meet the 95% confidence level. The geometric factor is found to have an effect only on secondary crashes when determined using a fixed spatial criterion.

Chapter V

Conclusions and Future Study

Conclusion

This study developed an integrated method using ArcGIS and proved its feasibility as an effective tool to determine secondary crashes due to the primary incidents on the interstate highway system in Florida. The secondary crash identification used to be a time-consuming and labor-intensive work. It involves integrating the large data scale including crash database, incident records, traffic performance data, and geometric features. The method used in this study utilizes the functions in ArcGIS to quickly identify the potential secondary crashes and link them with the primary incidents based on the selected criteria. This method was proved to be labor-saving and can be applied in various criteria based on specific traffic conditions and environments.

This study assumes that crashes occurring within the determined spatial and temporal boundaries were secondary crashes. Based on previous studies, the temporal criteria were selected to be 2 hours, the clearance time plus 15 minutes and the clearance time plus 30 minutes, and the spatial criteria were 2 miles and the maximum queue lengths that were calculated by the 3rd polynomial model. The secondary crashes databases were built under 6 different temporal-spatial criteria.

The findings are listed as follows:

- Most of the secondary crashes were careless driving. Using static method leads to more crashes exceeding the safe speed limit, but using the dynamic spatial criteria finds more crashes caused by following too closely and improper backing.

- Rear-end crashes are the most common crash type for secondary crashes. Using different spatial criteria, more angle crashes have been found than using the fixed spatial criteria. The results of sideswipe crashes and collisions with moving vehicle on the roadway are similar to the findings of rear-end crashes
- Under the same temporal thresholds, the results using the calculated queue lengths have lower injury severity level.
- The test-test results among different groups indicate that the influence of the spatial is significantly higher than that of the temporal criteria. The effect of the temporal criteria is very limited.
- The t-tests results between the primary incident and secondary crashes demonstrate that the secondary crashes are more likely to have the same crash types with the primary incidents, especially on angle crashes and crashes that moving vehicles hit guardrails. As for the injury severity level, the probability of secondary crashes with low injury severity levels is significantly higher if the primary incidents are not serious.
- The modeling results indicate that LN of AADT on major streets, the posted speed limits on the major approaches, the crash counts of the rear-end primary incidents and possible injury primary incidents significantly increase the probability of secondary crashes.
- The geometric factor is found to have an effect only on secondary crashes when using a fixed spatial criterion, such as roadway condition.

This study aims to verify the method developed in ArcGIS. The results find that the criteria of group 5 and 6 are best-fitted to identify secondary crashes. The hypothesis tests'

results of group 1 vs. 4, group 2 vs. 5 and group 3 vs. 6 show that under the same temporal criteria, the spatial criteria have a strong influence. Using the maximum calculated queue length can lead to a better result. As for the temporal criteria, the significant differences are only found between group 4 and 5, and group 4 and 6. As a result, the performances of using the clearance time plus 15 minutes and the clearance time plus 30 minutes are more accurate. In conclusion, this study provides traffic agencies with the most appropriate criteria to identifying secondary crashes, dynamic spatial thresholds with the clearance time plus 15 minutes and the clearance time plus 30 minutes, assisting them to enhance the traffic safety performance.

Future Study

For the future study, the most important thing is to find an appropriate application to improve the secondary crash safety performance. Nowadays, there is a new technology under research, which is called as vehicle-to-vehicle communication technology. This new technology aims to improve the traffic safety and mobility on roadways. It is trying to make it possible to allow vehicles ranging from cars to trucks to convey important safety and mobility information that can help to save lives prevent injuries and ease traffic congestion with one another. Currently, there are a lot of V-to-V safety applications that help enhance the safety performance for specific crash types. Table 5.1 lists the summary of different V-to-V applications.

Table 5.1 V-to-V Safety Applications

Crash Type	Safety Application
Rear-End	Forward Collision Warning (FCW)
	Electronic Emergency Brake Light (EEBL)
Opposite Direction	Do Not Pass Warning
	Left Turn Assist (LTA)
Junction Crossing	Intersection Movement Assist (IMA)
Lane Change	Blind Spot Warning + Lane Change Warning (BSW+LCW)

Note. Adapted from “Vehicle-to-vehicle communications: Readiness of V2V technology for application.” by Harding, J., Powell, G., R., Yoon, R., Fikentscher, J., Doyle, C., Sade, D., Lukuc, M., Simons, J., & Wang, J. 2014, (Report No. DOT HS 812 014).

The analysis results indicate that over 30% of the primary incidents with secondary crashes are rear-end crashes. Moreover, the increment of rear-end primary incident counts will significantly increase the secondary crash counts. In order to reduce the secondary crash rate, preventing rear-end crashes can be considered as an efficient countermeasure. FCW, which is Forward Collision Warning, is an application that focuses on avoiding rear-end crashes. It is able to warn the driver of the impending rear-ends crash with another vehicle ahead in the same traffic lane and direction of travel. (Powell, 2014) FCW system consists of a detective system and a warning system. The detective system usually is installed at the front of the vehicle. Once the system detects a sudden stop within the detective distance which is 300 meters based on current technology, the warning system starts to work, assisting the driver to speed down. According to the literature review, FCW

system support may help reduce rear-end collision by 10 %. (Foundation for Traffic Safety, 2014) Currently, there are two major types of FCW System: Camera-based FCW System and Radar-based FCW System.

Camera-based FCW System: The camera-based forward collision warning installs a forward-looking monocular camera with object recognition, which is usually mounted behind the rearview mirror.

Radar-based FCW System: The radar-based forward collision warning consists of a radar sensor installed at the front of the vehicle.

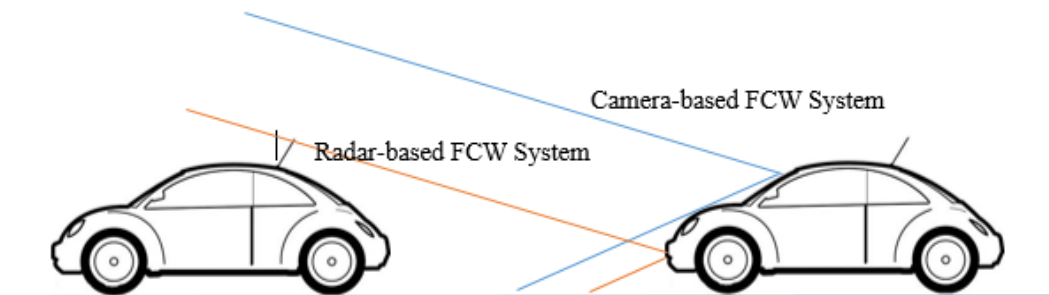


Figure 5.1 Camera-based FCW System and Radar-based FCW System

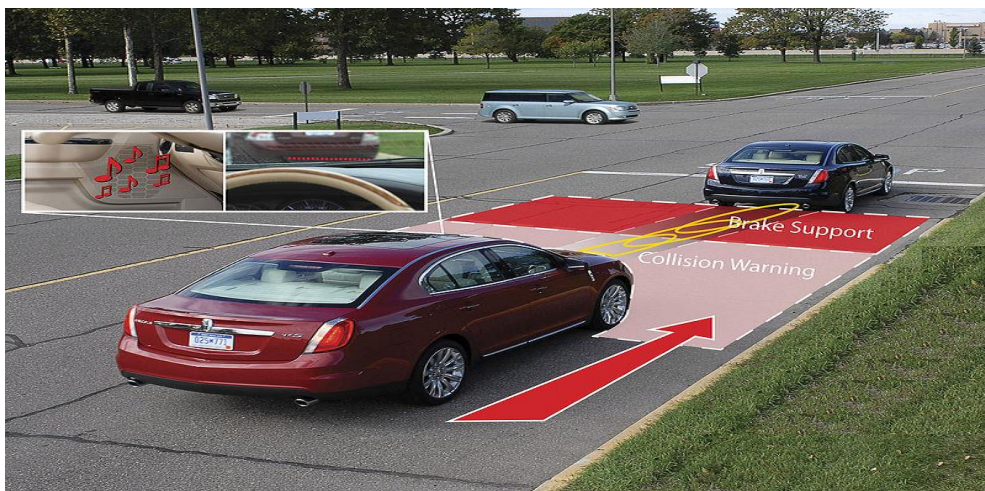


Figure 5.2 Collision Warning with Brake Support on the 2009 Lincoln MKS

(Mehler et al., 2014)

Limitations

The safety performance of the FCW system has not been found yet. The future works are expected to focus on how much it can help with reducing secondary crashes in the state of Florida. The B/C of this product is also expected in the future study.

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