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ANALYSIS OF LARGE-SCALE TRAFFIC INCIDENTS AND EN ROUTE DIVERSIONS DUE TO CONGESTION ON FREEWAYS

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I am submitting herewith a dissertation written by Xiaobing Li entitled "ANALYSIS OF LARGE-SCALE TRAFFIC INCIDENTS AND EN ROUTE DIVERSIONS DUE TO CONGESTION ON FREEWAYS." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

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ANALYSIS OF LARGE-SCALE TRAFFIC INCIDENTS AND EN ROUTE DIVERSIONS DUE TO CONGESTION ON FREEWAYS

A Dissertation Presented for the

Doctor of Philosophy

Degree

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Xiaobing Li

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DEDICATION

This dissertation is dedicated to my wife, Qing Yao, who constantly encouraged me to pursue my dreams and finish my dissertation.

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Thanks to everyone who have inspired me, guided me and helped me throughout the whole process of writing this dissertation. This dissertation will never be achieved without your support.

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ABSTRACT

En route traffic diversions have been identified as one of the effective traffic operations strategies in traffic incident management. The employment of such traffic operations will help relieve the congestion, save travel time, as well as reduce energy use and tailpipe emissions. However, little attention has been paid to quantifying the benefits by deploying such traffic operations under large-scale traffic incident-induced congestion on freeways, specifically under the connected vehicle environment. New Connected and Automated Vehicle technology, known as “CAV”, has the potential to further increase the benefits by deploying en route traffic diversions. This dissertation research is intended to study the benefits of en route traffic diversion by analyzing large-scale incident-related characteristics, as well as optimizing the signal plans under the diversion framework. The dissertation contributes to the art of traffic incident management by 1) understanding the characteristics of large-scale traffic incidents, and 2) developing a framework under the CAV to study the benefits of en route diversions.

Towards the end, 4 studies are linked together for the dissertation. The first study will be focusing on the analysis of the large-scale traffic incidents by using the traffic incident data collected on East Tennessee major roadways. Specifically, incident classification, incident duration prediction, as well as sequential real-time prediction are studied in detail. The second study mainly focuses on truck-involved crashes. By incorporating injury severity information into the incident duration analysis, the second study developed a bivariate analysis framework using a unique dataset created by matching an incident database and a crash database. Then, the third study estimates and evaluates the

benefit of deploying the en route traffic diversion strategy under the large-scale traffic incident-induced congestion on freeways by using simulation models and incorporating the analysis outcomes from the other two studies. The last study optimizes the signal timing plans for two intersections, which generates some implications along the arterial corridor under connected vehicles environment to gain more benefits in terms of travel timing savings for the studies network in Knoxville, Tennessee. The implications of the findings (e.g. faster response of agencies to the large-scale incidents reduces the incident duration, penetration of CAVs in the traffic diversion operations further reduces traffic network system delay), as well as the potential applications, will be discussed in this dissertation study.

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CHAPTER 1
INTRODUCTION

Traffic incidents are non-recurring events imposing enormous costs on society in terms of productivity loss and delays. Federal Highway Administration (FHWA) has identified about 25% of the unexpected traffic congestion is caused by the traffic incidents. In a report recently released by Texas Transportation Institute (TTI) in 2015 termed the U.S. nation's congestion problem as "very large" (Schrank, Eisele, Lomax, & Bak, 2015). Traffic congestion in 2014 across 471 metropolitan regions of the United States wastes a significant amount of nation's time causing annual travel delay of $6.9-billion hours that accounts for $3.1-billion "wasted" gallons of fuel, summing up to a total of $121-billion annual congestion costs nationally (Schrank et al., 2015).

Traffic incidents, not only cause congestion on the freeway system but also cause fatalities and injuries. In 2015, there were an estimated 6,296,000 police-reported traffic crashes, in which 35,092 people were killed and an estimated 2,443,000 people were injured. The 2016 fatality count (37,461) is the highest since 2007. Among light-truck categories, occupant fatality rates increased by 8.4% for vans, 5.2% for SUVs, and 1.5% for pickup trucks. As for large-truck categories, there were 722 people killed in crashes involving large trucks, an 8.6-percent increase from 2015 to 2016, and an estimated 116,000 people were injured in crashes involving large trucks in 2015 - an increase of 4% from an estimated 111,000 in 2014. 74% of people killed in large-truck involved crashes were occupants of the other vehicles (NHTSA, 2017a, 2017b). On average, 96 people died each day in motor vehicle crashes in 2015, one fatality every 15 minutes (NHTSA, 2017c).

Therefore, it is necessary to study the incident management in terms of both mobility as well as safety. From the perspective of traffic safety that is associated with freeway incidents, truck-involved crashes are of top concern to both society and research community. These crashes are usually involved with substantial loss of lives, properties, and other resources. These crashes are usually considered as large-scale accidents. For example, a head-on collision with a truck carrying chemical products and a passenger vehicle. It can block all the lanes for a couple of hours. Such an accident might create a huge delay if it is happening during rush hours, where tons of traffic are delayed by these long-lasting incidents. Long congestion caused by large-scale traffic incidents are most not welcome by commercial vehicles because their value of travel time (VOT) is way higher than other vehicles. If their delivery business is delayed by a certain amount of time, extra money could be charged (Dong, Nambisan, Richards, & Ma, 2015; Golob, Recker, & Leonard, 1987; Golob & Regan, 2001; Knorring, He, & Kornhauser, 2005; Lutsey, Brodrick, Sperling, & Oglesby, 2004; Ng, Cheu, & Lee, 2006; NHTSA, 2017a).

From the perspective of mobility, while short to medium duration incidents can affect traffic operations and mobility, large-scale incidents substantially disrupt traffic flow by blocking lanes for long periods of time. Large-scale traffic incidents are more complex and require more response resources and close coordination between different agencies to clear the incident scene and restore to normal traffic (Zhang, Zhang, & Khattak, 2012). Large-scale traffic incidents are more likely to trigger traffic en route diversion to deal with diverted traffic, detours, special resources for cleanup, and dissemination of dynamic information to the public. Such a traffic operation has been evaluated to be one of the effective and efficient ways that can help relieve the negative impact of long periods of congestion caused by the large-scale traffic incidents on the freeway (P.E. Dunn Engineering Associates, Consulting Services, 2006; Liu, Chang, & Yu, 2011; Liu, Kim, & Chang, 2012).

However, there are still gaps within the studies of deploying the en route diversion strategy, especially when taking into account the large-scale traffic incidents, commercial vehicles, as well as the Connected and Automated Vehicle (CAV) technology. Therefore, to improve the traffic en route diversion operations along the freeway system, this dissertation study intends to first identify and analyze the key characteristics of large-scale freeway traffic incidents; and then evaluate the benefits of deploying the en route traffic diversion under large-scale incident-induced congestion. Specifically, the truck en route diversions, since these types of vehicles need to be carefully handled, otherwise, potential safety issues such as intersection crashes might happen. In addition, en route diversion under such situations also needs to be analyzed further by taking account of the intersection traffic control. Because poor signal timing will hinder a smooth traffic flow along the arterial when a sudden rush of traffic diverts from the freeway and enters the arterial.

A text mining analysis is done to further explore how each topic is related to each other. QDA text mining tool (a qualitative data analysis software developed by Provalis Research) is applied and the key topics discussed in the selected literature include incident management, truck, diversion strategies, classification, fatalities, injuries, and control. A derived cloud graph representing each discussed topic (see Figure 1.1) is presented. They are clustered based on previous research. This graph shows incident management and agency response is grouped together while routing and network simulation is grouped where traffic delay is mostly related to. Interstate and arterial control is another topic,

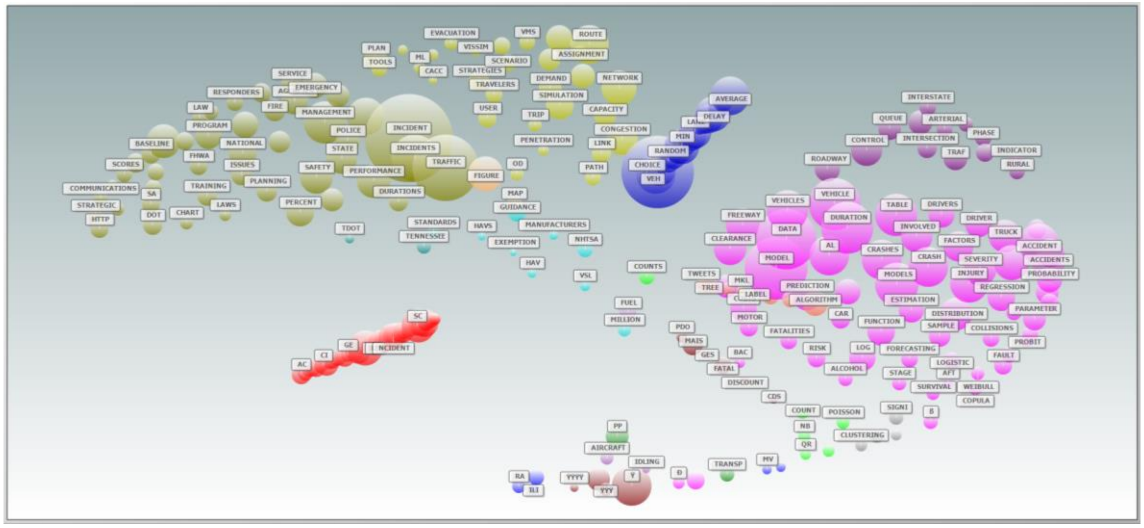

FIGURE 1.1 Text mining analysis among different topics.

and severity, as well as injury modeling, is another research aspect. Such isolated research islands are not integrated into a complete study framework, and most of the time CAV is not selected as the main topic. Therefore, by integrating them together into a framework where large-scale traffic incidents/accidents, as well as CAV technologies, are accounted for, this study will make a difference from previous studies.

In summary, the dissertation research study provides a way in integrating the data source to achieve the intended goal of research. The overall study framework is presented in Figure 1.2 to present the organization of the whole dissertation study. It is linking the pre-crash, crash, and after crash 4 studies. More importantly, this research will apply statistical and simulation methods to evaluate the effectiveness of en route diversion strategy. The analysis results will help us better understand large-scale traffic incidents, and how en route diversion can help improve the traffic congestion management. This dissertation will enhance our understanding of the areas by studying the following subjects:

- Integrating the incident data, crash data, and other related databases (e.g. weather);
- Exploring the key aspects of large-scale traffic incidents on major freeways;
- Evaluating the en route diversion under large-scale incident scenarios; and
- Optimizing the signal timing plans at intersections and along key corridors under CAV to save travel time for both truck traffic as well as passenger vehicles.

The dissertation is organized in multi-journal article format since each chapter is a modified version of an article, which is either published in a journal or submitted for a presentation in a conference or submitted for a peer review academic journal. The second chapter studies the how large-scale traffic incidents are classified, the characteristics of large-scale traffic incidents, the real-time sequential prediction and other empirical

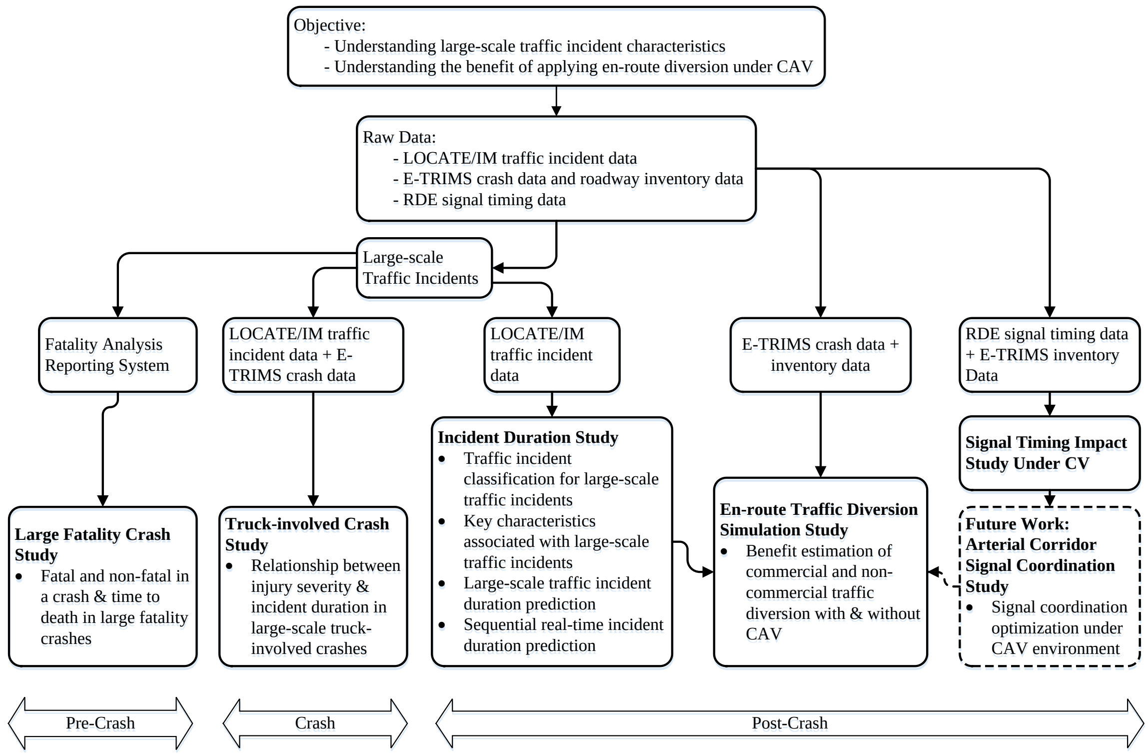

FIGURE 1.2 Dissertation structure.

Note: Solid rectangle boxes indicate the work is finished, while dashed rectangle box indicates future work to be done.

prediction of incident duration. The third chapter is the extended study of the large-scale truck-involved crashes and how injury severity relates to incident duration under a bivariate modeling framework. Then, the en route traffic diversion is evaluated under the large-scale traffic incident and CAV in Chapter 4 by using simulation models. In addition to this, Chapter 5 evaluates the impact of signal timing plans under CAV to further improve the en route traffic diversion system. Finally, Chapter 6 completes the dissertation study by drawing the conclusion of the above studies.

CHAPTER 2
LARGE-SCALE TRAFFIC INCIDENT DURATION ANALYSIS: THE ROLE OF MULTI-AGENCY RESPONSE AND ON-SCENE TIMES

This chapter presents a revised version of a research paper by adding additional classification analysis and sequential prediction analysis. The original research paper was published by Li, Xiaobing, Asad J. Khattak, and Behram Wali:

Li, Xiaobing, Asad J. Khattak, and Behram Wali. "Role of Multiagency Response and On-Scene Times in Large-Scale Traffic Incidents." Transportation Research Record: Journal of the Transportation Research Board 2616 (2017): 39-48.

Xiaobing Li’s effort on data collection, preprocessing and paper writing, Asad Khattak’s effort on idea formation, and Behram Wali’s effort on model construction, interpretation and paper writing are all recognized.

2.1 ABSTRACT

Traffic incidents often known as non-recurring events impose enormous economic and social costs. Compared to short duration incidents, large-scale incidents can substantially disrupt traffic flows by blocking lanes on highways for long periods of time. A careful examination of large-scale incidents and associated factors can assist with actionable large-scale incident management strategies. For such an analysis, a unique and comprehensive 5-year incident database on East Tennessee roadways was assembled to conduct an in-depth investigation of large-scale incidents, especially focusing on operational responses, i.e., response and on-scene times by various agencies. Incidents longer than 120 minutes and blocking at least one lane are considered large-scale, giving 890 incidents, which are about 0.69% of all reported incidents in the database. Fixed- and random-parameter hazard-based duration models are estimated to account for the possibility of unobserved heterogeneity in large-scale incidents. The modeling results reveal significant heterogeneity in associations between operational responses and large-scale incident durations. A 30-minute increase in response time for first, second, and third (or more) highway response units translates to 2.8, 1.6, and 4.2 percent increase in large-scale incident durations, respectively. In addition, longer response times for towing and highway patrol are also significantly associated with longer incident durations. Given large-scale incidents, associated factors include vehicle fire, unscheduled roadwork, weekdays, afternoon peaks, and traffic volume. Notably, the associations are heterogeneous, i.e., the direction can be positive in some cases and negative in other cases. Practical implications of the results for large-scale incident management are discussed.

***Keywords*:** Large-Scale, Incident Duration, Random-Parameters, Hazard-Based Modeling, Survival Analysis

2.2 INTRODUCTION & BACKGROUND

In December 2011, a tractor-trailer combination hauling potatoes crashed on Interstate-40 in the US between Nashville and Knoxville, closing that Interstate for 12 hours. This widely publicized occurrence prompted an aggressive initiative aimed at improved incident management conducted jointly by Tennessee Department of Transportation (TDOT) and Tennessee's Department of Safety and Homeland Security (TDOS). Improving roadway availability through incident prevention, particularly, large-scale incident management is a TDOT priority. Incidents like the infamous potato spill not only delay motorists but also impose significant costs on motor carriers. Generally, traffic incidents are non-recurring events imposing enormous costs on society in terms of productivity loss and delays. Recently in 2015, the Urban Mobility Scorecard released by Texas Transportation Institute (TTI) analyzed mobility data from 1982 to 2014 and termed the nation's congestion problem as “very large” (Schrank et al., 2015). It revealed that traffic congestion in 2014 across 471 metropolitan regions of the United States wastes a significant amount of nation’s time causing annual travel delay of $6.9-billion hours that accounts for $3.1-billion “wasted” gallons of fuel, summing up to a total of $121-billion annual congestion costs nationally (Schrank et al., 2015). Conservatively, traffic incidents account for approximately 25% of traffic congestion and is a leading cause of unexpected traffic congestion (FHWA, 2015). While short to medium duration incidents can affect traffic operations and mobility, large-scale incidents substantially disrupt traffic flow by blocking lanes for long periods of time (Zhang et al., 2012). Specifically, a 10-minute lane blockage can cause 40+ minutes of extra travel delay (Schrank, Lomax, & Turner, 2010). Also, large-scale traffic incidents are more complex and require more response resources and close coordination between different agencies to clear the incident scene and restore to normal traffic (Zhang et al., 2012). Large-scale incidents may trigger special arterial signal coordination plans to deal with diverted traffic, detours, special resources for cleanup, and dissemination of dynamic information to the public. Despite their costs and adverse consequences resulting from large-scale incidents, in-depth analysis of large-scale incidents and identification of key associated factors has received limited attention in the literature.

From incident duration modeling perspective, a broad spectrum of studies has focused on analyzing traffic incidents, specifically incident durations to identify key factors associated with incidents, for better incident management strategies (Chimba, Kutela, Ogletree, Horne, & Tugwell, 2013; Jones, Janssen, & Mannering, 1991; Nam & Mannering, 2000; Sullivan, 1997) and the references therein. From a methodological standpoint, incident durations and associated factors have been modeled successfully using diverse set of rigorous statistical tools such as truncated and quantile regressions (A. Khattak, et al., 2016; A. J. Khattak, Schofer, & Wang, 1995), hazard-based duration models (Hojati, Ferreira, Washington, & Charles, 2013; Nam & Mannering, 2000), Bayesian Network tools (Boyles, Fajardo, & Waller, 2007; Ozbay & Noyan, 2006; Stephen, David, & Travis, 2007), Artificial Neural Networks (Vlahogianni & Karlaftis, 2013; Wei & Lee, 2007), text analysis and competing risk models (R. Li, Pereira, & Ben-Akiva, 2015; Pereira, Rodrigues, & Ben-Akiva, 2013), and recently finite mixture models (Zou, Henrickson, Lord, Wang, & Xu, 2016) among others. Several correlates such as accidents and injuries involvement, lane closure, number of vehicles, temporal/spatial factors, heavy truck involvement, and adverse weather were found positively associated with longer incident durations (Boyles et al., 2007; A. Khattak, et al., 2016; Nam & Mannering, 2000; Stephen et al., 2007). Zhang and Khattak can be referred to for a summary of findings from different studies (Zhang et al., 2012). However, the aforementioned studies did not explicitly focus on identifying key correlates that may be associated with durations of large-scale incidents, which are different from other traffic incidents in that they typically require multi-agency coordination in case there are multiple injuries or a spill of hazardous materials. A thorough understanding of the important correlates is needed to devise strategies for responding to such incidents effectively.

While there is considerable literature on the general analysis of incidents, very few studies have explicitly focused on analyzing large-scale incidents. Zhang and Khattak conducted an in-depth spatial-temporal and statistical analysis of large-scale incidents on urban freeways in Hampton Roads, Virginia (Zhang et al., 2012). They were found 16 times (on average 216 minutes) longer than non-large-scale incidents (16 minutes). While the average incident duration was found to be 163 minutes by Nam and Mannering (Nam & Mannering, 2000). Furthermore, Zhang and Khattak identified locations prone to large-scale incidents, and large-scale incidents typically occur during morning and evening peak (Zhang et al., 2012). Empirically, large-scale incidents showed significant positive association with work zones, the presence of curvature, and occurrence of secondary incidents (Zhang et al., 2012). Similar results were obtained from analysis of cascading incident events on urban freeways (Zhang & Khattak, 2010).

Previous studies have provided actionable strategies for large-scale incident management, but they did not focus on multi-agency operational responses, specifically response and on-scene times that are likely to be associated with longer durations of large-scale events. From a methodological perspective, fixed associations between large-scale incident durations and associated factors were assumed in most studies - these assumptions are restrictive given the presence of several unobserved factors in incident databases and in light of the new methods that have emerged to deal with heterogeneity. Recent studies have identified the importance of addressing unobserved heterogeneity and the implications for general incident duration analysis (Hojati et al., 2013; R. Li et al., 2015).

2.2.1 Research Objective and Contribution

The present study conducts an in-depth analysis of large-scale incidents. The main objectives are to:

- Identify large-scale traffic incidents using appropriate criteria and create a comprehensive database that can allow in-depth investigation of such crashes;

- Conceptualize and quantify the associations between large-scale incident durations and multi-agency operational responses, especially their response and on-scene times; and
- Investigate unobserved heterogeneity in large-scale incident duration analysis by developing random-parameter hazard-based duration models.

Such an analysis is important in the sense given the disproportionately high costs of large-scale incidents. A careful examination of large-scale incident durations and associated factors can assist in developing actionable large-scale incident management improvement strategies. It is also original and timely in the sense that a unique database was assembled allowing exhaustive investigation of large-scale incidents and its associations with multi-agency operational responses. TDOT has an incident database that contains information about incident duration, incident type, lane block duration, response time, and incident location. However, several new variables were coded manually from detailed incident reports for large-scale incidents that include response and on-scene times for multiple agencies, i.e., service patrols, incident response units, police, fire, emergency, and towing, and other variables such as number of vehicles involved, highway advisory radio (HAR)/dynamic message sign (DMS) usage, etc. Unobserved heterogeneity is often present in incident duration data, which is explored in this study. Present study contributes methodologically by estimating rigorously fixed- and random- parameter hazard-based duration models. To the best of our knowledge, such random parameter models have not been applied in incident duration modeling.

2.3 METHODOLOGY

2.3.1 Data Source

Data analyzed in this study was obtained from TDOT Region 1 Traffic Management Center (TMC). A web-based archiving tool called LOCATE/IM is used to access the incident database. TMC maintains the database through Tennessee SmartWay and TDOT HELP program.

As for the classification purpose, the incident data is obtained for 2017 year-round in TDOT Region 1 area. The total number of incident records is 24,015. Due to the missing route information of some incidents records, these incident data are removed for the classification purpose. The final number of incidents collected is 24,003.

As for empirical study, and incident duration prediction purpose, the data contains traffic incident summary and detailed operational reports. Summary data were collected from Sep. 29. 2010 to Dec. 31. 2015, covering 26 counties with 17 routes (7 freeways, 10 major highways). 129,088 total incident records were obtained.

2.3.2 Large-scale Traffic Incident Classification

The Manual on Uniform Traffic Control Devices (MUTCD) has a standard in classifying the traffic incidents in Section 6I.01 General. It says "Traffic incidents can be divided into three general classes of duration, each of which has unique traffic control characteristics and needs. These classes are:

- Major - expected duration of more than 2 hours,
- Intermediate - expected duration of 30 minutes to 2 hours, and
- Minor - expected duration under 30 minutes."

Such a general classification criterion does not apply to different regions due to the heterogeneity among various traffic incident cases. A new proposed machine learning classification method called K-means Clustering is applied to classify those traffic accidents and the classification results will be used for further traffic incident duration prediction.

2.3.2.1 K-Means Clustering Algorithm

The K-Means clustering algorithm begins with a predefined number of clusters, and each observation is belonging to a single cluster. A measure of within cluster variance is defined, thus such variation is minimized in each cluster. Squared Euclidean distance is commonly used for this clustering purpose, and the clustering algorithm proceeds iteratively until each observation is assigned to the clusters. The formulation of the problem can be written as follows:

$$\min_{C_1,\ldots,C_K} \left\{\sum_{k=1}^{K} \left[\frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^{p} \left(x_{ij} - x_{i'j}\right)^2\right]\right\} \qquad \textbf{Eq. 2.1}$$

Where,

K is the number of clusters chosen,

k is the index, $\left[\frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^{p} \left(x_{ij} - x_{i'j}\right)^2\right]$ is the within cluster variant for cluster $\boldsymbol{C_k}$.

$|\boldsymbol{C_k}|$ is the number of observations in cluster k. i and j denotes the observation index.

The K-Means clustering algorithm follows the iterative steps,

Step 1. Randomly select K clusters and assign them to each observation. These will be the initial assignments;

Step 2. (1) For each of the K clusters, the mean value based on feature is calculated as the centroid; (2) Then assign the observations using the least squared Euclidean distance. These two steps are repeated until all the assignments are done.

2.3.2.2 Classification Results

The incident data is first error checked to validate whether there is any missing information for different variables. 12 incident records were found to have missing route information, and they are removed from the main body of the data. 19 different types of incident are identified including Aban Vehicle, Amber Alert, Debris, Disabled Vehicle, JK TR TR, Multivehicle Crash, Overturned Vehicle, PD/MED/FIRE Activity, Sched Roadwork, Single Vehicle Crash, Special Evt/PSA, Test Incident, Travel Time, Unknown, Unsched Roadwork, Vehicle Fire, Weather, Oversize load, and Grass Fire. Those incidents either happened on interstate freeways (e.g. I-40, I-75, I-81, I-640, and I-26) or state routes (e.g. SR115, SR158). These incident types, routes, as well as travel direction, morning peak hour, afternoon peak hour, and urban/rural area are all coded as binary variables. The hierarchical clustering method is preliminarily adopted instead of K-means clustering method because K-means clustering method cannot deal with ordinal or categorical variables. However, hierarchical clustering method does not produce good results. Figure 2.1 presents the change in within cluster sum of squares. Notice that a single classification result cannot represent well of the separation of incidents. An interactive clustering method is developed to cluster those incidents by removing a cluster with a small number at each step. At first, those incidents without response time are clusters together. So, these incidents are removed from the incidents for better classification (total number of incidents removed is 4,041).

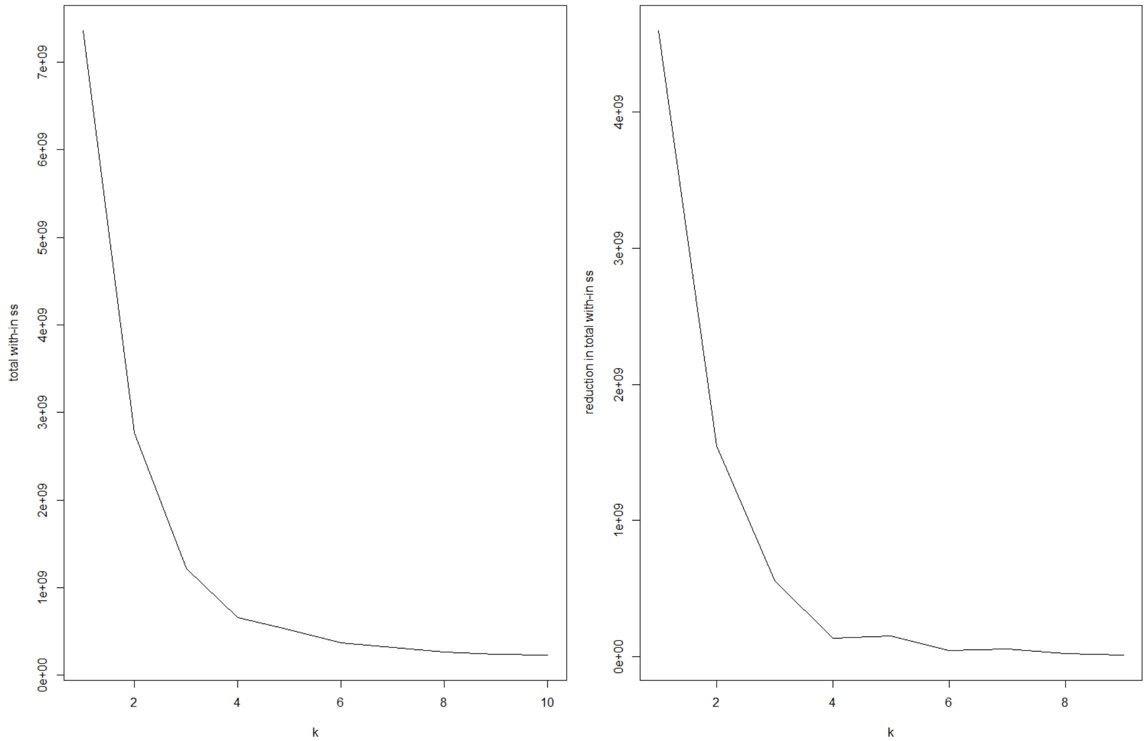

FIGURE 2.1 Change in within cluster sum of squares for the first iteration.

By inferring only from Figure 2.1, 4 or 5 clusters would be a good choice for classifying those data, because the reduction in within cluster sum of squares is large before 5, and after that, it becomes stable, meaning there is no much change afterwards. Finally, five clusters are chosen because it can further reduce the variance within each cluster. In total, 19,962 incidents are clustered, and the clustering results are shown in Figure 2.2. Figure 2.2 is suggesting pyramid classification where huge numbers of observations are on the top, and on the bottom, fewer observations are clustered. In cluster 1, the incidents are all abandoned vehicles, and the average incident duration is about 7,009 minutes; In cluster 2, they are either abandoned vehicle or disabled vehicles, and average incident duration is about 3,047 minutes; In cluster 3, mixed incident types are found, and the average incident duration is about 1,388 minutes; In cluster 4, majority of incidents are all in this cluster (about 90%), and the average incident duration is about 40 minutes; and in cluster 5, the incidents are mixed types, and the average incident duration is about 594 minutes. Thus, we can see that cluster 1 and cluster 2 are close to each other in terms of incident duration. While cluster 3 and cluster 5 are close to each other, and cluster 4 is a cluster with the majority of the data. Detailed descriptions of those incident groups (extreme, large-scale, and small-medium) are presented as follows:

In group 1, which extreme long incident duration incidents, the majority of the incidents types are abandoned vehicles (98.7%), and the rest are disabled vehicles (1.3%). While in group 2, the majority of the incidents are also abandoned vehicles (87.4%), then disabled vehicles (10.1%), etc. Only 9 multi-vehicle crashes, and 5 single-vehicle crashes. In group 3, the majority of the incidents are disabled vehicles (72.6%), then abandoned vehicles (8.1%), debris (8.0%), multi-vehicle crash (7.5%), single-vehicle crash (2.4), etc.

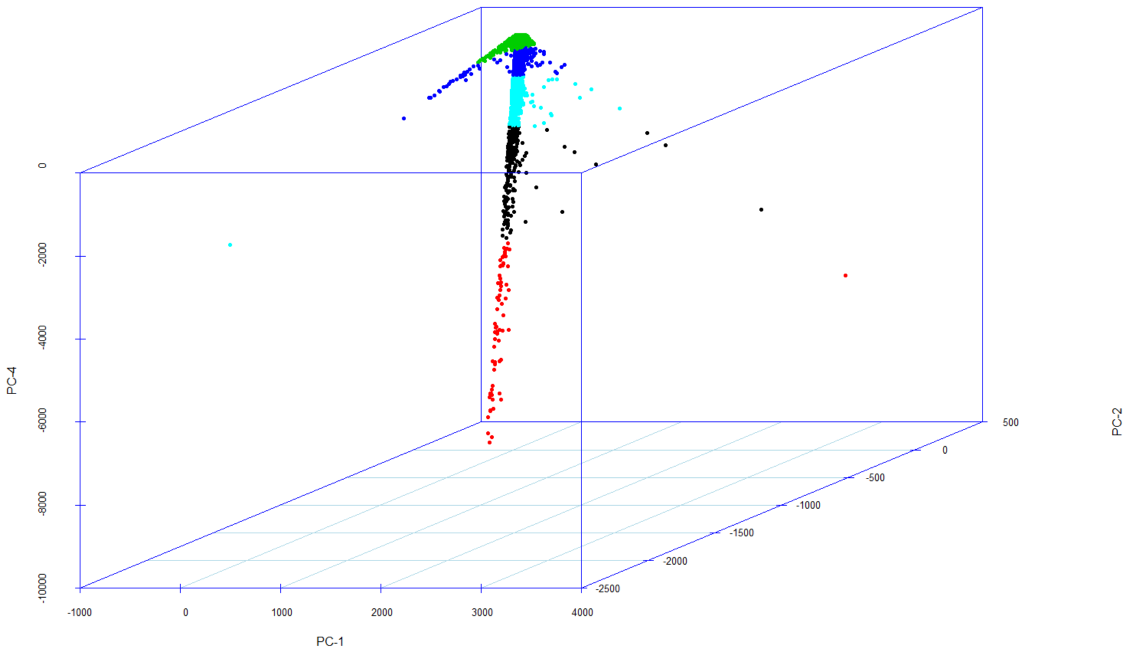

FIGURE 2.2 Three-Dimensional representation of 5 clusters of the incident data (green represents group 3, dark blue represents group 2, and black represents group 1).

These results indicate that majority of those incidents are not crashes. Looking at the route characteristics, 98.1% of group 1 incidents happened on the freeway, where about 68.4% of the freeway incidents happened on I-40. Similar statistics can be found for other groups. Average AADT for group 1 incidents on freeway routes is 60,817, and 35,550 for non-freeway routes. Average AADT for group 2 incidents on freeway routes is 61,769, and 38,733 for non-freeway routes. Average AADT for group 3 incidents on freeway routes is 59,366, and 37,327 for non-freeway routes. The truck percentage of all traffic (single unite trucks and multi-unit trucks) is 16.27% for the freeway, and 4.17% for non-freeway routes in group 1 incidents. They are 15.36% for the freeway, and 3.87% for non-freeway routes in group 2 incidents, 16.8% for the freeway, and 4.21% for non-freeway routes in group 3 incidents, respectively. In group 1 incidents, 26.2% of them happened in morning peak hours, and 23.6% of them happened in afternoon peak hours. Totally, about 50% of those incidents happened during peak hours. While in group 2, 34% in morning peak hours, and 27.3% in afternoon peak hours, and in group 3, 20.3% in morning peak hours, and 28.9% in afternoon peak hours. In terms of the location of those incidents, about 95% of them happened in urban areas in each group.

2.3.2.3 Key Characteristics

Lane blockage is an important characteristic. Table 2.1 presents the descriptive statistics based on the distribution of number of lanes blocked during an incident. In group 1, 99.4% of those incidents do not involve the lane blockage, with 2 incidents have 1 lane blocked. In group 2 incidents, 97.1% of the incidents have no lane blockage, only about 3% of them have lane blockage. In group 3, 93% of them have no lane blockage, and about 7% have either 1 lane, 2, 3, 4, 5, or 8 lanes blocked. Table 2.1 also shows when there is

TABLE 2.1 Descriptive Statistics for Incident Duration (in Minutes) based on Lane Blockage

Incident duration / Group 1 Incidents / No. of lanes blocked	N	Mean	Std.	Median	Min	Max
0	311	3,954	1,887	3,091	2,225	9,843
1	2	2,639	417.9	2,638	2,343	2,934
Incident duration / Group 2 Incidents / No. of lanes blocked	**N**	**Mean**	**Std.**	**Median**	**Min**	**Max**
0	1,600	925.7	464.4	847	318	2,215
1	29	715.4	424.3	535	315	2,207
2	18	512.4	208.1	422.5	351	1,118
3	3	524.33	248.2	434	334	805
Incident duration / Group 3 Incidents / No. of lanes blocked	**N**	**Mean**	**Std.**	**Median**	**Min**	**Max**
0	16,690	38.7	53.34	17	0	317
1	872	60.68	51.34	48	1	304
2	312	69.07	45.98	57	5	295
3	51	89.57	63.04	71	9	288
4	8	83.75	32.71	69.5	55	139
5	3	60.33	21.36	69	36	76
8	3	7.67	3.51	8	4	11

no lane blockage, the average incident duration for group 1 and group 2 incidents are usually longer, on average it is 3,954 minutes for group one incidents, and 925.7 minutes for group 2 incidents. When there is 1 lane or more lanes blocked during the incident, the average incident duration becomes shorter (e.g. from 3,954 minutes to 2,639 minutes for group 1 incident, and from 925.7 to 715.4 to 512.4 to 524.3 for group 2 incidents). However, such a trend is not represented in group 3 incidents. On contrary, the average incident duration increases when the number of lanes blocked ranges from 0 to 3, and after that, it decreases. For example, the average incident duration increases from 38.7 minutes to 89.57 minutes and then it decreases to 83.75 minutes for 4-lane blockage, 60.33 minutes for 5-lane blockage, and significantly short incident duration 7.67 minutes for 8-lane blockage incidents. Therefore, in identifying large-scale incidents, lane blockage is one of the important characteristics.

In terms of lane blockage duration and response time for the incidents, Table 2.2 and 2.3 present the descriptive statistics for block duration and response time. For large-scale incidents (group 2 incidents), the block duration is much longer than other groups. 19 times longer than block duration in group 1 and 8.5 times longer than it is in group 3. In terms of response time, on average it takes about 77 minutes to respond to group 1 incidents, and 19.5 minutes to respond to group 2 incidents, and 3.8 minutes to group 3 incidents. Generally, it takes a longer time to respond to large-scale incidents.

In summary, large-scale incidents usually are associated with lane blockage, and the blockage duration is much higher than small scale or medium scale incidents. For those extreme long incidents, they are usually abandoned or disabled vehicles which does not block lanes. Therefore, the classifying standards in MUTCD based on just incident duration

TABLE 2.2 Descriptive Statistics for Block Duration (in Minutes) for Each Cluster

Group \ Block duration	N	Mean	Std.	Median	Min	Max
1	2	15	19.80	15	1	29
2	50	303.58	354.2	297	0	2,137
3	1,249	31.64	38.79	20	0	287

TABLE 2.3 Descriptive Statistics for Response Time based on Lane Blockage

Group 1 Incidents / No. of lanes blocked \ Response time	N	Mean	Std.	Median	Min	Max
0	311	77.23	461.84	0	0	5,723
1	2	1	1.414	1	0	2
Group 2 Incidents / No. of lanes blocked \ Response time	**N**	**Mean**	**Std.**	**Median**	**Min**	**Max**
0	1,600	19.66	92.09	0	0	1,750
1	29	16.34	51.44	2	0	274
2	18	14.28	18.2	5.5	0	53
3	3	1	1.732	0	0	3
Group 3 Incidents / No. of lanes blocked \ Response time	**N**	**Mean**	**Std.**	**Median**	**Min**	**Max**
0	16,690	3.72	10.42	0	0	186
1	872	5.01	9.07	2.5	0	102
2	312	5.25	9.51	2	0	88
3	51	5.04	9.49	3	0	68
4	8	2.25	1.67	2	0	5
5	3	2.33	2.52	2	0	5
8	3	0	0	0	0	0

is not the best method. Other important characteristics discussed should also be added.

2.3.3 Data Assembly and Large-scale Incident Selection

Large-scale incidents are identified using the obtained data. The past methodology, MUTCD, TN traffic incident management goals (removing incidents within 90 minutes), and mean durations in this database, all contribute to the selection that incidents lasting more than 120 minutes and at least one lane is blocked are identified as large-scale. A total of 890 out of 129,088 incidents approximately 0.69% are selected of all incidents. Their locations are displayed in following Figure 2.3, indicating that most of them occurred near urban areas.

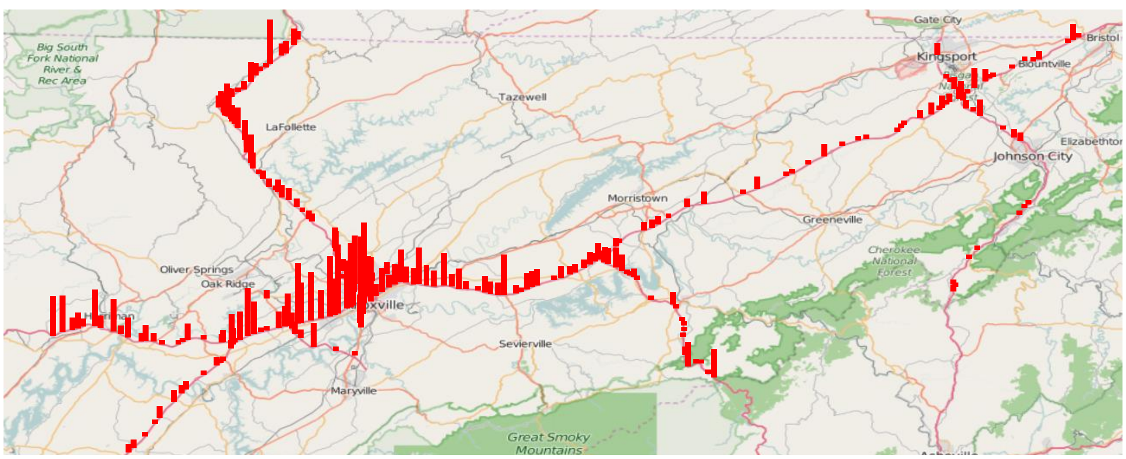

FIGURE 2.3 Spatial distributions of large-scale incidents within TN region 1.

Substantial effort went into creating a comprehensive database for the selected large-scale incidents. The data was collected and enhanced by creating new variables from incident operations reports, as well as using Google Earth to obtain spatial information, e.g., number of lanes. Tennessee crash reports are also used to obtain data, e.g. AADT.

Figure 2.4 shows the general structure of incident management process over time (upper part) and the data obtained (lower part). Focusing on multi-agency operational response during large-scale incidents, detailed incident reports were reviewed to extract relevant temporal operational data such as response times and On-Scene times for each agency (i.e., highway incident response unit (HIRU), police, emergency medical services, etc.). Incident reports maintained by TDOT contain detailed information about response and on-scene times for different agencies, but the data are not readily available for statistical analysis. To capture these operational characteristics of each agency such as highway safety patrol (HSP) administered by TDOS, HIRU administered by TDOT, local police/fire departments, etc., detailed incident reports are downloaded from TDOT database and used for coding new variables such as HIRU response, number of vehicles involved, lane blockage percentage, secondary incident occurrence, and HAZMAT incident, which are either directly obtained from the database or indirectly calculated from detailed incident reports, Google earth, and Tennessee crash reports. Newly coded variables are integrated with existing incident variables creating a unique database. Potential relationships between incident duration and multi-agency response variables can be causal or non-causal. For example, shorter response time of ambulances may be associated with reduced duration of an incident, while usage of a towing service may be associated with longer duration incidents. However, this does not mean that the use of towing service "caused" the incident to be longer incidents - it may be that they were likely to be used for larger duration accidents. These relationships are investigated further within the paper.

Note that bi-directional relationships may exist between incident durations and

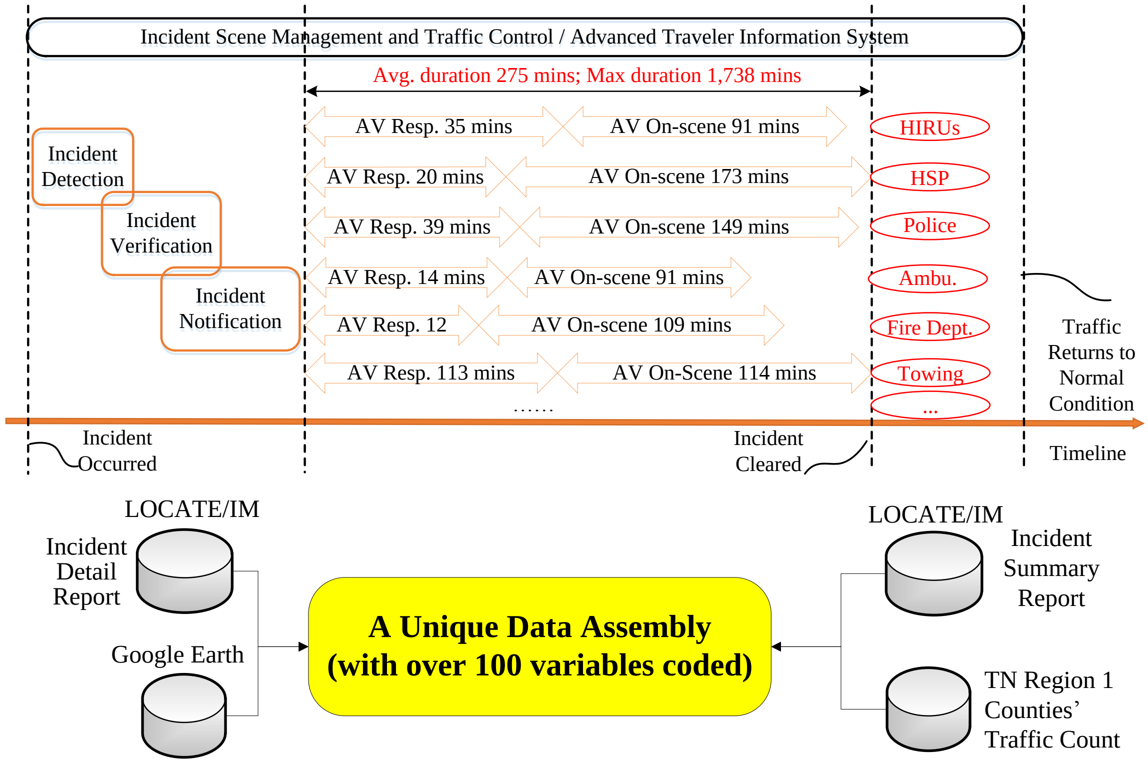

FIGURE 2.4 Critical traffic incident management components & framework of data integration from different data sources.

response times, as opposed to unidirectional relationships assumed in this study. Specifically, we have assumed response times of various agencies as correlates of incident duration, but it is also possible that incident managers may respond more promptly to larger duration incidents. This may show up as a negative correlation between response times and incidents durations, indicating that "potentially" longer incident durations can be a predictor of agency's response time. This simultaneity issue is recognized. However, capturing simultaneity through modeling was not done due to a large number of missing values for response times of different agencies. For example, response time for the first highway response unit was available for only 44.2% of the sampled large-scale incidents (See Table 2.4). Also, the modeling will be complicated by the presence of several response times, given that multiple agencies are often involved. Nevertheless, it will be valuable to investigate the bi-directional relationships between incident duration and response times using a simultaneous multi-equation modeling framework.

2.3.4 Incident Duration Modeling

The hazard-based modeling approach is adopted in this study based on theoretical and empirical criteria. First, numerous researchers have used this technique for modeling of durations (Hojati, Ferreira, Washington, Charles, & Shobeirinejad, 2014; Nam & Mannering, 2000). Second, incident durations are time dependent for which this approach is particularly suitable. Third, hazard-based approach facilitates interpretation of duration data using a dynamic sequence of conditional probabilities. Formation of hazard-based modeling approach is described as follows.

Let T be a non-negative random continuous variable representing duration time of an incident. Let $h(t)$ denote the hazard at time t on the continuous time scale, and it is

TABLE 2.4 Descriptive Statistics of Variables Associated with Large-Scale Incidents Variables

Variable	Sample size	Mean	SD	Min	Max	VIF
Incident Durations (in minutes)	890	274.90	199.22	121	1,738	---
	10th Percentile: 132 minutes, 25th Percentile: 152 minutes, 50th Percentile: 203 minutes, 75th Percentile: 321 minutes, and 90th Percentile:497 minutes					
Incident type						
Multivehicle crash	890	0.316	0.465	0	1	1.246
Vehicle fire	890	0.079	0.271	0	1	1.109
Unscheduled roadwork	890	0.128	0.334	0	1	1.265
Temporal factors						
Afternoon peak	890	0.228	0.419	0	1	1.08
Weekday	890	0.794	0.404	0	1	1.048
Traffic volume						
AADT (log form)	890	11.057	0.553	10.087	12.162	0.112
Operational Responses						
Response time of first HIRU	394	1.18	2.928	0.033	30.033	1.364
Response time of second HIRU	245	2.585	6.358	0.033	60.133	1.559
Average response time if 3rd or more HIRUs responded	75	4.498	6.789	0.166	44.133	1.624
Response time of HSP	102	0.668	1.165	0.032	5.266	1.32
Response time for police	232	1.3011	8.874	0.033	132.8	6.405
Response time for ambulance	130	0.473	0.886	0.0333	5.7	1.283
Response time for towing company	229	3.761	9.389	0.033	132.8	7.237
Average on-scene time for HIRU	432	3.026	3.434	0.0333	27	1.607
On-scene time for HSP	95	5.775	6.007	0.1	36.033	2.138
On-scene time for police	226	4.951	5.17	0.033	49.3	1.893
On-scene time for ambulance	120	3.026	4.466	0.033	29.533	2.047
On-scene time for towing company	219	3.812	5.231	0.033	29.4	2.032
Indicators for missing values of response and on-scene times of different agencies						

TABLE 2.4 Continued

Variable	Sample size	Mean	SD	Min	Max	VIF
Indicator variable for 1st HIRU	890	0.556	0.497	0	1	2.051
Indicator variable for 2nd HIRU	890	0.723	0.447	0	1	2.095
Indicator variable for 3rd or more HIRUs	890	0.915	0.277	0	1	1.85
Indicator variable for HIRU average On-Scene time	890	0.514	0.5	0	1	1.32
Indicator variable for HSP	890	0.885	0.318	0	1	1.972
Indicator variable for police	890	0.739	0.439	0	1	2.538
Indicator variable for ambulance	890	0.853	0.353	0	1	2.209
Indicator variable for towing company	890	0.742	0.437	0	1	2.877
Other deployed resources						
Response time for HAZMAT	14	2.233	2.301	0.0333	7.933	8.369
On-scene time for HAZMAT	13	3.674	2.934	0.067	10.1	6.176
Number of HAR deployed	705	2.850	1.806	1	8	96.25
Average HAR deployment time	685	7.370	10.20	0.000	76.533	63.78
Number of DMS deployed	751	2.500	2.024	1	26	1.938
Average DMS deployment time	743	6.547	7.735	0.0000	108.13	96.02

Notes: All response, on-scene times and deployment time are scaled in 30 minutes; HIRU refers to Highway Response Units; HSP refers to Highway Safety Patrol; AADT refers to Annual Average Daily Traffic; afternoon peak refers to 4 PM to 8 PM; SD is the standard deviation and VIF is the variance inflation factor.

defined as an instantaneous probability that incident duration will end in an infinitesimally small time Δt after time t, given that the incident duration has already lasted until time t. This is referred to as duration dependence. Precise mathematical definition for $h(t)$ in terms of probability is:

$$\boldsymbol{h(t) = \lim_{\Delta t \to 0^+} Pr(t \leq T < t + \Delta t | T > t)/\Delta t} \qquad \textbf{Eq. 2.2}$$

Where,

T = a non-negative random continuous variable representing duration time of an incident;

t = time t;

Δt = infinite small duration of time.

This mathematical form makes it possible to relate the hazard to the probability density function and the cumulative distribution function for T. Specifically, the probability that the incident does not elapse before time t is $F(t) = Pr(T < t)$. The probability of the duration terminating in an infinitesimally small time Δt after time t is written as $f(t) = dF(t)/dt$. So, the survival function, which gives the probability that an incident has a duration greater than or equal to t is written as $S(t) = Pr(T \geq t) = 1 - F(t)$. Thus, the hazard can be reformulated as,

$$\boldsymbol{h(t) = F(t)/S(t)} \qquad \textbf{Eq. 2.3}$$

Where,

$\boldsymbol{F(t)}$ = the probability that the incident does not elapse before time t;

$\boldsymbol{S(t)}$ = the probability that an incident has a duration greater than or equal to t.

If the hazard function slopes upward, $d\,h(t)/dt > 0$ at time t, the function will have positive duration dependence, meaning the probability that the incident will end soon increases as the incident duration lasts longer. Otherwise, it is negative duration dependence. If $d\,h(t)/dt = 0$, then the probability is independent of incident duration. Therefore, the shape (underlying distribution of hazard function) has important implications for duration dynamics, because an incorrect specification may result in severe biases when attempting to quantify factor effects. Three distributions, Log-normal, Log-logistic, Weibull, are employed to study extreme values which matches the intention of large-scale incidents, and to find the best fit using maximum likelihood for fixed parametric models. To explore the effect of exogenous variables on incident duration, fixed and random parameter hazard-based models are employed to accommodate the effect of external covariates on hazard at any time t. Proportional Hazards (PH) form and Accelerated Failure Time (AFT) form are two alternatives. Previous research reveals no strong theoretical or empirical argument to choose one over the other. Because AFT assumes that covariates rescale time directly, which can capture the direct effect of an exposure on survival time, provide more easily interpretable parameters, and a linear relationship between the logarithm of duration and covariates, it is more favored. ATF equation is written as,

$$\boldsymbol{ln(T) = \beta X + \varepsilon} \qquad \textbf{Eq. 2.4}$$

Where,

β = the coefficient vector of covariates;

X = represents the covariates, and

ε = an error term.

Since the data are truncated, left truncated hazard-based models are estimated, based on Eq. 2.6 with 120 as the truncation point. To overcome potential issues that erroneous inferences may occur if the incident duration is not homogeneous across observations, two options are available. First, the gamma distribution can be applied to incorporate heterogeneity in the Weibull model with mean 1 and variance θ. Second, a pre-specified distribution can be assumed to incorporate unobserved heterogeneity, allowing the parameters to change over observations. Random parameters are estimated in the hazard-based models by adding a randomly distributed term. A normally distributed $\sim N(0, \sigma^2)$) term is added to the original β, and simulation based maximum likelihood using Halton draws is applied to estimate random parameter incident duration models (Kamrani, Wali, & Khattak, 2017). Finally, nine models are estimated using the maximum likelihood or simulated maximum likelihood methods. These are fixed- and random-parameter hazard-based models with and without truncation, based on log-normal, log-logistic, Weibull and Weibull with gamma heterogeneity distribution.

2.4 ANALYSIS RESULTS

The data are error-checked and some of the unreasonable duration observations were excluded. Based on the 890 large-scale incident observations, TDOT region 1 averages about one large-scale incident every other day.

2.4.1 Descriptive Statistics

Table 2.4 presents descriptive statistics showing the mean duration of the large-scale incidents is 275 minutes, which is 129% larger than mean duration of all incidents in the database. Almost 10% of the large-scale incidents last more than 497 minutes. Key variables (out of all variables in Figure 2.4) descriptive statistics are also shown including multi-agency responses and incident types. The resulting 890 large-scale traffic incidents exhibit a dispersed distribution with an average duration of 274 minutes and maximum duration of 1,738 minutes respectively. Multi-vehicle crashes, vehicle fire, and unscheduled roadwork type incidents account for 32%, 8%, and 13% of total large-scale incidents sample, respectively (out of 17 incident types, outliers are removed, and these three types show their significance in the model). Approximately, 23% of incidents occurred during afternoon peak (4 PM – 8 PM), whereas 80% of large-scale incidents occurred during weekdays.

Importantly, data on response and on-scene times of different agencies are compiled and used in analyses. Note that data on response and on-scene times for different agencies have a substantial number of missing values and are not available for all coded large-scale incidents. As such, to utilize the available information on key operational variables without losing significant data, indicator variables are created for missing values of response and on-scene times of different agencies (A. Khattak & Targa, 2004). For example, response times for HSP are available for 102 large-scale incidents. Thus, an indicator variable is created for HSP which equals 1 if response time is missing and zero otherwise. It is important to note that, in LOCATE/IM detailed operational reports, agency on-scene times at specific incident scene may not be available for all cases where a specific agency responded. To illustrate this, consider HSP response to 102 incidents for which response times are available; However, the on-scene times are available only for 95 incidents to which HSP responded. Keeping in view the negligible differences between sample sizes of response and the on-scene times of same agency, and to avoid collinearity issues among different variables, single indicator variables are created both for missing response and on-scene times of specific agency and are used in subsequent analyses. Note that separate indicator variables for response and on-scene times are considered and used in the modeling process. However, the estimation results were not significantly different from using single indicator variables for both response and on-scene times and thus are removed from final models for ease of discussion and interpretation.

Regarding multiple agency responses to large-scale incidents, HIRU, HSP/police, ambulance, and towing companies are the main agencies observed in detailed TDOT operational reports. HIRU are TDOT trucks equipped with recovery tools for response traffic incidents; while Tennessee HSPs are police units responsible for enforcement and accident investigations, reports, etc. Regarding HIRU, the operational reports provide information about response times of HIRU (1^{st}, 2^{nd}, 3^{rd} unit, and so on). However, average response times of 3 or more than 3 HIRUs are reported in Table 2.4 due to their small sample size. Likewise, response times (in 30 minutes) are reported for HSP, police, ambulance, and towing company. Overall, the descriptive statistics for response and on-scene times of different agencies spot important patterns embedded in data.

In detail, Table 2.4 shows the average response times for 1^{st}, 2^{nd}, and more than two HIRUs are 35.4 (1.18*30), 77.5 (2.58*30), and 134.9 (4.49*30) minutes, respectively. The larger response times for greater number of HIRUs may reflect the severity of large-scale incidents. Intuitively, among other response agencies, ambulance has the shortest average response time (14 minutes) followed by police (39 minutes). The response time for towing companies is highest with average response time of approximately 112 minutes with a maximum response time of approximately 217 minutes. In terms of on-scene times, on average, HSP and police spend highest amount of time (173 and 148 minutes respectively) at large-scale incident scenes. While for towing company it is 114 minutes and HIRU 90 minutes. Notably, only 1.6% of the large-scale incidents involved hazardous materials, and mean response and on-scene for the hazard material removal agency were 54 and 110 minutes. Regarding dissemination of incident information to the public through HAR and DMS, these media are heavily used during large-scale incidents, as expected. Specifically, HAR and DMS are used in 84.6% and 92.3% of the large-scale incidents, respectively. On average, 2.27 HARs are used with average 148-minute usage; while 2.11 DMS are used with average 156-minute usage.

For modeling, due to several explanatory variables, it is suspected that multicollinearity may affect modeling results if not addressed properly. As such, variance inflation factors (VIF) are reported in Table 2.4 for key variables. It can be seen that VIF values for key explanatory variables are smaller than 10, which indicates that multicollinearity is not a concern (A. Khattak, et al., 2016).

2.4.2 Model Selection and Performance Comparison

Before estimating incident duration models, potential explanatory variables are identified by developing simple correlation matrices and ordinary least squares regression models (Washington, Karlaftis, & Mannering, 2010). This helped in identification and conceptualization of explanatory variables. Next, a series of fixed-parameter accelerated failure time (AFT) hazard-based duration models were developed. Following (Washington et al., 2010), different distributions are tested such as log-normal, log-logistic, Weibull, and Weibull with gamma heterogeneity. All the variables shown in Table 2.4 were included in the models. The fixed-parameter hazard-based duration models are developed using standard maximum likelihood estimation techniques. For brevity, we only present the final summary statistics (goodness-of-fit measures) in Table 2.5. To compare the fixed-parameter models with different distributional assumptions, likelihood ratio statistics are calculated in order to select statistically superior model (Wali, Ahmed, Iqbal, & Hussain, 2017 (forthcoming)). For details regarding likelihood ratio statistics, interested readers are referred to Washington et al. (Washington et al., 2010). Higher value of likelihood ratio statistic for a specific model indicates improved statistical fit to data at hand compared to other fixed-parameter models (Washington et al., 2010). It can be seen that Weibull model resulted in best fit among all other fixed-parameter models with the highest likelihood ratio statistic of 449.48. In the Weibull model, P parameter (2.08) is greater than one and statistically significant, indicating that hazard is monotone increasing in duration (Washington et al., 2010). Truncated hazard-based duration models are also developed with log-logistic, log-normal, Weibull, and Weibull with gamma heterogeneity. However, the estimation results were approximately similar in terms of parameter estimates and likelihood ratio statistics (results can be requested from the authors). Thus, the models with no truncation (due to simplicity) are presented and discussed next.

Given that several observed and unobserved factors can contribute to large-scale incident durations, random-parameters are incorporated in fixed-parameter Weibull hazard-based duration models. Conceptually, random parameter models provide the flexibility to allow parameter estimates to vary across sample observations with some pre-specified distribution (Washington et al., 2010). As such, random parameter Weibull model is estimated to allow parameter estimates to vary across observations. The goodness of fit measures indicates the statistically significant superior performance with the highest

TABLE 2.5 Summary Goodness-of-Fit Measures for Hazard Based Duration Models

Performance Indices	Fixed Parameters				Random Parameters
	Log-Normal	Log-Logistic	Weibull	Weibull with Gamma heterogeneity	Random Parameter Weibull
Theta	---	---	---	6.97*	---
Sigma	0.232*	0.243*	0.48*	0.068*	0.12*
P	4.3*	4.1*	2.08*	14.52*	8.33*
LL(0)	-695.16	-691.24	-880.65	-457.79	-880.65
LL(β)	-480.99	-478.12	-655.91	-426.72	-462.14
Number of Observations	890	890	890	890	890
Likelihood ratio statistics	428.3	426.24	449.48	62.14	831.02
Rho-Squared	0.308	0.308	0.255	0.068	0.475

Notes: * shows statistically significant estimates at 99% level of confidence; LL(0) is log-likelihood of the constant only model; LL(β) is log-likelihood at convergence; P is hazard distribution parameter, and Theta is heterogeneity parameter. "---" = Not applicable.

likelihood ratio statistic of 831.02.

The results of fixed- and random- parameter Weibull models are presented in Table 2.6. The final random parameter model includes 26 correlates (including indicator variables for missing data), of which seven parameters exhibited statistically significant variability (as indicated by the standard deviation of parameter estimates for random parameters) across the large-scale incidents. For random-parameters, different distributions are tested such as normal, uniform, Weibull, and tent distributions, with normally distributed random parameters having the best fit. This finding is in agreement with several studies that focused on non-large-scale incident duration modeling (Hojati et al., 2013; Hojati et al., 2014). Finally, the distributions of normally distributed random parameters are also illustrated.

2.4.3 Key Findings of Hazard-based Prediction Models

Table 2.6 presents the fixed- and random- parameter Weibull model for large-scale traffic incidents. A positive parameter estimate for an explanatory variable correlates with an increase in incident duration or decrease in hazard function with a unit increase in the value of explanatory variables and vice versa for negative parameter estimates. To obtain deeper insights, the exponents of parameter estimates in Table 2.6 translate to percent increase/decrease in large-scale incident durations as a result of a unit change in explanatory variables. As such, the percent changes in incident durations associated with a unit increase in explanatory variables are given in Table 2.6 for the random-parameter Weibull model. For response and on-scene times, the percent changes show the percent increase/decrease in large-scale incident duration for each 30-minute increase in response or on-scene times. For indicator variables, it translates the percent change in large-scale incident durations, while indicator variable changing from zero to one (notes of Table 2.4).

Regarding estimation results are shown in Table 2.6. Response and on-scene times of different agencies are observed to play important role in the determination of large-scale incident durations, while HAZMAT, HAR, and DMS were not found to be statistically significant. The associations between response and on-scene times of different agencies (except response time for the ambulance and on-scene time for HSP) and large-scale incident durations are fixed across incident observations, i.e. the parameter estimates did not vary across incidents. However, incorporation of random-parameters significantly enhanced the statistical significance of parameter estimates. For instance, a 30-minute increase in response time for 1st, 2nd, and 3rd (or more) (averaging 3rd, 4th, 5th, or 6th unit, if they responded and data are available) HIRUs translates to 2.83%, 1.61%, and 4.28% increases in incident durations, respectively. The mean incident duration is 338 minutes for 3rd or more HIRUs responded, and the mean response time is 135. This is an important finding as it suggests that the association of response times for the 3rd or more HIRUs is more pronounced compared to the response times for 1st or 2nd HIRU on incident durations. This finding seems intuitive in the sense that 3 or more HIRUs may respond to large-scale incidents that are excessively severe, and an increase in response times at this point is likely to result in even longer incident durations.

Likewise, an increase of 30-minute in response times of HSP and towing company are associated with 3.9% and 3.25% increases in large-scale incident durations. This is understandable as HSP and towing company may be required to undertake specific operations at the incident scene, and an increase in response times of these agencies (specifically, towing agency) may delay operations of other agencies. This finding is in agreement with Hojati et al. who found a positive correlation between indicator variable

TABLE 2.6 Model Estimation Results for Fixed- and Random-Parameter Models

Variables	**Fixed Parameters Weibull***		**Random Parameters Weibull***		
	Parameter	t-stat	Parameter	t-stat	% Changes***
Incident type					
Multivehicle crash	-0.159	-4.52	-0.138	-14.13	-12.90%
Vehicle fire	0.092	1.6	0.16	10.28	17.30%
Unscheduled roadwork	0.4	11.7	0.28	20.59	32.30%
Temporal factors					
Afternoon peak	-0.007	-0.24	-0.021	-2.14	-2.08%
standard deviation	---	---	0.173	18.24	---
Weekday	-0.052	-1.41	-0.037	-3.61	-3.64%
standard deviation	---	---	0.07	15.36	---
Traffic volume					
AADT (log form)	-0.1	-2.26	-0.062	-6.48	-6.01%
standard deviation	---	---	0.021	27.39	
Operational Response					
Response time of first HIRU**	0.028	1.28	0.028	13.14	2.83%
Response time of second HIRU**	0.03	6.23	0.016	12.57	1.61%
Average response time: 3rd or more HIRUs**	0.061	7.64	0.042	18.94	4.28%
Response time of HSP**	-0.017	-0.27	0.039	3.62	3.90%
Response time for police**	-0.021	-2.28	-0.025	-11.86	-2.50%
Response time for ambulance**	-0.003	-0.05	-0.028	-2.29	-2.77%
standard deviation	---	---	0.017	1.98	---
Response time for towing company**	0.029	3.53	0.032	15.57	3.25%
Average on-scene time for HIRU**	0.042	4.23	0.044	23.93	4.40%
on-scene time for HSP**	0.012	1.22	0.005	2.01	0.50%
standard deviation	---	---	0.002	1.73	---
on-scene time for police**	0.014	2.9	0.01	8.01	1%

TABLE 2.6 Continued

Variables	Fixed Parameters Weibull*		Random Parameters Weibull*		
on-scene time for ambulance**	0.005	0.33	0.013	4.3	3%
on-scene time for towing company**	0.045	4.3	0.047	26.14	4.80%
Dummies for missing values of response and on-scene times of different agencies (1 if response or on-scene time is missing, 0 otherwise)					
Dummy variable for 1st HIRU	-0.019	-0.21	-0.041	-2.57	---
standard deviation	---	---	0.099	12.66	---
Indicator variable for 2nd HIRU	0.138	1.86	0.081	5.81	---
Indicator variable for 3 or more HIRUs	0.053	0.45	0.043	2.06	---
Indicator variable for HIRU average on-scene time	0.249	2.49	0.195	10.34	---
Indicator variable for HSP	0.001	0.03	0.054	3.05	---
Indicator variable for police	0.004	0.07	0.006	0.47	---
Indicator variable for ambulance	0.095	1.01	0.064	3.66	---
Indicator variable for towing company	0.311	4.78	0.281	17.98	---
standard deviation	---	---	0.071	7.73	---
Constant	6.03	10.8	5.56	46.81	

Notes: * Dependent variable is the log of incident duration in minutes; ** response and on-scene times scaled in 30 minutes for ease of interpretation; *** Percent changes in incident duration with respect to unit changes in each explanatory variable. Zero to one for binary variables, one-unit increase/decrease in logarithm for log-transformed variables, and 30 minutes' increase for response and on-scene times. "---" = Not applicable.

for towing and non-large-scale incident duration (Hojati et al., 2013).

An increase in response times for the police department and the ambulance is associated with 2.5% and 2.7% shorter incident durations respectively, contrary to expectations. However, it is possible that responses by police and ambulance to larger incidents in the database are quicker, while responses may be relatively slower to shorter duration incidents. This may result in the unexpected direction of correlation observed. Even if an incident is large-scale, ambulance department may respond slower if no severe injuries are reported. Notably, longer response times by police or ambulance itself does not indicate reductions in incident durations. It is also possible that efficient responses and operations of other agencies may have resulted in the reduction of incident durations. In Figure 2.5, the response times for ambulance is found to be a normally distributed random parameter implying significant heterogeneity (on average 95.02% of the distribution is less than zero and about 4.98% greater than zero) in associations between ambulance response time and incident durations.

The analysis explicates associations between large-scale incident durations and on-scene times of different agencies. For instance, a 30-minute increase in average on-scene time for HIRU translates to 4.4% increase in incident durations. Likewise, a 30-minute increase in on-scene times for HSP, police, ambulance, and towing company is associated with 0.5%, 1%, 3%, and 4.8% longer incident durations. However, the on-scene time for HSP is a normally distributed random parameter implying heterogeneity in the magnitude of associations albeit the direction of the association is positive for 99.3% of observations (Table 2.6, Figure 2.5). These findings do not imply causation in the sense that agencies may have to stay longer at large-scale incident sites to respond to injuries, remove damaged

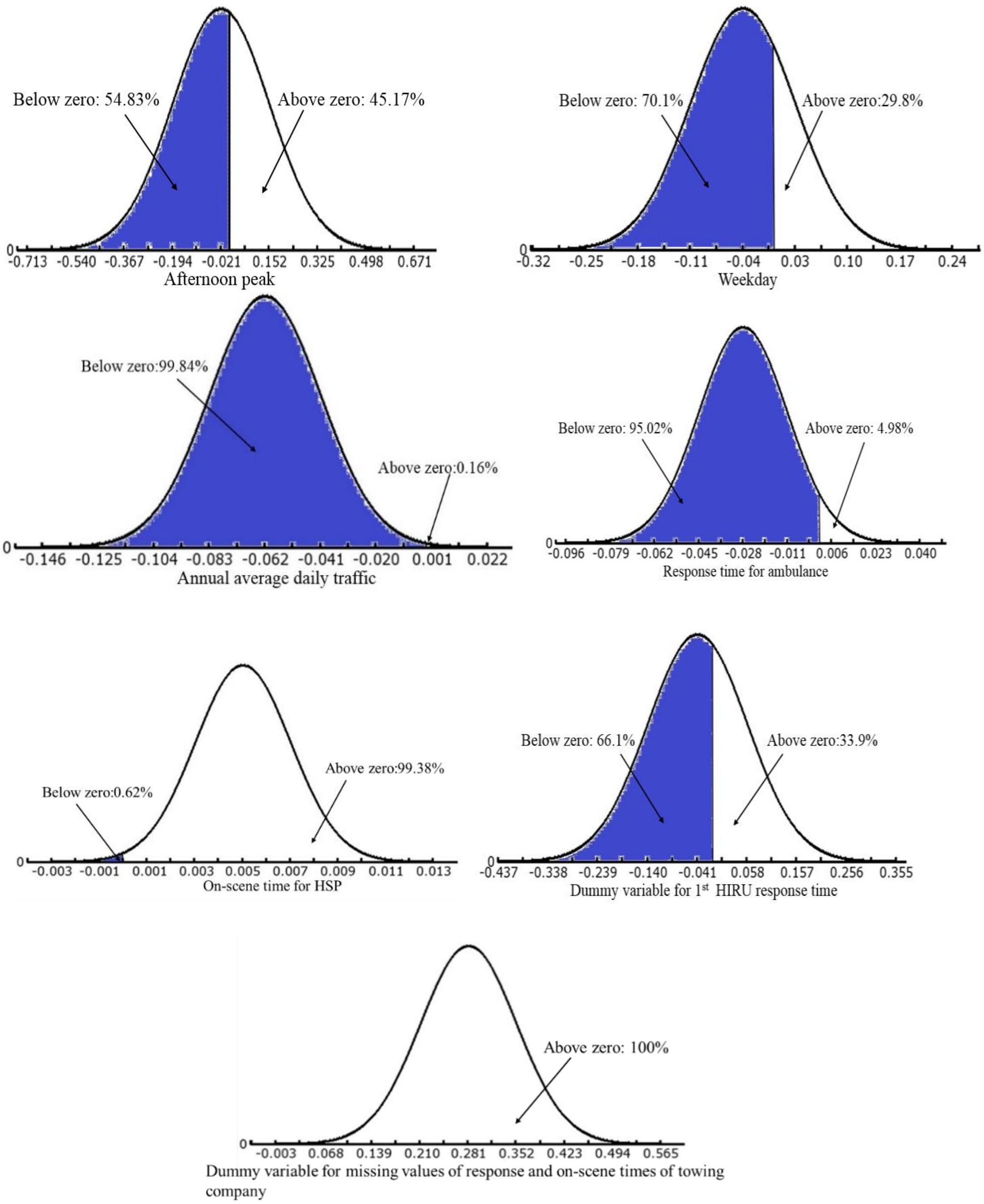

FIGURE 2.5 Distributions of normally distributed random parameters.

vehicles, clear debris, manage traffic at the scene, etc. In fact, large-scale incidents may have lasted even longer if the agencies would not have responded or stayed.

Finally, incident types, vehicle fire, and unscheduled roadwork are associated with 17.3% and 32.3% increase in large-scale incident durations, respectively. Incidents in afternoon peak are associated with relatively shorter durations. However, the associations vary substantially across observations—they are positive for 45.1% and negative for 54.9% of the data (Figure 2.5). Likewise, large-scale incidents during weekdays are on average associated with shorter durations, again found to be a normally distributed random parameter with significant heterogeneity (mean of -0.037 and standard deviation of 0.07) (Table 2.6, Figure 2.5). Regarding traffic characteristics, the results suggest that incidents on higher AADT roadways are relatively shorter; a unit increase in the log of AADT is associated with approximately 6% reduction in incident durations. Roadways with higher volumes may receive higher priority, more resources, and quicker response times. These findings are generally in agreement with the study by Zhang et al. (2012), focusing on large-scale incidents on urban freeways in Virginia (Zhang et al., 2012). The indicator variables for missing data are statistically insignificant implying missing values are randomly distributed, which is the case for most indicated variables.

2.4.4 Sequential Prediction for Real-Time Incident Duration

From a practical standpoint, traffic information is obtained chronologically and transmitted to Traffic Management Centers. Due to this inherent property of information collection procedure, it is better to update the incident duration for practical use by traffic operations managers based on the availability of the incident information during different stages. A literature review shows that time sequential prediction approach is studied to be practical for traffic operations, and simple regression models, hazard-based models, combined topic modeling and hazard-based models, and Artificial Neural Networks has been applied (A. J. Khattak et al., 1995; R. Li et al., 2015; Qi & Teng, 2008; Wei & Lee, 2007). However, these studies as we discussed before to not sophisticated enough to capture the heterogeneity, and obtain high accuracy, so hazard-based parametric survival models with frailty distribution and multilevel mixed-effects hazard-based parametric survival models are adopted to compare their performance.

2.4.4.1 Parametric Survival Models

As discussed before, AFT models are more appropriate for modeling our data, and the equation for the logarithm model is expressed as,

$$\boldsymbol{log t_i = x_i \beta + \varepsilon_i} \qquad \textbf{Eq. 2.5}$$

Where x_i is a vector of covariates, and β denotes the vector of regression coefficients. ε_i represents the error term with a certain density function and depending on this density function, that model will be defined either as lognormal or log-logistic. In our analysis, the preliminary results show that log-logistic density function is the best choice due to its long-tail in the data distribution. The log-logistic survival and density functions for log-logistic AFT models are,

$$\boldsymbol{S(t) = \left\{1 + (\lambda_i t_i)^{1/\gamma}\right\}^{-1}} \qquad \textbf{Eq. 2.6}$$

$$\boldsymbol{f(t) = {\lambda_i}^{1/\gamma} (t_i)^{1/\gamma - 1} \Big/ \gamma\{1 + (\lambda_i t_i)^{1/\gamma}\}^2} \qquad \textbf{Eq. 2.7}$$

Where $\lambda_i = \exp(-x_i\beta)$, and γ is an ancillary scale parameter.

To better capture the unobservable heterogeneity, frailty is used as an unobservable multiplicative effect on the hazard function, denoted as α assumed to have mean 1 and variance θ, so that $h(t|\alpha) = \alpha h(t)$, and the new survival function is written as,

$$\boldsymbol{S(t|\alpha) = \exp\left\{-\int_0^t h(u|\alpha)\,du\right\} = exp\left\{-\alpha\int_0^t \frac{f(u)}{S(u)}\,du\right\} = \{S(t)\}^{\alpha}} \qquad \textbf{Eq. 2.8}$$

Assuming $g(\alpha)$ is the probability density function of the unobservable α, the unconditional survival frailty function is obtained as,

$$\boldsymbol{S_\theta(t) = \int_0^\infty S(t|\alpha)g(\alpha)\,d\alpha = \int_0^\infty \{S(t)\}^{\alpha} g(\alpha)\,d\alpha} \qquad \textbf{Eq. 2.9}$$

And the unconditional density and hazard functions are also obtained as,

$$\boldsymbol{f_\theta(t) = -\frac{d}{dt}S_\theta(t)} \qquad \textbf{Eq. 2.10}$$

$$\boldsymbol{h_\theta(t) = \frac{f_\theta(t)}{S_\theta(t)}} \qquad \textbf{Eq. 2.11}$$

For mathematical tractability, the choice of $g(\alpha)$ is limited to either the gamma distribution denoted as gamma$(1/\theta\,, \theta)$ or the inverse-Gaussian distribution with denoted as IG$(1, 1/\theta)$. The probability density function of $gamma(a, b)$ distribution is,

$$\boldsymbol{g(x) = \frac{x^{a-1}e^{-x/b}}{\Gamma(a)b^{a}}} \qquad \textbf{Eq. 2.12}$$

And, the probability density function of $IG(a, b)$ distribution is,

$$\boldsymbol{g(x) = \left(\frac{b}{2\pi x^3}\right)^{1/2} \exp\left\{-\frac{b}{2a}\left(\frac{x}{a} - 2 + \frac{a}{x}\right)\right\}} \qquad \textbf{Eq. 2.13}$$

Thus, the frailty models for gamma, and inverse-Gaussian, separately will become,

$$\boldsymbol{S_\theta(t) = [1 - \theta log\{S(t)\}]^{-1/\theta}} \qquad \textbf{Eq. 2.14}$$

$$S_{\theta}(t) = exp\left\{\frac{1}{\theta}\left(1 - [1 - 2\theta log\{S(t)\}]^{1/2}\right)\right\} \quad \textbf{Eq. 2.15}$$

More details of the frailty models, interested readers can refer to (Hougaard, 1986).

2.4.4.2 Multilevel Mixed-effects Parametric Survival Models

By adding random effects into the log-logistic AFT models, this generates new models as,

$$logt_{ji} = x_{ji}\beta + z_{ji}u_j + v_{ji} \quad \textbf{Eq. 2.16}$$

Where j represents M number of clusters. $\boldsymbol{z_{ji}}$ denotes the covariates with random effects (either random intercepts or coefficients). The random effects $\boldsymbol{u_j}$ are M realizations from a multivariate normal distribution with mean 0 and variance matrix Σ. $\boldsymbol{v_{ji}}$ represents the observational-level errors with density distribution $\varphi(\cdot)$, and in our case, this distribution is log-logistic.

The density and survival function conditional on the linear prediction η as,

$$g(t|\eta) = g\left(t_{ji}|x_{ji}\beta + z_{ji}u_j\right) \quad \textbf{Eq. 2.17}$$

$$S(t|\eta) = S\left(t_{ji}|x_{ji}\beta + z_{ji}u_j\right) \quad \textbf{Eq. 2.18}$$

The contribution to the likelihood from each observation is written as,

$$f\left(t_{ji}|\eta_{ji}\right) = \left\{\frac{g\left(t_{ji}|x_{ji}\beta+z_{ji}u_j\right)}{S\left(t_{0ji}|x_{ji}\beta+z_{ji}u_j\right)}\right\}^{d_{ji}} \left\{\frac{S\left(t_{ji}|x_{ji}\beta+z_{ji}u_j\right)}{S\left(t_{0ji}|x_{ji}\beta+z_{ji}u_j\right)}\right\} \quad \textbf{Eq. 2.19}$$

The conditional distribution of t_j for cluster j is,

$$f\left(t_j|\eta_j\right) = \prod_{i=1}^{n_j} f\left(t_{ji}|\eta_{ji}\right) \quad \textbf{Eq. 2.20}$$

The model has no closed form and must be approximated based on the likelihood of all the clusters by integrating $\boldsymbol{u_j}$ out of the joint density distribution $f\left(t_j, u_j\right)$. Maximum likelihood optimization technique is adopted, and Stata is used for the modeling tasks.

$$\mathcal{L}_j(\boldsymbol{\beta}, \Sigma) = (2\boldsymbol{\pi})^{-q/2}|\Sigma|^{-1/2} \int \boldsymbol{f}(\boldsymbol{t}_j|\boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{Z}_j\boldsymbol{u}_j)\boldsymbol{exp}(-\boldsymbol{u}_j'\Sigma^{-1}\boldsymbol{u}_j/2)\, \boldsymbol{du}_j \qquad \textbf{Eq. 2.21}$$

2.4.4.3 Data

The data used for this analysis comes from the same LOCATE/IM incident database. They are collected from 2015 to 2016, and the selection criterion for large-scale incidents is that if it lasts longer 90 minutes and blocking at least one lane on the roadway. The selection criterion is intuitive due to the TDOT traffic operations goal to clear the road incident with 90 minutes. Finally, after removing outliers, a sample of 603 incident records are collected. They have almost the same variables compared to the last incident sample used for purely empirical prediction purpose. The only different is that the first and second HIRU information are combined in terms of their response time and on-scene time. The descriptive statistics are shown in the following Table 2.7.

2.4.4.4 Model Comparison and Results Discussion

All the models discussed above show their good performance in terms of capturing the unobserved heterogeneity in the models in various ways either by adding a multiplicative effect to the hazard or adding cluster-level random effects to the covariates. In looking at the model's significance statistics, AIC (Akaike information criterion), BIC (Bayesian information criterion) can be used to compare to the model performance. However, for practical use, Root Means Square Error (RMSE) is one of the most common ways to compare those models, where smaller values of RMSE are preferred.

Five stages are used for sequential prediction based on the availability of incident-related information. These 5 stages are:

- Stage 1: Location, temporal information, weather;
- Stage 2: Location, temporal information, weather, incident characteristics (incident

TABLE 2.7 Descriptive Statistics of Variables Associated with Large-Scale Incidents Variables (Time in Minutes)

Variable	Sample size	Mean	SD	Min	Max
Incident Durations (in minutes)	603	233.97	142	90	5,727
Incident type					
Aban Vehicle	603	0.06	0.24	0	1
Debris	603	0.01	0.08	0	1
Disabled Vehicle	603	0.11	0.32	0	1
JK TR TR	603	0.02	0.16	0	1
Multivehicle Crash	603	0.37	0.48	0	1
Overturned Vehicle	603	0.10	0.30	0	1
PD/MED/FIRE Activity	603	0.01	0.12	0	1
Single Vehicle Crash	603	0.14	0.34	0	1
Special Evt/PSA	603	0.01	0.09	0	1
Unsched Roadwork	603	0.08	0.27	0	1
Vehicle Fire	603	0.07	0.26	0	1
Weather	603	0.00	0.26	0	1
Grass Fire	603	0.00	0.04	0	1
Spatial-Temporal & Weather factors					
Weekday	603	0.78	0.42	0	1
MorPeak (morning peak=1)	603	0.20	0.40	0	1
AftPeak (afternoon peak=1)	603	0.30	0.46	0	1
Route (freeway=1)	603	0.98	0.16	0	1
WeaCond (bad weather=1)	603	0.53	0.49s	0	1
Urban (yes=1)	603	0.62	0.49	0	1
RAMP (yes=1)	603	0.06	0.24	0	1
Other Incident Characteristics					
NumVeh (number of vehicle involved)	603	1.41	0.99	0	9
DetcCCTV	603	0.63	0.48	0	1

TABLE 2.7 Continued

Variable	Sample size	Mean	SD	Min	Max
Lanecount (number of lanes blocked)	603	1.49	0.76	1	8
BlkDuration (lane blockage duration)	603	81.62	137.53	0	1,275
No_HAR (number of HAR deployed)	603	1.84	1.82	0	6
HAR_AveUseTim (average time used)	603	91.63	140.06	0	1,077
No_DMS (number of HAR deployed)	603	2.01	1.64	0	11
DMS_AveUseTim (average time used)	603	105.89	138.58	0	1,011
No_BEA (number of Beacon used)	603	1.21	2.01	1	20
Agency Responses Characteristics					
1^{st}RespAgen (1^{st} response agency) – HSP (safety patrol)	441	0.09	0.3	0	1
1^{st}RespAgen – HIRU (highway incident response unit)	441	0.53	0.49	0	1
1^{st}RespAgen – PD (police)	441	0.22	0.42	0	1
1^{st}RespAgen – FD (fire department)	441	0.06	0.24	0	1
1^{st}RespAgen – AMB (ambulance)	441	0.05	0.21	0	1
1^{st}RespAgen – CS (county sheriff)	441	0.006	0.08	0	1
1^{st}RespAgen – Tow (towing company)	441	0.02	0.16	0	1
1^{st}RespAgen – ST (service truck)	441	0.007	0.08	0	1
1^{st}RespAgen – TM (TDOT maintenance)	441	0.002	0.05	0	1
RespTime (1^{st} agency response time)	441	12.56	37.72	0	480
TotalResp (total number of response agencies)	603	2.37	2.04	0	8
HSP_ResTim (safety patrol response time)	72	18.68	31.39	1	157
HSP_OnsTim (safety patrol on-scene time)	66	131.97	120.07	1	586
No_HIRU (number of HIRU responded)	603	0.93	0.94	0	4
HIRU_AveResTim12 (Avg. Response time of first 2 HIRUs)	361	30.5	66.39	0	463
HIRU_AveOnsTim12 (Avg. On-scene time of first 2 HIRUs)	355	63.61	86.35	1	810
HIRU_AveResTim36 (Avg. response time if 3^{rd} or more HIRUs)	35	109.06	139.1	1	576
HIRU_AveOnsTim36 (Avg. On-scene time if 3^{rd} or more HIRUs)	34	82.74	90.25	1	382
PD_ResTim (Response time for police)	234	17.89	28.28	1	208
PD_OnsTim (On-scene time for police)	220	99.9	102.47	1	651

TABLE 2.7 Continued

Variable	Sample size	Mean	SD	Min	Max
FD_ResTim (Response time for fire department)	161	10.2	13.153	1	114
FD_OnsTim (On-scene time for fire department)	156	70.00	90.36	1	593
AMB_ResTim (Response time for ambulance)	117	11.50	21.00	1	171
AMB_OnsTim (On-scene time for ambulance)	116	38.92	44.55	1	365
CS_ResTim (Response time for county sheriff)	7	17.86	29.58	1	84
CS_OnsTim (On-scene time for county sheriff)	7	57.14	28.69	21	92
Tow_ResTim (Response time for towing company)	235	91.07	121.23	1	996
Tow_OnsTim (On-scene time for towing company)	230	63.41	92.75	0	615
ST_ResTim (Response time for service truck)	28	103	114.01	2	480
ST_OnsTim (On-scene time for service truck)	27	91.74	108.97	4	495
TM_ResTim (Response time for TDOT maintenance)	13	77.23	133.79	2	512
TM_OnsTim (On-scene time for TDOT maintenance)	11	269.82	181.38	66	628

type, number of lanes blocked, number of vehicles involved);

- Stage 3: Location, temporal information, weather, incident characteristics (incident type, number of lanes blocked, number of vehicles involved), incident response (first response agency, response time of first response agency, number of dynamic message signs (DMS) activated, number of highway advisory radio (HAR) used);

  Stage 4: Location, temporal information, weather, incident characteristics (incident type, number of lanes blocked, number of vehicles involved), incident response (first response agency, response time of first response agency, number of dynamic message signs (DMS) activated, number of highway advisory radio (HAR) used), other response agencies' response time;

- Stage 5: Location, temporal information, weather, incident characteristics (incident type, number of lanes blocked, number of vehicles involved), incident response (first response agency, response time of first response agency, number of dynamic message signs (DMS) activated, number of highway advisory radio (HAR) used), other response agencies' response time, on-scene time for the response agencies, DMS and HAR usage information, lane block duration.

At each stage, the information of the incident gathered is more than that from the previous stage. However, that does not mean all the information in each stage should be used. By selecting important variables for each stage, the models can predict a reasonable incident duration. The model performance comparison (see Table 2.7 & Figure 2.6) and best modeling results for each stage (see Table 2.8) are presented.

Based on the results on Table 2.8, the performance indicators for AIC is constantly decreasing, meaning the model is getting better from stage 1 to stage 5. For each stage, the

TABLE 2.8 Model Comparison

Performance Indices		Fixed-effects Log-Logistic Models		Multilevel Mixed-effects Log-Logistic Models
		Inverse-Gaussian	**Gamma**	**Random Effects**
Stage 1	Theta	12.876	0.8389	---
	Gamma	0.0483	0.1565	---
	LL(0)	-451.54	-513.45	---
	LL(β)	-448.65	-504.33	-3692.49
	N	603	603	603
	AIC	**917.29**	1028.67	7400.99
	BIC	**961.31**	1072.69	7436.2
	Rho-Squared	0.006	0.018	---
Stage 2	Theta	19.246	0.7725	---
	Gamma	0.0346	0.1611	---
	LL(0)	-451.53	-513.45	---
	LL(β)	-426.56	-486.06	-3623.06
	AIC	**889.12**	1008.12	7272.12
	BIC	**968.35**	1087.35	7329.35
	Rho-Squared	0.055	0.053	---
Stage 3	Theta	20.38	0.7163	---
	Gamma	0.0309	0.1592	---
	LL(0)	-451.54	-513.45	---
	LL(β)	-384.02	-452.05	-3593.97
	AIC	**876.04**	992.09	7279.93
	BIC	**1113.74**	1185.78	7482.42
	Rho-Squared	0.15	0.12	---
Stage 4	Theta	6.697	0.7038	---
	Gamma	0.0653	0.1498	---
	LL(0)	-451.53	-513.45	---
	LL(β)	-369.46	-408.01	-3567.64
	AIC	**816.91**	878.02	7211.28
	BIC	**988.59**	1014.48	7378.55
	Rho-Squared	**0.182**	0.205	---
Stage 5	Theta	4.5172	0.8235	---
	Gamma	0.0621	0.098	---
	LL(0)	-451.23	-513.39	---
	LL(β)	-196.52	-219.68	-3443.989
	AIC	**483.04**	529.35	6975.98
	BIC	**681.28**	727.59	7169.81
	Rho-Squared	0.564	0.572	---

Note: “---” = Not applicable.

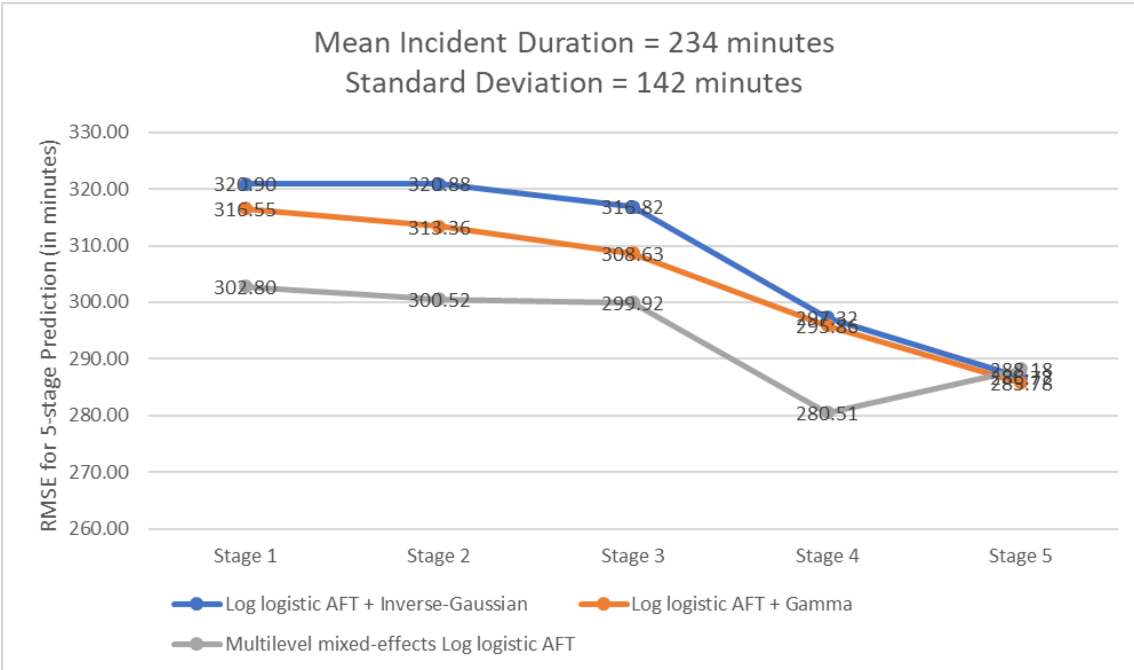

FIGURE 2.6 Root mean square error performance for each prediction stage.

likelihood ratio test statistics (p-value <0.05) for all models show that there is unobserved heterogeneity existing in each model. Comparing to the base fixed-effects models, these models have already solved this issue either by adding frailty or by using random effects. Also, for each stage, even though the AIC and BIC values are higher for multilevel mixed-effects survival models compared with other fixed-effects survival models, the RMSE is smaller, except for stage 5. One explanation for this outcome is that multilevel mixed-effects use additional one more level random effect, e.g. incident type, in addition to individual random effect for each observation to account for unobserved heterogeneity. While fixed-effect models only account for observational level unobserved heterogeneity. These random effects really play an important role in the first 4 stages, because most of the information gathered at the beginning are categorical variables. They can be easily clustered into a different group such as the incident types. Thus, the effect in improving prediction accuracy is obvious by adding one more level random effect. However, at the last stage when a lot of information is gathered, especially the duration of lane blockage, DMS average time usage, HAR average time usage, that information is closely related to incident duration, and they are statistically significant, so the effect of additional level clustered covariates is not making any contribution to the improvement of prediction accuracy.

Table 2.9 present the model specifications of the best model chosen for each stage. Based on the results, in stage 1 prediction model, morning peak and after peak hours, as well as weather condition, are statistically, significant because the simple information obtained in this stage prohibits us to have good predictions. Negative signs are seen for three of them, meaning if it is morning or afternoon peak, or bad weather conditions, then

TABLE 2.9 Model Estimations Result for Multilevel Mix-effects (Stages 1-4) and Gamma Frailty Model (Stage5)

Stage 1	**Variables**	**Coef.**	**SE.**
	Constant	5.378***	0.183
	Incidentid (level)	0.0044	0.0057
Location Characteristics	Route	-0.1616	0.1731
	Urban (level)	0.0044	0.0057
Temporal Characteristics	MorPeak	-0.2007**	0.0968
	AftPeak	-0.1536***	0.0567
	MorPeak*WeaCond	0.1583	0.1213
Weather Characteristics	WeaCond	-0.0975*	0.0553
Stage 2			
	Constant	5.375***	0.123
	Incidentid (level)	0.0473	0.0566
Temporal Characteristics	MorPeak	-0.156***	0.0585
	AftPeak	-0.139***	0.0526
Weather Characteristics	WeaCond	-0.0432	0.0447
Incident Characteristics	Inctype (Level)	0.1285	0.0587
	DetcCCTV	-0.0739	0.0494
	NumVeh	-0.0347	0.0322
	Lanecount=2 (base=1)	0.026	0.4158
	Lanecount=3	0.209**	0.4173
	Lanecount=4	0.186	0.4253
	Lanecount=8	-0.901**	0.4619
Stage 3			
	Constant	5.222***	0.452
	Incidentid (level)	8.72e-31	8.32e-16
Incident Characteristics	Inctype (Level)	0.1265	0.0571
	RAMP	0.1714*	0.0953
	Lanecount=2 (base=1)	0.04	0.051

TABLE 2.9 Continued

	Variables	Coef.	SE.
	Lanecount=3	0.23**	0.099
	Lanecount=4	0.185**	0.194
	Lanecount=8	-0.704*	0.439
	1STRespAgen=HSP (base=no agency)	-0.0996	0.0931
	1stRespAgen=HIRU	-0.194***	0.0617
	1stRespAgen =POLICE	-0.181**	0.0751
	1stRespAgen =FIRE	-0.241**	0.1097
	1stRespAgen =AMBULANCE	-0.231**	0.1151
	1stRespAgen =COUNTY SHERRIF	-0.143	0.3589
	1stRespAgen =TOW	-0.358**	0.1618
	1stRespAgen =SERVICE TRUCK	-0.307	0.2938
	1stRespAgen =TDOT MAINTAINANCE	0.724	0.4413
	RespTime	0.003***	0.0007
	No_DMS	0.032**	0.0164
	No_HAR	-0.004	0.0137
Stage 4			
	Constant	5.221***	0.086
	Incidentid (level)	3.28e-32	4.20e-17
Incident Characteristics	Inctype (Level)	0.004**	0.0018
	HSP_ResTim	0.251	0.2324
	No_HIRU=1 (base=0)	0.255	0.2339
	No_HIRU=2	0.464	0.4635
	No_HIRU=3	1.125**	0.4872
	No_HIRU=4	0.003***	0.0004
	HIRU_AveResTim12	0.0009	0.0006
	HIRU_AveResTim36	0.004**	0.0018

TABLE 2.9 Continued

	Variables	Coef.	SE.
	AMB_ResTim	0.003*	0.0019
	Tow_ResTim	0.0011***	0.0003
Stage 5			
Incident Characteristics	Constant	4.628***	0.026
	HSP_ResTim	0.002***	0.0008
	HIRU_AveResTim12	0.0002	0.0002
	HIRU_AveResTim36	0.0004	0.0003
	PD_ResTim	0.0009	0.0006
	FD_ResTim	-0.004**	0.001
	AMB_ResTim	0.0006	0.0009
	Tow_ResTim	0.003***	0.0002
	HSP_OnsTim	0.0005	0.0003
	HIRU_AveOnsTim12	0.001***	0.0003
	HIRU_AveOnsTim36	0.001**	0.0005
	Tow_OnsTim	0.002***	0.0003
	ST_OnsTim	0.001***	0.0005
	HAR_AveUseTim	0.001***	0.0002
	DMS_AveUseTim	0.0006***	0.0002
	BlkDuration	0.0009***	0.0002

Note: "***" represent a 99% significant level. "**" represent a 95% significant level. "*" represents a 90% significant level.

the chance of the incident being cleared in the next infinite small second is small. In another word, potentially, the incidents will last longer. Similarly, the explanations can be extended to other variables obtained in other stages. For example, in stage 2, number of vehicles has a negative sign, so more number of vehicles involved in the incident means potentially incident duration will be longer. Other variables having a similar effect on incident duration at each stage include number of lanes blocked, 1st arriving agent HIRU, etc. For these variables that do not mean they cause the incident to be longer. It just indicates that presence of these variables, such as 1st arriving agent being HIRU, have some correlation with longer incident duration. In another word, if HIRU arrives, it usually means it might be a large-scale incident that needs longer time to deal with. Therefore, there is no causal relationship between these kinds of variables and incident duration.

Another interesting implication based on those results is that variables that are significant in the earlier stages might not be a significant at all at later stages. Because variable information obtained at later stages have more valuable information directly or indirectly related to the incident itself, such lane blockage information, agency on-scene time information, and so on. However, in practical applications, these models might have a good prediction on the incident duration outcome at earlier stages, but bad incident duration outcomes in later stages. For example, the model might predict an incident to be 650 minutes long, while the block duration or on-scene time has already exceeded that 650 minutes. So, in such cases, engineering judgment should be used together with incident duration prediction models to provide real-time incident duration prediction, which will provide better suggestions towards improved traffic operation.

2.5 CONCLUSIONS

This study contributes by creating a unique incident database to investigate and analyze large-scale incidents, focusing on the role of multi-agency operational responses. The study identifies large-scale traffic incidents and their correlates while accounting for unobserved heterogeneity. Before investigating large-scale incidents empirically, significant efforts went into assembling a unique database from different sources including TDOT SmartWay, LOCATE/IM, and Google Earth. Then in-depth investigations of large-scale incidents and associations of duration with the operational response and on-scene times of different agencies can be conducted.

To conceptualize and quantify the associations between large-scale incident durations and associated factors, hazard-based duration models with different distributional assumptions are developed. Methodologically, this study contributes by addressing unobserved heterogeneity in large-scale duration modeling through estimation of random-parameter hazard-based duration models. Among all competing models, the random-parameter Weibull model is observed to be most suitable from a statistical perspective. The final model quantifies associations between large-scale incident durations and several explanatory factors, out of which seven variables exhibit statistically significant heterogeneity across observations. The key findings are:

- Out of 129,088 traffic incidents in TDOT Region 1 that occurred during 2010-2015, large-scale incidents constitute 0.69%, which require significant response resources.
- A 30-minute increase in response time for TDOT's 1^{st}, 2^{nd}, and ≥ 3 highway HIRUs translates to 2.83%, 1.61%, and 4.28% increase in large-scale incident durations.

This is an important finding as it suggests the association of response times for the 3rd (or more) unit is more pronounced as compared to those who respond earlier to large-scale incidents. An increase of 30-minute in response times of HSP and towing company are associated with 3.9% and 3.25% increase in large-scale incident durations, respectively.

- Given large-scale incidents, incidents involving vehicle fire or unscheduled roadwork are likely to last longer on average. Large-scale incidents on weekends, non-afternoon peaks, and on lower AADT roads last relatively longer; however, the magnitude (in some cases direction) of associations are heterogeneous.

The results obtained from this study have several implications for large-scale incident management. The findings suggest a reduction in response times for HIRU and HSP can significantly reduce large-scale incident durations. Specifically, the reduction in response times for the 3rd (or more) HIRU unit (when needed) can potentially reduce large-scale incident durations. However, finding additional units may be difficult. Segments such as I-40 and I-75 near urban areas are identified as high-risk segments. Incident managers can also potentially reduce incident duration by working with towing companies to perhaps respond more quickly to large-scale incident situations. As such, facilitating close coordination between different response agencies and companies can enhance response resource deployment, if required. Researchers can extend the methodology proposed to other locations in order to further explore practical solutions for mitigating negative consequences of large-scale incidents. Future research on incident duration management can use a case-based approach where they analyze individual large-scale incidents to obtain insights on how operations could be improved through better coordination. Also, HAZMAT incidents, route diversion and detours management, and spatial analysis need to be investigated further, based on additional information obtained from other databases maintained by various response agencies.

CHAPTER 3
INJURY SEVERITY AND INCIDENT DURATION ANALYSIS OF TRUCK-INVOLVED CRASHES USING RECURSIVE BIVARIATE ORDERED PROBIT MODEL

A version of this chapter was originally written by Xiaobing Li and Jingjing Xu. This chapter presents a revised version of this research paper by adding additional fatality data analysis. This paper was presented at the Transportation Research Board (TRB) 97th Annual Meeting at the Walter E. Washington Convention Center, in Washington, D.C. January 7, 2018.

Xiaobing Li's effort on idea formation, data collection, model construction, interpretation, and paper writing, Jingjing Xu's effort on model refinement, interpretation, and paper writing are recognized.

3.1 ABSTRACT

Injury severity and incident duration are two main indicators to measure the impact of truck-involved collisions on traffic flows and follow-up incident clearance operations. Injury severity often reflects the nature of the collision and persons involved, while incident duration partly reflects the effectiveness of incident recovery operations in clearing the site. Given that truck-involved crashes are often more disruptive and associated with more severe injury and longer durations, this study simultaneously analyzes injury severity and incident duration of truck-involved crashes. Given that injury severity may also to some extent affect incident duration, a recursive bivariate ordered probit model was estimated in this analysis. A unique database was created by integrating crash and inventory data with operational response data. These databases are maintained by the Tennessee Department of Transportation. The databases are linked by the date, time, route, direction, and type of the accident. Final modeling results indicate, as expected, that higher injury severity is robustly positively associated with incident duration. Also, response times are not strictly

positively associated with incident durations. More findings and practical implications are discussed in this study, and that will be essential for future accident management operations.

***Keywords*:** Injury Severity, Incident Duration, Truck-involved Crashes, Recursive Bivariate Ordered Probit

3.2 INTRODUCTION

Incidents can not only result in severe injuries and damage to the facilities but also cause traffic congestion and take a long time for clearance and recovery. Large-scale crashes can even lead to secondary incidents causing further disruptions. As freeway demand increases in recent years, transportation safety becomes more of concern to travelers as well as traffic operations managers. Notably, truck-involved crashes are becoming disruptive, costly, contributing to fatalities/severe injuries, and related to longer incident duration, all of which catches more and more attention of state departments, local transportation authorities, and other transportation-related communities.

Federal Motor Carrier Safety Administration reported that the truck- and bus-involved crashes increased by 5% from 2014 to 2015. Many studies have indicated that if trucks were involved in a crash, there were supposed to be more fatalities and injuries (Duncan, Khattak, & Council, 1998; Zong, Zhang, Xu, Zhu, & Wang, 2013). Compared with single truck crashes, multi-vehicle truck-involved crashes are more likely to contribute to severer injury accidents. Therefore, reducing the number of truck-involved crashes and their injury severity has been a critical goal in enhancing the safety of the occupants in both trucks and other vehicles. In other words, identifying and analyzing the risk factors related to injury severity is essential and meaningful for transportation safety.

On the other hand, when a truck-involved accident occurs on highway, it will have a huge negative impact on the traffic flow, then a series of accident management processes are requested to clear the incident, such as incident detection, verification, notification, response, and recovery, which often contributes to a long incident duration. Improving the efficiency of management operations after the occurrence of a truck-involved crash can help reducing the impact on congestion and reducing the probability of secondary incidents. Therefore, reducing the truck-involved crash duration has also become a critical strategy for improving the highway operations, and studying the risk factors that are associated with incident duration can enhance our understanding of the mechanism of the incident and search for the effective methods for reducing the duration.

Many contributions have been made on investigating the risk factors such as crash, vehicle, driver, roadway, and environmental factors with injury severity. There were also several studies focusing on exploring the underlying factors strongly correlated with incident duration such as response time, lane blockage, and so on. But those studies seldom focusing on revealing the relationship between injury severity and incident duration, as well as analyzing both simultaneously. This is because the information of injury severity and crash related factors are often achieved in the crash database, and the information about response time and the incident duration is usually achieved in the incident database. Previous studies seldom matched the accidents from the two databases and analyzed them together. To better understand the correlation between the injury severity and incident duration, this study first links the two databases (crash database and incident database) both from Tennessee Department of Transportation (TDOT). Given that injury severity may, to some extent, affect incident duration, a recursive bivariate ordered probit model has been adopted in this analysis to investigate such relationship.

3.2.1 Research Objective and Contribution

The key contributions and objectives of this study are to:

1) Integrate the Tennessee crash database and incident database to create a unique database with the information of both injury severity and incident duration, which previous studies rarely did before.
2) Investigate the injury severity and incident duration simultaneously using one modeling system. Previous studies often only focused on one of them or analyzed injury severity and incident duration by two separate models.

Integrating the information on injury severity and incident duration can better understand the close relationship among incident occurrence, incident management, and recovery operations. To achieve the objectives, two databases (Tennessee crash database and incident database) are matched by the date, time, route, direction, and incident type. A recursive bivariate ordered probit model is adopted for analyzing the injury severity and duration simultaneously. The methodology is technically sound. Results from the models will provide actionable safety countermeasures in a timely manner for Tennessee Department of Transportation.

3.3 LITERATURE REVIEW

When an accident occurs, injury severity and incident duration are two main indicators to measure the outcome of the accident, and two topics have long been recognized and discussed for research. Researchers have considerable efforts on uncovering the relationships between risk factors and injury severity, and the contributing variables that may be associated with incident duration. In this section, we summarize previous studies

(Table 3.1) with the focus on factors that were related to injury severity and duration, and the methodologies they used.

The impact of various factors on injury severity has long been highly concerned. A broad range of studies focused on the associations between injury severity and several factors such as crash, vehicle, driver, roadway and environmental factors. From the perspective of the driver, driver factors such as distraction, physical and emotional impairment were found to be associated with higher injury severity in large-truck crashes (Khorashadi, Niemeier, Shankar, & Mannering, 2005; Kostyniuk, Streff, & Zakrajsek, 2002; Zhu & Srinivasan, 2011). Besides, female, older persons without using seat belt were also documented to be associated with higher injury severity (Duncan et al., 1998; Islam & Hernandez, 2013; Lemp, Kockelman, & Unnikrishnan, 2011). Regarding the vehicle type, Zhu and Srinivasan (Zhu & Srinivasan, 2011) claimed that truck-car crashes are estimated to be the most serious crashes. Duncan et al. (Duncan et al., 1998) concluded higher likelihood of severe injuries to passenger car occupants if it was struck by a truck. Chang and Mannering (L.-Y. Chang & Mannering, 1999) also identified that large trucks significantly associated with injury severity of the most severely injured occupants. They examined the association between occupancy and injury severity and found that the more occupancies involved, the higher probability of serious injury would be.

With respect to incident duration, Khattak et al. (A. J. Khattak et al., 1995) discovered that if trucks are involved in the accident, then the incident duration would be longer since they are more likely to interfere with incident clearance operations. Garib et al. (Garib, Radwan, & Al-Deek, 1997) also found the importance of truck involvement in building the incident duration prediction model. Moreover, Nam and Mannering

TABLE 3.1 Summary of Selected Studies for Injury Severity and Incident Duration

Author/ year	Safety topic			Methodology	
	Truck-involved	Severity	Duration	Data source	Model
Golob et al. (1987)	Yes	Yes	Yes	Accident database from Los Angeles, CA (1983-1984)	Log-linear models
Khattak et al. (1995)	No	No	Yes	Incident records from Illinois DOT (1989-1990)	Truncated regression models
Garib et al. (1997)	Yes	No	Yes	Incident data from Oakland, CA (1993)	Incident delay model and incident duration prediction model
Duncan et al. (1998)	Yes	Yes	No	HSIS from North Carolina (1993-1995)	Ordered probit model
Chang and Mannering (1999)	Yes	Yes	No	Accident data from Washington State DOT (1994)	Nested logit model
Nam and Mannering (2000)	Yes	No	Yes	Incident database from Washington State (1994-995)	Hazard-based duration model
Zhu and Srinivasan (2011)	Yes	Yes	No	Crash data	Ordered probit model
Zong et al. (2013)	Yes	Yes	Yes	Traffic accident data from Jilin DOT, China (2010)	Ordered probit model and hazard model

(Nam & Mannering, 2000) identified that detection/reporting, response time, and clearance time were significantly correlated with incident duration. Garib et al. (Garib et al., 1997) concluded that most of the incident durations were found to be predicted by lane counts, the number of vehicles involved, time, response, weather, and truck involvement. Khattak et al. (A. J. Khattak et al., 1995) identified a series of factors that affected the incident duration and predicted the incident duration. The results showed that the response time was positively associated with incident duration, which is a little bit different from the results of our study.

Nevertheless, studies that focused on both injury severity and duration were quite rare. Nam and Mannering (Nam & Mannering, 2000) revealed a positive relationship between the presence of fatality or injury and incident detection/ reporting/ clearance time. Golob et al. (Golob et al., 1987) investigated the associations among underlying factors and collision type, injury severity and duration separately in the freeway large truck-involved crashes, but the study analyzed the injury severity and incident duration separately and did not discover the associations between injury severity and duration. Zong et al. (Zong et al., 2013) applied ordered probit model and hazard model and predicted the accident severity and incident duration, respectively. They claimed that the duration of truck-involved crashes is 58% longer than other accidents and identified that number of fatalities and injuries is a critical factor related to duration, but they only claimed more fatalities and injuries (not focused on injury severity) would lead to longer incident duration, so it’s necessary to analyze the injury severity and incident duration together within one model.

In sum, previous studies revealed the possibility of analyzing injury severity and incident duration together, but to the best of our knowledge, most of them only used separate models for identifying them. Moreover, rare studies integrated the crash database and incident database together, so it remains a gap for both obtain the information of injury severity and incident duration in a unique database and modeling them within a model simultaneously. Furthermore, the risk factors influencing the truck-involved accidents are still underexplored, especially taking a specific region into consideration. It has been a long time since this area has been fully studied; the temporal and spatial characteristics also make this study different from others. Therefore, different from previous studies, this analysis mainly focuses on creating a unique database, and exploring the association between injury severity and incident duration for a specific region in Tennessee, as well as the underlying factors related to injury severity and incident duration simultaneously.

3.4 METHODOLOGY

3.4.1 Data Source

The unique database in this study was integrated from two different databases both from Tennessee Department of Transportation (TDOT). One is crash data from Region 1 (Figure 3.1), East Tennessee, Enhanced Tennessee Roadway Information Management System (E-TRIMS); another is incident data from TDOT Traffic Management Center (TMC), obtained through a web-based archiving tool call LOCATE/IM. All the data were collected from September 29th, 2010 to December 31st, 2016. To analyze the injury severity and incident duration simultaneously, this study collected truck-involved crashes from both databases, then linked the two databases by the time (date, time), location (route, direction), and incident type (single- or multi-vehicle involvement) of the accident. Except for crash time variable, all other link variables must be strictly matched. Due to the crash time from two different databases are reported by two different reporting systems, the crash start time may be slightly different. Finally, the cases from two databases with same crash date, the crash start time difference was less than 1 hour being matched.

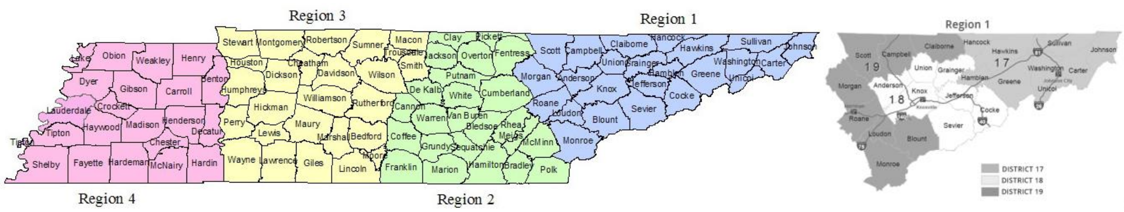

FIGURE 3.1 Tennessee state map and region/district information.

Eventually, 442 truck-involved crashes are matched and obtained, 68 of them are single truck crashes, and 374 of them are multi-vehicle truck-involved crashes. The data has been error-checked for the modeling purpose. The maximum and minimum start time difference are 54 minutes and 0 minutes, respectively, and around 95% of matched data are within 30-minutes reporting time range, which indicates the different operational procedures (or response time) among two different reporting systems.

For the data collected from TDOT region 1, there are 24 counties (Figure 3.1), and 13 of them are found to have truck-involved crash records. Among 442 truck-involved crashes, 372 are from Knox County, 24 are from Roane County, less than 50 records are found from other counties. Also, the majority truck-involved crashes are from the city of Knoxville. For route information, most accidents occurred on Interstate route 40 (70.14%) and 75 (9.95%).

To investigate the contributing driver and vehicle factors related to injury severity, detailed information of the contributed vehicle was collected based on: (1) If the total vehicle number is one or two, the information of all vehicles was kept; (2) If the total vehicle number is three or more, only the information of the truck (no matter contributed or not) and the other contributed vehicle was kept. Driver fault was assigned if the driver made any unsafe driver action, distraction, under unsafe driving condition or alcohol involvement.

In terms of injury severity, the most severe injury in the crash was considered as the injury level in this study. There are five categories: (1) fatal; (2) incapacitating injury; (3) non-incapacitating injury; (4) possible injury or damage (over); (5) possible injury or damage (under).

Due to injury severity is categorical variable, and in the modeling task, both dependent variables should be categorical variables, this study classified incident duration into three categories based on the definition from the Manual on Uniform Traffic Control Devices (MUTCD) (Agenda, 2017): (1) low congestion: duration is 30 minutes or less; (2) medium congestion: duration is between 30 and 120 minutes; (3) high congestion: duration is more than 120 minutes. The response time and lane block duration had also been classified. Response time: (1) 10 minutes or less; (2) between 10 to 20 minutes; (3) between 20 to 30 minutes; (4) more than 30 minutes. Lane block duration: (1) 30 minutes or less; (2) between 30 to 120 minutes; (4) more than 120 minutes.

Based on the idea of analyzing the injury severity and incident duration simultaneously, a conceptual framework has been constructed (Figure 3.2). Injury severity and incident duration are two dependent variables, and both are associated with some risk factors. As can be seen from the literature, the crash, vehicle, and driver factors were associated with injury severity. Some incident factors such as response time, lane block

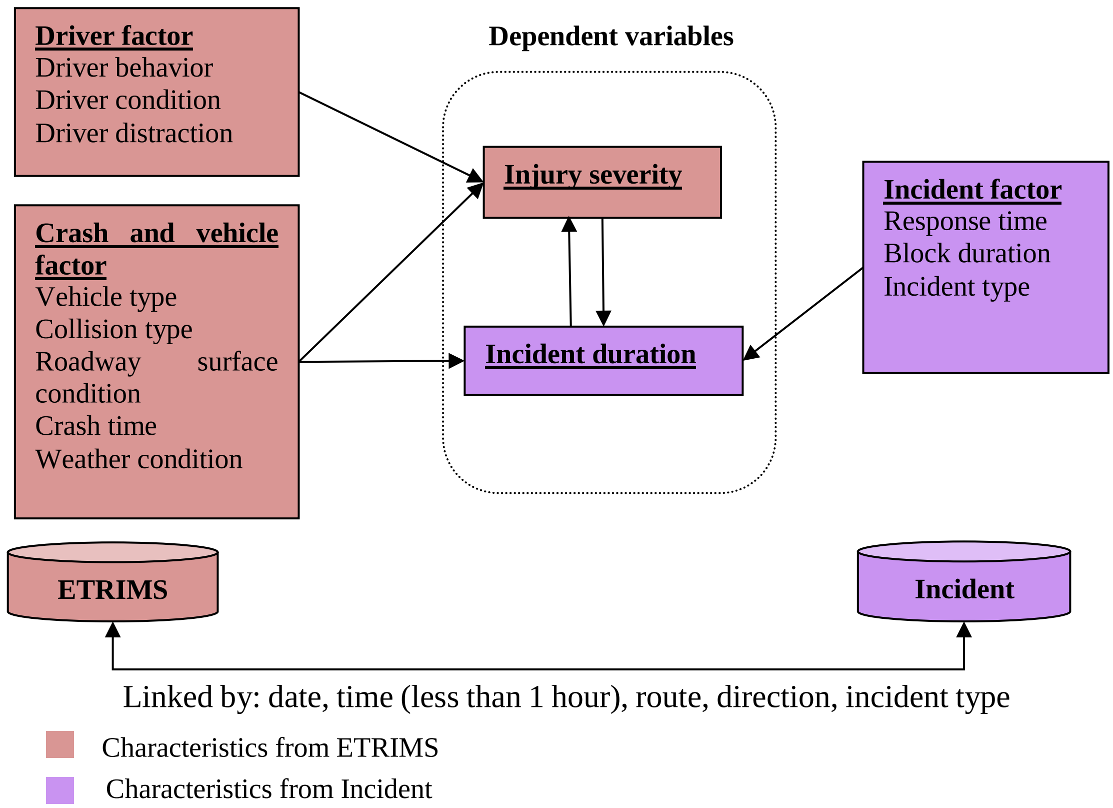

FIGURE 3.2 Data structure and conceptual framework.

duration, and incident type are correlated with incident duration. Besides, the crash factors like collision types may also affect the incident duration. Given the idea that the injury severity has an impact on incident duration, the injury severity is considered as both dependent variable for injury equation, and the independent variable of incident duration equation.

3.4.2 Recursive Ordered Probit Model

The bivariate regression model has been used in many studies (Caliendo & Guida, 2014; Dong, Clarke, Nambisan, & Huang, 2016; Dong et al., 2015; Xu, Wong, & Choi, 2014). In this study, injury severity is a categorical variable, while the incident duration is a continuous variable. Since in the modeling task, both dependent variables should be categorical variables, in this case, the incident duration was classified into 3 categories based on the definition from the MUTCD (Agenda, 2017), which was stated before. Moreover, based on the proposed idea that the injury severity may somewhat related to incident duration, and to deal with these categorized dependent variables simultaneously, a recursive bivariate ordered probit model was adopted.

The two dependent variables are determined as below:

$$\begin{cases} \boldsymbol{y_1^* = \alpha_1 X_1 + \beta y_2^* + \varepsilon_1} \\ \boldsymbol{y_2^* = \alpha_2 X_2 + \varepsilon_2} \end{cases} \qquad \textbf{Eq. 3.1}$$

Where,

y_1^* = incident duration level;

y_2^* = injury severity level (the most severe injury level in the crash);

X_1 and X_2 = explanatory variables;

α_1 and α_2 = the unknown parameters of X_1 and X_2;

β = an unknown parameter of y_2^*

ε_1 and ε_2 = the error terms.

The explanatory variables and error terms satisfy the conditions $\mathrm{E}(X_1\varepsilon_1) = 0$, and $\mathrm{E}(X_2\varepsilon_2) = 0$. The two dependent variables are categorized as the following conditions:

$$\boldsymbol{y_1^* = \begin{cases} 1 \ if\ y_1^* \le b_1 \\ 2\ if\ b_1 < y_1^* \le b_2 \\ \vdots \\ l\ if\ y_1^* > b_{l-1} \end{cases} \qquad y_2^* = \begin{cases} 1 \ if\ y_2^* \le c_1 \\ 2\ if\ c_1 < y_2^* \le c_2 \\ \vdots \\ m\ if\ y_2^* > c_{m-1} \end{cases}} \qquad \textbf{Eq. 3.2}$$

The unknown cutoffs satisfy that $b_1 < b_2 \cdots < b_{l-1}$ and $c_1 < c_2 \cdots < c_{m-1}$, the probability of $y_1^* = i$ and $y_2^* = j$ is:

$$\boldsymbol{Pr(y_1 = i, y_2 = j) = Pr\left(b_{i-1} < y_1^* \le b_i, c_{j-1} < y_2^* \le c_j\right) = Pr\left(y_1^* \le b_i, y_2^* \le c_j\right) - Pr\left(y_1^* \le b_{i-1}, y_2^* \le c_j\right) - Pr\left(y_1^* \le b_i, y_2^* \le c_{j-1}\right) + Pr\left(y_1^* \le b_{i-1}, y_2^* \le c_{j-1}\right)} \qquad \textbf{Eq. 3.3}$$

If ε_1 and ε_2 are bivariate standard normally distributed with the correlation ρ, the likelihood function is:

$$\boldsymbol{Pr(y_1 = i, y_2 = j) = \emptyset\left(b_i - X_1\alpha_1, (c_j - \beta X_1\alpha_1 - X_2\alpha_2)\tau, \rho\right) - \emptyset\left(b_{i-1} - X_1\alpha_1, (c_j - \beta X_1\alpha_1 - X_2\alpha_2)\tau, \rho\right) - \emptyset\left(b_i - X_1\alpha_1, (c_{j-1} - \beta X_1\alpha_1 - X_2\alpha_2)\tau, \rho\right) + \emptyset\left(b_{i-1} - X_1\alpha_1, (c_{j-1} - \beta X_1\alpha_1 - X_2\alpha_2)\tau, \rho\right)} \qquad \textbf{Eq. 3.4}$$

Where,

$\emptyset$ = the bivariate standard normal cumulative distribution function;

$\tau = \frac{1}{\sqrt{1+2\beta\rho+\beta^2}}$;

$\rho = \tau(\beta + \rho)$. If $\beta = 0$ it is a seemingly unrelated specification.

The logarithmic likelihood for the whole sample size N is:

$$\ln L = \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{k=1}^{K} I(y_1 = i, y_2 = j) \ln Pr(y_1 = i, y_2 = j) \qquad \textbf{Eq. 3.5}$$

3.5 RESULTS

3.5.1 Descriptive Statistics

This study analyzes 442 truck-involved crashes, including 68 single truck crashes, 374 multi-vehicle truck-involved crashes. Totally 957 vehicles are involved. The data looks reasonable and it has been error-checked. This section mainly focuses on the descriptive statistics of key variables related to injury severity and incident duration.

3.5.1.1 Injury Severity and Incident Duration

The descriptive statistics display the distributions of injury severity by incident duration (Table 3.2). It shows most of the incident durations are between 30 and 120 minutes, accounting for 74.89%, while the incident duration is less than or equal to 30 minutes accounts for 16.97% of the whole truck-involved crashes. Crashes with incident duration more than 120 minutes are comparably less, only 8.14%. We can see that most of the incidents can be cleared within 120 minutes. The incident duration is normally distributed.

Injury severity is also normally distributed. A large proportion of injury level is property damage (over), accounting for 68.10% (301 out of 442). As the injury severity increases, the frequency of crashes decreases. 113 out of 442 accidents are non-incapacitating injury, while only 4.30% (19/442) and 0.68% (3/442) of them are incapacitating injury and fatal injury.

Given the injury severity level may affect the incident duration, this section presents the distribution of injury severity by incident duration. Among all incident duration categories, the proportions of fatal (100%) and incapacitating (15.79%) injury incidents that durations are more than 120 minutes is higher than non-incapacitating injury (8.85%),

TABLE 3.2 Distribution of Injury severity by Incident Duration

Injury severity	Incident duration			Total
	Duration<=30	30<duration<=120	Duration>120	
Prop damage (under)	2 33.33%	2 33.33%	2 33.33%	6 100.00%
Prop damage (over)	58 19.27%	225 74.75%	18 5.98%	301 100.00%
Non-incapacitating injury	14 12.39%	89 78.76%	10 8.85%	113 100.00%
Incapacitating injury	1 5.26%	15 78.95%	3 15.79%	19 100.00%
Fatal	0 0.00%	0 0.00%	3 100.00%	3 100.00%
Total	75 16.97%	331 74.89%	36 8.14%	442 100.00%

which is followed by property damage (over) (5.98%). And for the incident duration is 30 minutes or less, the proportion of property damage (under) (33.33%), property damage (over) (19.27%), and non-incapacitating injury (12.39%) is much higher than fatal (0%) and incapacitating injury (5.26%). It indicates that the probability of severer injury accidents' duration being more than 120 minutes is higher than that of minor injury accidents.

3.5.1.2 Explanatory Variables

Regarding the key independent variables, the descriptive statistics of explanatory variables are presented. It displays the mean, standard deviation (SD), minimum and maximum value for each variable (Table 3.3).

Descriptive statistics show that majority of lane block duration is 30 minutes or less, and most of the response time is 10 minutes or less, provide 82.81% and 74.21%, respectively (Table 3.3). Almost 60% of accidents are rear end collisions, and 18.33% of them are no vehicle collision (single truck collisions or collisions with objects, animals, train, and motorcyclist). Among all the accidents, most of the roadway surface conditions for the other vehicle are dry (67.42%), and 15.38% of them are wet, whereas the proportions of ice, snow or slush are rare, only 0.23% and 0.68%, respectively.

3.5.2 Modeling Results and Discussion

The results of recursive bivariate ordered probit model has been presented in Table 3.3. Note that this model estimated robust standard error. The chi-square is 4.85, which is higher than 3.84 (chi-square test statistic at 95% confidence level), which indicates that the bivariate ordered probit model is significant at 95% confidence level and suitable for this analysis. The explanatory variables with a p-value of ±0.05 or less; or t-statistic of ±1.96

TABLE 3.3 Descriptive Statistics for Explanatory Variables

Variables		Description	Obs	Mean	Std. Dev.	Min	Max
Lane block duration	Block duration≤30	1 if block duration≤30, 0 otherwise	442	0.828	0.378	0	1
	30<Block duration≤120	1 if 30<block duration≤120, 0 otherwise	442	0.158	0.366	0	1
	Block duration>120	1 if block duration>120, 0 otherwise	442	0.014	0.116	0	1
Response time	Response≤10	1 if response≤10, 0 otherwise	442	0.742	0.438	0	1
	10<Response≤20	1 if 10<response≤20, 0 otherwise	442	0.104	0.306	0	1
	20<Response≤30	1 if 20<response≤30, 0 otherwise	442	0.023	0.149	0	1
	Response>30	1 if response>30, 0 otherwise	442	0.016	0.125	0	1
	unknown	1 if unknown, 0 otherwise	442	0.11	0.319	0	1
Collision type	No vehicle collision	1 if no vehicle collision, 0 otherwise	442	0.183	0.387	0	1
	Angle	1 if angle, 0 otherwise	442	0.077	0.267	0	1
	Head on	1 if head on, 0 otherwise	442	0.011	0.106	0	1
	Other	1 if other, 0 otherwise	442	0.011	0.106	0	1
	Rear to side	1 if rear to side, 0 otherwise	442	0.002	0.048	0	1
	Rear end	1 if rear end, 0 otherwise	442	0.595	0.491	0	1
	Sideswipe- opposite direction	1 if sideswipe- opposite direction, 0 otherwise	442	0.005	0.067	0	1
	Sideswipe- same direction	1 if sideswipe- same direction, 0 otherwise	442	0.113	0.317	0	1
Driver fault	The other vehicle driver at fault	1 if the other vehicle driver at fault, 0 otherwise	442	0.441	0.497	0	1
	Truck driver at fault	1 if truck driver at fault, 0 otherwise	442	0.516	0.500	0	1

TABLE 3.3 Continued

Variables		Description	Obs	Mean	Std. Dev.	Min	Max
Other vehicle roadway surface condition	Dry	1 if dry, 0 otherwise	442	0.674	0.469	0	1
	Ice	1 if ice, 0 otherwise	442	0.002	0.048	0	1
	Snow or slush	1 if snow or slush, 0 otherwise	442	0.007	0.082	0	1
	Wet	1 if wet, 0 otherwise	442	0.154	0.361	0	1
	unknown	1 if unknown, 0 otherwise	442	0.163	0.369	0	1

Note: "No vehicle collision" represents single truck collision or collision types such as hit object, collided with animal, train, and motorcyclist.

or more will significantly affect the dependent variable at 95% confidence level. Similarly, explanatory variables with a p-value of ±0.1 or less, or statistic of ±1.64 or more, will significantly affect dependent variable at 90% confidence level.

While the results of the associations between the independent and dependent variables are presented in Table 3.4, the marginal effects of the independent variables are estimated in Table 3.5. The marginal effects present the change of the probability of a specific dependent variable outcome for a one-unit change in an independent variable. To facilitate discussion, the explanatory variables are classified as injury severity, response time, lane block duration, collision type, driver fault, and roadway surface condition.

3.5.2.1 Injury Severity

Based on the idea that injury severity is the most critical variable in this study, the important association was found between injury severity and incident duration outcome (Table 3.4). Property damage (under) was applied as the base level. Most of the injury severity levels, except property damage (over), were statistically significant (at 95% confidence level) in the recursive bivariate ordered probit model. It shows there is a strong correlation between injury severity and incident duration, which is consistent with the hypothesis at the beginning of this paper, and also in agreement with Zong et al. *(Zong et al., 2013)*, but the study of Zong *(Zong et al., 2013)* only investigated the association between the number of fatalities/ injuries and the incident duration.

This study investigates the relationship between injury severity and incident duration. The severer the injury severity is, the longer the incident duration will be. The incident duration is often much longer for fatal crashes, and its coefficient is much higher than other injury levels. From an incident management perspective, this finding is essential

TABLE 3.4 Modeling Results for Recursive Bivariate Ordered Probit Model (Estimated Standard Errors in Robust)

Variables		Coef.	Robust Std. Err.	Z	P>|Z|
Incident duration					
Injury severity (base: prop damage (under))	Prop Damage (over)	1.547	0.981	1.58	0.115
	Non-Incapacitating Injury	2.707	1.182	2.29	0.022
	Incapacitating Injury	3.295	1.378	2.39	0.017
	Fatal	11.837	0.893	13.26	0.000
Lane block duration (min) (base: block duration<=30)	30<Block duration<=120	0.747	0.163	4.57	0.000
	Block duration>120	8.176	2.239	3.65	0.000
Response time (base: response time<=10)	10<Response time<=20	0.461	0.164	2.81	0.005
	20<Response time<=30	0.396	0.219	1.81	0.070
	30<Response time	0.562	0.422	1.33	0.183
	Response time is NA	-0.365	0.177	-2.06	0.040
Collision type (base: no vehicle collision)	Angle	0.431	0.233	1.85	0.065
	Head on	0.420	0.157	2.67	0.008
	Other	0.231	0.618	0.37	0.709
	Rear to side	-7.583	1.758	-4.31	0.000
	Rear end	-0.0002	0.138	0	0.999
	Sideswipe-opposite direction	-0.849	0.629	-1.35	0.178
	Sideswipe-same direction	0.073	0.204	0.36	0.719
	Unknown	0.333	0.173	1.92	0.055
Injury severity					
Driver fault (base: not at fault)	The other vehicle driver at fault	0.301	0.156	1.92	0.054
	Truck driver at fault	0.231	0.138	1.68	0.094

TABLE 3.4 Continued

Variables		**Coef.**	**Robust Std. Err.**	**Z**	**P>|Z|**
Roadway surface condition (base: dry)	Ice	1.149	0.550	2.09	0.037
	Snow or slush	0.635	0.279	2.27	0.023
	Wet	0.111	0.148	0.75	0.454
	Unknown	0.142	0.164	0.87	0.384
	athrho				
	_cons	-0.998	0.453	-2.2	0.028
	/µ11	1.288	1.137		
	/µ12	3.412	0.897		
	/µ21	-1.936	0.211		
	/µ22	0.810	0.157		
	/µ23	1.964	0.177		
	/µ24	2.794	0.262		
	rho	-0.761	0.191		

TABLE 3.5 Marginal Effects

Incident duration				
	Variables	**Duration<=30**	**30<Duration<=120**	**Duration>120**
Injury severity (base: prop damage (under))	Prop Damage (over)	-0.464	0.226	0.238
	Non-Incapacitating Injury	-0.392	-0.379	0.771
	Incapacitating Injury	-0.206	-0.675	0.881
	Fatal	-0.189	-0.704	0.893
Lane block duration (min) (base: block duration<=30)	30<Block duration<=120	-0.144	-0.053	0.196
	Block duration>120	-0.198	-0.701	0.899
Response time (base: response time<=10)	10<Response time<=20	-0.096	-0.018	0.114
	20<Response time<=30	-0.082	-0.017	0.098
	30<Response time	-0.106	-0.045	0.150
	Unknown	0.104	-0.041	-0.062
Collision type (base: no vehicle collision)	Angle	-0.090	-0.017	0.106
	Head on	-0.085	-0.021	0.106
	Other	-0.052	-0.001	0.053
	Rear to side	0.836	-0.710	-0.126
	Rear end	0.00006	-0.00001	-0.00005
	Sideswipe- opposite direction	0.286	-0.186	-0.101
	Sideswipe- same direction	-0.018	0.003	0.015
	Unknown	-0.071	-0.010	0.081

TABLE 3.5 Continued

Injury severity						
	Variables	**Prop Damage (under)**	**Prop Damage (over)**	**Non-Incapacitating Injury**	**Incapacitating Injury**	**Fatal**
Driver fault (base: not at fault)	The other vehicle driver at fault	-0.010	-0.096	0.075	0.025	0.006
	Truck driver at fault	-0.008	-0.073	0.057	0.019	0.004
Roadway surface condition (base: dry)	Ice	-0.012	-0.421	0.179	0.172	0.083
	Snow or slush	-0.011	-0.234	0.141	0.078	0.025
	Wet	-0.003	-0.036	0.028	0.010	0.002
	Unknown	-0.004	-0.047	0.036	0.013	0.003

and meaningful since it highlights that severer injured accidents are often correlated with longer incident duration. Consequently, some actionable countermeasures for reducing the injury severity may also decrease the incident duration, thus improving the management of transportation safety. The marginal effects also reveal that when the injury severity level is non-incapacitating injury, there is a 0.7709 increase in the probability of incident duration being more than 120 minutes (Table 3.5). And for incapacitating injury and fatal injury level, there is a 0.8807 increase, and a 0.8931 increase in the probability of incident duration being more than 120 minutes, respectively.

3.5.2.2 Response Time

Response time indicates the time of the first responder (e.g. highway incident response unit, police, Emergency Medical Services, and so on) responds to the incident. Interestingly, the response time is not strictly positively correlated with incident duration. Compared with the base level (response time is 10 minutes or less), response time (between 10 and 20 minutes, between 20 and 30 minutes) is closely associated with incident duration. But it indicates that response time is less than 20 minutes is more likely to associate with a longer duration than response time between 20 minutes to 30 minutes. The reason might be the severer injury is, the faster the rescue response would be. But given the severer injury severity often relates to longer incident duration, so even though the response is very fast, it is also usually correlated with longer incident duration. This result is consistent with the study of Li et al. (Xiaobing Li, Asad J Khattak, & Behram Wali, 2017).

As we all know, the response time is a critical factor in traffic recovery. To a certain extent, the time of response also determines the incident duration. The marginal effects present that compared with the response time being 10 minutes or less (base level) if the response time is between 10 minutes and 20 minutes, there is a 0.1137 increase in the probability of incident duration being more than 120 minutes. For the response time ranging from 20 to 30 minutes, the probability increases by 9.83%, which a little bit lower than response time ranging from 10 to 20 minutes. Thus, the response time is ranging from 10 to 20 minutes seems more likely to contribute to longer incident duration (more than 120 minutes) than response time that is between 20 and 30 minutes.

3.5.2.3 Lane Block Duration

Lane block duration is a major proportion of incident duration. The lane block duration is expected to be positively related to incident duration outcome. Lane block duration is seen to be significantly associated with incident duration (Table 3.4). Compared with the lane block duration being 30 minutes or less (base level), the lane block duration being more than 120 minutes is more likely to associate with longer incident duration. A similar relationship can be found when compared with duration being between 30 minutes and 120 minutes. It shows that the longer the lane block duration is, the longer the incident duration will be. Especially for the cases when lane block duration is more than 120 minutes, it is often related to longer incident duration.

As can be seen from Table 3.5, the marginal effects indicate the lane block duration also greatly affects the results of incident duration. It shows when the lane block duration is more than 120 minutes, the probability of incident duration being more than 120 minutes increases by 89.87%.

3.5.2.4 Collision type

Out of all collision types, angle and head on collisions are found to be statistically associated with incident duration, though the proportion of rear end collisions is much greater than others. Modeling results indicate that head on collision is significantly associated with longer incident duration at 99% confidence level, while the angle collision is significantly related with incident duration at 90% confidence level (Table 3.4). The coefficients of angle and head on collisions are similar. On the contrary, the rear end collision that provides the most proportion in descriptive statistics section is not significantly associated with incident duration. The marginal effects show that when a head on collision occurs, there is a 0.1059 increase in the probability of more than 120 minutes incident duration, while for angle collision, it is 0.1061 (Table 3.5).

3.5.2.5 Driver Fault

Unsafe driver actions, driver distractions, unsafe driver conditions, and alcohol involvement are all belonged to driver errors. Driver fault has been assigned if there is any driver action, distraction, driver condition, or alcohol involvement. Series of studies have successfully examined the associations between driver errors (driver actions, distractions, conditions, and so on) and injury severity (Khorashadi et al., 2005; Kostyniuk et al., 2002; Zhu & Srinivasan, 2011). Given injury severity strongly contributes to incident duration, risk factors like driver fault and roadway surface condition which are correlated with injury severity have been considered in this study.

Modeling results show that the other vehicle (non-truck) driver at fault is more likely to associate with severer injury severity than the truck driver at fault (Table 3.4). Truck driver at fault is significantly correlated with injury severity at 90% confidence level, and the coefficient of the truck driver is a little bit lower than that of the other vehicle driver. The marginal effects also show the other vehicle driver at fault increases more likelihood of severely injured crash than the truck driver.

3.5.2.6 Roadway Surface Condition

Roadway surface condition often affects the injury outcome. We have considered the roadway surface condition for both trucks and the other vehicles, but it shows some roadway surface conditions of the other vehicles are more likely to associate with injury severity, and that of trucks are not significantly related to injury severity. The reason might be truck occupants are less likely to get injured than occupants in the other vehicles, so the roadway surface condition of trucks may not likely to affect the injury severity of occupants in other vehicles. It also shows the roadway surface condition (ice, snow or slush) of the other vehicle is significantly associated with injury severity, and ice surface condition for the other vehicle is correlated with higher injury level than snow or slush. The marginal effects also indicate that when the roadway surface condition is ice, snow or slush, there is an increased chance of severe injury outcome. For instance, when the roadway surface condition is ice, the chance of getting incapacitating injury increases by 17.21%, while for snow or slush, that chance increases by 7.81%.

3.5.3 Injury Severity Analysis Based on Fatality Analysis Reporting System

In this part, additional analysis is provided specifically to analyze the injury severity information for truck-involved crashes based on the Fatality Analysis Reporting System data. This analysis will further provide details of the injury severity information associated with each crash. This analysis is meaningful in the sense that in large-scale traffic incident or accidents, injury severity plays an important role and such a characteristic will help better understand large-scale traffic incident or accidents. Furthermore, by analyzing the covariates associates with injury severity, other important variables could be selected in future work as an additional indirect relationship with incident duration.

3.5.3.1 Data

The data used for this analysis is collected through the Fatality Analysis Reporting System (FARS) maintained by National Highway Traffic Safety Administration (NHTSA). The 2016 crash data was collected. The original sample size is 85,496. After removing the missing data records, focusing on truck-involved crashes and removing the records with not available injury severity information, the final sample size is 4,997 on the person level, which is about 5.84% of the original sample size. The descriptive statistics for the collected variables are shown in Table 3.6.

Based on the results, total 3, 941 crashes are identified. Some of the variables are not listed in this table due to its lack of significance in the modeling process. They are sex, manor of collision, roadway functional class, urban, location, etc. Similar to other data sets with crash injury severity information, the distribution of the injury severity has a long tail, with many crashes with low level of injury severity such as no injury or property damage, and fewer crashes with high level injury severity such as fatal injury in the data.

3.5.3.2 Analysis Methodology

As mentioned in the last chapter, multilevel mixed-effects models can capture some random effects due to the unobserved heterogeneity. For this reason, this analysis also applied a multilevel mixed-effects ordered probit regression model, which contains both fixed effects and random effects. Its formulation is introduced.

Now, consider a two-level ordered probit regression model with a series of M clusters, which are conditional on a set of fixed effects x_{ij}, a set of cutpoints ϰ, and a set of random effect u_j. Then the cumulative probability of the response being in a category higher than ϰ is written as,

TABLE 3.6 Descriptive Statistics for Explanatory Variables

Description		**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Injury Severity (Severity of the injury of a person using the KABCO scale)	Injury Severity=0 (No injury)	4,997	0.597	0.491	0	1
	Injury Severity=1 (Possible Injury)	4,997	0.102	0.302	0	1
	Injury Severity=2 (Non-Incapacitating injury)	4,997	0.102	0.303	0	1
	Injury Severity=3 (Incapacitating Injury)	4,997	0.045	0.208	0	1
	Injury Severity=4 (Fatal)	4,997	0.155	0.362	0	1
Crash Characteristics	Number of vehicles	4,997	2.291	3.239	1	64
	First harmful event, base - other	4,997	0.012	0.109	0	1
	First harmful event - Motor Vehicle in Transport	4,997	0.717	0.451	0	1
	First harmful event - Parked Motor Vehicle	4,997	0.021	0.144	0	1
	First harmful event - Rollover/Overturn	4,997	0.056	0.230	0	1
	First harmful event - Non-Motorist	4,997	0.090	0.287	0	1
	First harmful event - Fixed object	4,997	0.097	0.296	0	1
	First harmful event - Moving object	4,997	0.006	0.079	0	1
	ROLLOVER base - no rollover	4,997	0.853	0.354	0	1
	ROLLOVER - First event rollover	4,997	0.115	0.319	0	1
	ROLLOVER - Subsequent rollover	4,997	0.024	0.154	0	1
	ROLLOVER - Unknown	4,997	0.007	0.086	0	1
	Fire in a crash, base - no fire	4,997	0.940	0.238	0	1
	Fire occurred in a crash	4,997	0.060	0.238	0	1
Vehicle Characteristics	Body type of trucks	4,997	---	---	---	---
	Air bag deployment, base – not deployed	4,997	0.409	0.492	0	1
	Air bag deployed	4,997	0.044	0.204	0	1
	Air bag deployment not applicable or unknown	4,997	0.547	0.498	0	1
Person Characteristics	AGE	4,997	44.93	13.839	0	89
	Role of this person in a crash - driver	4,997	0.828	0.377	0	1
	Role of this person - Passenger in transport	4,997	0.153	0.360	0	1

TABLE 3.6 Continued

Description		Obs.	Mean	Std. Dev.	Min	Max
	Role of this person, base - Passenger not in transport	4,997	0.018	0.132	0	1
	Role of this person - Unknown	4,997	0.002	0.042	0	1
	Seat position in a vehicle, base - Front seat	4,997	0.931	0.254	0	1
	Seat position in a vehicle - second seat	4,997	0.015	0.121	0	1
	Seat position in a vehicle - Other locations	4,997	0.050	0.218	0	1
	Seat position in a vehicle - Unknown	4,997	0.005	0.068	0	1
	Restraint equipment used, base=0 none restraint	4,997	0.155	0.362	0	1
	Restraint equipment used - Shoulder belt only	4,997	0.003	0.051	0	1
	Restraint equipment used - Lap belt only	4,997	0.013	0.112	0	1
	Restraint equipment used - Lap and shoulder	4,997	0.749	0.443	0	1
	Restraint equipment used - Child safety seat	4,997	0.002	0.040	0	1
	Restraint equipment used - Unknown	4,997	0.0789	0.270	0	1
	Ejection path for a person, base - not ejected	4,997	0.953	0.211	0	1
	Ejection path for a person - Side door	4,997	0.002	0.049	0	1
	Ejection path for a person - Side window	4,997	0.005	0.073	0	1
	Ejection path for a person - Windshield	4,997	0.005	0.069	0	1
	Ejection path for a person - Other	4,997	0.002	0.045	0	1
	Ejection path for a person - Unknown	4,997	0.032	0.176	0	1
	Drunk driving, base - no drinking	4,997	0.6450	0.477	0	1
	Drunk driving	4,997	0.011	0.104	0	1
	Drunk driving - Unknown	4,997	0.339	0.473	0	1
	Drug use, base - no drug	4,997	0.599	0.490	0	1
	Drug used	4,997	0.015	0.122	0	1
	Drug use - Unknown	4,997	0.386	0.487	0	1

Note: “---” denotes that the body types of the trucks are not listed due to space (totally there are 19 types of trucks in those crashes).

$$\boldsymbol{Pr}(\boldsymbol{y_{ij}} > \boldsymbol{k}|\boldsymbol{x_{ij}}, \varkappa, \boldsymbol{u_j}) = \boldsymbol{\Phi}(\boldsymbol{x_{ij}\beta} + \boldsymbol{z_{ij}u_j} - \varkappa_{\boldsymbol{k}}) \qquad \textbf{Eq. 3.6}$$

Where j is the index of M clusters, each cluster has n_j observations. And k is the index for the cutpoints. $\Phi(\cdot)$ represents the standard normal cumulative distribution probability. z_{ij} are the covariates corresponding to the random effects. Based on equation 3.6, the derived probability for outcome k is written as,

$$\boldsymbol{Pr}(\boldsymbol{y_{ij}} > \boldsymbol{k}|\boldsymbol{x_{ij}}, \varkappa, \boldsymbol{u_j}) = \boldsymbol{Pr}(\varkappa_{\boldsymbol{k-1}} < \boldsymbol{x_{ij}\beta} + \boldsymbol{z_{ij}u_j} + \boldsymbol{\epsilon_{ij}} < \varkappa_{\boldsymbol{k}})$$

$$= \boldsymbol{Pr}(\varkappa_{\boldsymbol{k-1}} - \boldsymbol{x_{ij}\beta} - \boldsymbol{z_{ij}u_j} < \boldsymbol{\epsilon_{ij}} < \varkappa_{\boldsymbol{k}} - \boldsymbol{x_{ij}\beta} - \boldsymbol{z_{ij}u_j})$$

$$= \boldsymbol{\Phi}(\varkappa_{\boldsymbol{k}} - \boldsymbol{x_{ij}\beta} - \boldsymbol{z_{ij}u_j}) - \boldsymbol{\Phi}(\varkappa_{\boldsymbol{k-1}} - \boldsymbol{x_{ij}\beta} - \boldsymbol{z_{ij}u_j}) \qquad \textbf{Eq. 3.7}$$

Where $\varkappa_0$ can be taken as $-\infty$, and $\varkappa_K$ is the $+\infty$. K is the number of possible outcomes. ϵ_{ij} are error terms independent of u_j, and distributed as standard normal with mean 0 and variance 1. Based on above formulation, a model with observed response y_{ij} can be generated from a latent continuous response, it is written as,

$$\boldsymbol{y^*_{ij}} = \boldsymbol{x_{ij}\beta} + \boldsymbol{z_{ij}u_j} + \boldsymbol{\epsilon_{ij}} \qquad \textbf{Eq. 3.8}$$

And,

$$\boldsymbol{y_{ij}} = \begin{cases} \boldsymbol{1} & \boldsymbol{if}\ \boldsymbol{y^*_{ij}} \leq \varkappa_{\boldsymbol{1}} \\ \boldsymbol{2} & \boldsymbol{if}\ \varkappa_{\boldsymbol{1}} < \boldsymbol{y^*_{ij}} \leq \varkappa_{\boldsymbol{2}} \\ \vdots & \vdots \\ \boldsymbol{K} & \boldsymbol{if}\ \varkappa_{\boldsymbol{K-1}} < \boldsymbol{y^*_{ij}} \end{cases} \qquad \textbf{Eq. 3.9}$$

The conditional distribution of y_j given a set of cluster-level random effects u_j is written as,

$$\boldsymbol{f}(\boldsymbol{y_j}|\boldsymbol{u_j}) = \prod_{\boldsymbol{i=1}}^{\boldsymbol{n_j}} \boldsymbol{p_{ij}}^{\boldsymbol{I_k}(\boldsymbol{y_{ij}})} = \boldsymbol{exp} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n_j}} \{\boldsymbol{I_k}(\boldsymbol{y_{ij}}) \boldsymbol{log}(\boldsymbol{p_{ij}})\} \qquad \textbf{Eq. 3.10}$$

$$\boldsymbol{I_k(y_{ij})} = \begin{cases} \mathbf{1} & \boldsymbol{if\ y_{ij} = k} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \quad \textbf{Eq. 3.11}$$

The likelihood contribution of the clusters is obtained by integrating u_j out of the joint density function $f(y_j|u_j)$, based on the prior distribution of u_j as multivariate normal with mean 0, and variance matrix Σ. It is formulated using equation 3.12. But the integration has no closed form, thus it should be approximated using maximum likelihood procedure.

$$\boldsymbol{\mathcal{L}_j(\beta, \text{\textkappa}, \Sigma) = (2\pi)^{-q/2}|\Sigma|^{-1/2} \int f(y_j|\text{\textkappa}, u_j) exp(-u_j'\Sigma^{-1}u_j/2)\, du_j =}$$
$$\boldsymbol{(2\pi)^{-q/2}|\Sigma|^{-1/2} \int exp\{h(\beta, \text{\textkappa}, \Sigma, u_j)\}\, du_j} \quad \textbf{Eq. 3.12}$$

$$\boldsymbol{h(\beta, \text{\textkappa}, \Sigma, u_j) = \sum_{i=1}^{n_j}\{I_k(y_{ij}) log(p_{ij})\} - u_j'\Sigma^{-1}u_j/2} \quad \textbf{Eq. 3.13}$$

3.5.3.3 Model Results and Discussion

The model estimation results are presents in Table 3.7. Based on the results, the log-likelihood ratios test statistics is 182.21, with p-value as 0.0000. This means the additional level random effects have made this model much more significant when compared to fixed-effects ordered probit models. Those two levels are crash level and vehicle type level. Each truck-involved crash might have their own characteristics which might be not captured other seemingly independent variables. This is also true for vehicle type level random effects. 19 types of trucks are analyzed in our model, so being a certain type of truck will be different from others in terms of the effect on the outcome. Regarding the prediction accuracy, the model present 74.28% prediction accuracy, an acceptable accuracy for these models.

Regarding the impact of important variables, some suggestions towards good truck driving can be made. Rollover is a statistically significant variable. If trucks are turned

TABLE 3.7 Model Estimations of the 3-level Mixed-effects Ordered Probit Regression Model

Description		Coef.	SE.	Z	P_value
Case level	Crash case number	0.758	0.109	---	---
Crash Characteristics	Number of vehicles involved	-0.016	0.013	-1.24	0.216
	First harmful event - Motor Vehicle in Transport	-0.719	0.247	-2.92	0.004
	First harmful event - Parked Motor Vehicle	0.121	0.319	0.38	0.704
	First harmful event - Rollover/Overturn	0.021	0.281	0.07	0.941
	First harmful event - Non-Motorist	-2.482	0.299	-8.28	0.000
	First harmful event - Fixed object	0.758	0.258	2.93	0.003
	First harmful event - Moving object	0.635	0.413	1.54	0.125
	ROLLOVER - First event rollover	1.402	0.092	15.30	0.000
	ROLLOVER - Subsequent rollover	1.621	0.219	7.38	0.000
	ROLLOVER - Unknown	1.499	0.298	5.04	0.000
	Fire occurred in a crash	1.148	0.111	10.3	0.000
Vehicle Characteristics	Body type of trucks	0.054	0.034	---	---
	Air bag deployed	0.966	0.121	7.99	0.000
	Air bag deployment not applicable or unknown	0.454	0.057	7.98	0.000
Personal Characteristics	AGE	0.012	0.002	6.29	0.000
	Role of this person in a crash - driver	1.661	0.259	6.42	0.000
	Role of this person - Passenger in transport	1.332	0.259	5.12	0.000
	Role of this person - Unknown	1.373	0.678	2.03	0.043
	Seat position in a vehicle - second seat	-0.277	0.197	-1.40	0.161
	Seat position in a vehicle - Other locations	-0.592	0.142	-4.18	0.000
	Seat position in a vehicle - Unknown	-0.443	0.381	-1.16	0.245
	Restraint equipment used - Shoulder belt only	-1.244	0.179	-2.60	0.009
	Restraint equipment used - Lap belt only	-0.739	0.222	-3.33	0.001
	Restraint equipment used - Lap and shoulder	-0.987	0.089	-11.07	0.000
	Restraint equipment used - Child safety seat	-0.515	0.553	-0.93	0.352

TABLE 3.7 Continued

Description		Coef.	SE.	Z	P_value
	Restraint equipment used - Unknown	-0.237	0.117	-2.03	0.042
	Ejection path for a person - Side door	8.893	407.81	0.02	0.983
	Ejection path for a person - Side window	2.048	0.665	3.08	0.002
	Ejection path for a person - Windshield	1.275	0.486	2.63	0.009
	Ejection path for a person - Other	1.608	0.656	2.45	0.014
	Ejection path for a person - Unknown	1.369	0.169	8.10	0.000
	Drunk driving	0.165	0.259	0.64	0.524
	Drunk driving - Unknown	0.301	0.114	2.63	0.008
	Drug used	0.434	0.201	2.16	0.031
	Drug use - Unknown	0.049	0.109	0.45	0.651

Note: "---" represent that there are no values for corresponding cells because ST_CASE and BODY_TYP are treated as level random effects.

over, then the injury severity level will go up. Try avoiding those events in the future for truck driving. Also, if a fire is involved in the crash, then certainly the injury severity level will also go up. Compared to the passengers not in transport, passengers in transport will receive higher injury severity given a truck-involved crash happened. Compared to the seating position in the front driver, the injury severity level of other seating positions is much lower, indicating that it is much riskier to have a higher injury during a crash for the driver. In terms of the restraint use, the modeling results clearly show that comparing to non-restraint use, using whatever type of restraint will significantly reduce the chance of having a high injury during a truck-involved crash. Similarly, proper vehicle safety equipment such as air bag, if employed will largely reduce the chance of being highly injured. But if employed, it usually indicates a large crash. Alcohol use or drug use have long been discussed to have a negative impact on good driving. The same conclusion can be drawn from the model results here. To sum, multilevel mix-effect ordered probit model provides additional prediction power by incorporating the random effects in each level, so it is much favored in modeling ordinal response variables. Finally, the marginal effects based on the model with means values for each variable are presented in Table 3.8 using the Delta-method for estimation. The results are discussed as follows.

An interesting outcome is that if a non-motorist is involved in such a crash, the potential injury severity level is lower. As of the rollover event, it has a high impact on incapacitating injury severity level, no matter it is a first harm event or secondary event. But if it is a secondary rollover event, its impact is a little bit higher (0.07 >0.066). Similarly, if a fire is involved in a truck-involved crash, then the injury severity level tends to be higher, e.g. incapacitating injury or fatal. In terms of the air bag deployment in a

TABLE 3.8 Marginal Effects of Each Variable on Injury Severity Outcomes

Variables	Injury Severity=0 dy/dx.	SE.	Injury Severity=1 dy/dx.	SE.	Injury Severity=2 dy/dx.	SE.	Injury Severity=3 dy/dx.	SE.	Injury Severity=4 dy/dx.	SE.
Number of vehicles	0.005	0.004	-0.0005	0.002	-0.001	0.001	-0.001	0.001	-0.002	0.003
Motor Vehicle in Transport	0.208***	0.071	-0.0038	0.061	-0.049	0.051	-0.038***	0.013	-0.117	0.105
Parked Motor Vehicle	-0.032	0.085	-0.004	0.014	0.004	0.016	0.006	0.015	0.026	0.071
Rollover/Overturn	-0.006	0.076	-0.001	0.008	0.001	0.011	0.001	0.014	0.004	0.059
Non-Motorist	0.587***	0.173	-0.115	0.079	-0.179***	0.013	-0.092**	0.04	-0.2	0.205
Fixed object	-0.174	0.11	-0.038	0.044	-0.003	0.082	0.024	0.039	0.192	0.094
Moving object	-0.15	0.117	-0.031	0.045	0.002	0.07	0.022	0.033	0.157	0.125
First rollover	-0.381***	0.079	-0.014	0.106	0.067	0.112	0.066**	0.026	0.262	0.168
Subsequent rollover	-0.424***	0.112	-0.028	0.115	0.059	0.135	0.07*	0.039	0.322*	0.192
Unknown	-0.401***	0.107	-0.019	0.112	0.064	0.123	0.068**	0.032	0.289	0.193
Fire	-0.315***	0.072	-0.013	0.09	0.055	0.096	0.056**	0.022	0.217	0.143
Air bag deployed	-0.279***	0.036	0.014	0.078	0.07	0.057	0.051***	0.007	0.145	0.121
unknown	-0.133***	0.019	0.016	0.034	0.039***	0.015	0.024***	0.007	0.053	0.053
AGE	-0.003***	0.006	0.0004	0.001	0.001**	0.005	0.006***	0.002	0.002	0.001
Driver	-0.391**	0.16	0.102**	0.04	0.133***	0.037	0.059	0.04	0.098	0.119
Passenger in transport	-0.294*	0.152	0.089***	0.02	0.103**	0.046	0.042	0.035	0.06	0.081
Unknown	-0.306	0.238	0.091**	0.037	0.107	0.073	0.044	0.048	0.064	0.106
second seat	0.081	0.057	-0.011	0.022	-0.025	0.019	-0.014	0.011	-0.031	0.037
Other locations	0.168***	0.049	-0.029	0.037	-0.054***	0.015	-0.029**	0.014	-0.057	0.062

TABLE 3.8 Continued

Variables	Injury Severity=0		Injury Severity=1		Injury Severity=2		Injury Severity=3		Injury Severity=4	
	dy/dx.	SE.	dy/dx.	SE.	dy/dx.	SE.	dy/dx.	SE.	dy/dx.	SE.
Unknown	0.013	0.107	-0.019	0.037	-0.04	0.036	-0.022	0.019	-0.046	0.057
Shoulder belt only	0.356***	0.131	-0.021	0.099	-0.09	0.079	-0.064***	0.021	-0.18	0.153
Lap belt only	0.211***	0.073	0.003	0.063	-0.044	0.061	-0.039**	0.015	-0.13	0.099
Lap and shoulder	0.283***	0.037	-0.007	0.081	-0.066	0.066	-0.052***	0.007	-0.158	0.124
Child safety seat	0.144	0.165	0.007	0.044	-0.026	0.061	-0.026	0.032	-0.098	0.109
Unknown	0.064*	0.037	0.006	0.019	-0.009	0.024	-0.012	0.009	-0.049	0.039
Ejection Side door	-0.55***	0.026	-0.16***	0.007	-0.153	0.009	-0.058***	0.006	0.916***	0.034
Ejection Side window	-0.469***	0.076	-0.073	0.048	0.011	0.058	0.059***	0.019	0.472**	0.195
Ejection path Windshield	-0.344***	0.103	-0.019	0.031	0.055***	0.015	0.059***	0.013	0.249*	0.131
Ejection path Other	-0.408***	0.11	-0.042	0.047	0.042	0.038	0.064***	0.007	0.342*	0.189
Unknown	-0.364***	0.035	-0.025*	0.014	0.053***	0.012	0.061***	0.006	0.027***	0.047
Drunk driving	-0.049	0.076	0.005	0.015	0.014	0.023	0.009	0.014	0.02	0.039
Unknown	-0.089***	0.034	0.008	0.024	0.025	0.016	0.016**	0.007	0.039	0.039
Drug used	-0.128**	0.058	0.006	0.037	0.033	0.029	0.023**	0.01	0.065	0.065
Unknown	-0.015	0.032	0.002	0.005	0.004	0.009	0.003	0.006	0.006	0.015

Note: "***" represents those marginal effects are significant at 99% significance level. "**" represents those marginal effects are significant at 95% significance level. "*" represents those marginal effects are significant at 90% significance level.

truck-involved crash, if the air bag is deployed, it usually indicates such a crash has higher injury severity, and such a relationship is not causal. As for the old person in those crashes, higher age usually involved higher injury severity. Compared to an occupant of a motor vehicle not in transport, those divers or occupants in transport will have higher potential to have a possible injury or incapacitating injury. Regarding seating positions in the vehicle, if the person is not well seated, they have a lower potential to receive incapacitating or capacitating injury, but higher potential with no injury. It is an interesting outcome which needs further analysis. Coming to restraint use, contrary to our understanding, if no constraint is used, people usually receive lower injury severity. It's probably due to the reason that if people do use restraints, they potentially will drive better and cautiously. But such general guess to needs to be further validated by analyzing more person-level data such as stated preference survey data. Then, in terms of injection status and degree level of injection, the results show that if people are injected during the crash through whatever kinds of injection path (side door, side window, windshield, back window, etc.), they are generally more likely to be in a higher level of injury severity (Fatal is the most common seen outcome, see Table 3.8). So, a good suggestion to those who have bad habits not any wearing restraint system is to be restrained in whatever way and avoid death in a truck-involved crash. Lastly, if people are drunk or using drugs, they are also more likely to be in a higher injury severity level crash.

3.5.4 Fatal Crash Analysis using Multilevel Mixed-effects Logistic Regression Model

In addition to truck-involved crashes, large-scale fatal crashes are also analyzed based on the number of fatalities in a crash (e.g. in our example, 3 number of fatalities is chosen as the criteria). FARS data is used again for this analysis and the person file is merged with accident file to obtain more important variables in our analysis. This task is achieved by matching the crash case ID called ST_CASE in both files. After that, other data processing work in done to obtain the final merged file by removing the records with missing information. The final sample size 2,408. First, this sample data is used for modeling whether the person involved in the crash is dead or not, where the multilevel mixed-effects logistic regression model is used. Then the data set is further segmented to obtain the time to death information as the dependent variable, where the Heckman selection model is applied. Detailed descriptions and modeling results for each of them are discussed as follows.

3.5.4.1 Multilevel Mixed-effects Logistic Regression Model

The methodology is explained in part 3.5.3. Data descriptive are shown in Table 3.9. In this table, only the important variables are selected. Base on this descriptive, over 57% of the people involved in those crashes are dead. These important variables include whether the person in the vehicle was ejected or not, whether the airbag was deployed or not, the type of vehicles involved in those crashes also matters. In order to the investigate better of their effects on the death outcome of each person involved in the crashes, a 4-level mixed-effects logistic regression model is built. The results are discussed in the next part.

3.5.4.2 Modeling Results using 4-level Mixed-effects Logistic Regression

Geographically, the locations of these crashes happened all over the U.S. Following Figure 3.3. Table 3.10 presents the results of the 4-level mixed-effects logistic regression modeling. Three additional level random effects are added to the fixed-effects model, including the random effects on case level (variable name: ST_CASE), number of vehicles level (variable name: VE_TOTAL), and manner of collision level (MAN_COLL). The log

TABLE 3.9 Descriptive Statistics for Explanatory Variables

Description		Obs.	Mean	Std. Dev.	Min	Max
Dependent	DEATH=1 (If person is dead, 0 otherwise)	2,408	0.572	0.495	0	1
Crash Characteristics	Number of vehicles	2,408	0.08	0.054	1	64
	Vehicle body type, base - passenger vehicle)	2,408	0.629	0.483	0	1
	Vehicle body type - Van	2,408	0.223	0.416	0	1
	Vehicle body type - Truck	2,408	0.135	0.342	0	1
	Vehicle body type - Other	2,408	0.013	0.115	0	1
	Fire in a crash, base - no fire	2,408	0.872	0.334	0	1
	Fire occurred in a crash	2,408	0.128	0.334	0	1
	Crash location with respect to junction or interchange areas, base - non-junction	2,408	0.783	0.412	0	1
	Crash location - Intersection	2,408	0.163	0.37	0	1
	Crash location - Ramp	2,408	0.008	0.09	0	1
	Crash location - Railway	2,408	0.011	0.103	0	1
	Crash location - Other location	2,408	0.034	0.182	0	1
	location of crash on traffic way, base - on roadway	2,408	0.729	0.445	0	1
	location of crash on traffic way - outside roadway	2,408	0.249	0.433	0	1
	location of crash on traffic way - other	2,408	0.022	0.145	0	1
	Air bag deployment, base - not deployed)	2,408	0.173	0.378	0	1
	Air bag deployed	2,408	0.397	0.489	0	1
	Air bag deployment - Unknown	2,408	0343	0.495	0	1
Person Characteristics	AGE	2,408	33.11	20.28	0	93
	Seat position in a vehicle, base - front seat	2,408	0.569	0.495	0	1
	Seat position - second seat	2,408	0.246	0.431	0	1
	Seat position - third seat	2,408	0.026	0.159	0	1
	Seat position - other locations	2,408	0.098	0.298	0	1
	Seat position - Unknown	2,408	0.061	0.239	0	1

TABLE 3.9 Continued

Description		Obs.	Mean	Std. Dev.	Min	Max
	Restraint equipment use, base - none used	2,408	0.37	0.483	0	1
	Restraint equipment use - Shoulder belt only	2,408	0.002	0.049	0	1
	Restraint equipment use - Lap belt only	2,408	0.005	0.073	0	1
	Restraint equipment use - Lap and shoulder	2,408	0.444	0.497	0	1
	Restraint equipment use - Child safety seat	2,408	0.025	0.156	0	1
	Restraint equipment use - Helmet	2,408	0.004	0.064	0	1
	Restraint equipment use - Unknown	2,408	0.149	0.356	0	1
	Restraint equipment misuse, base – no misuse	2,408	0.993	0.086	0	1
	Restraint equipment misuse	2,408	0.007	0.086	0	1
	Ejection path for a person, base - not ejected	2,408	0.861	0.086	0	1
	Ejection path - Side door	2,408	0.007	0.084	0	1
	Ejection path - Side window	2,408	0.007	0.081	0	1
	Ejection path - Windshield	2,408	0.005	0.07	0	1
	Ejection path - Other	2,408	0.007	0.084	0	1
	Ejection path - Unknown	2,408	0.113	0.317	0	1
	Extrication equipment or force applied, base - no	2,408	0.749	0.433	0	1
	Extrication - yes	2,408	0.219	0.414	0	1
	Extrication - Unknown	2,408	0.032	0.175	0	1
	Number of persons not in motor vehicles in transport	2,408	0.103	0.584	0	11
	Number of persons in motor vehicles in transport	2,408	14.61	26.23	1	120

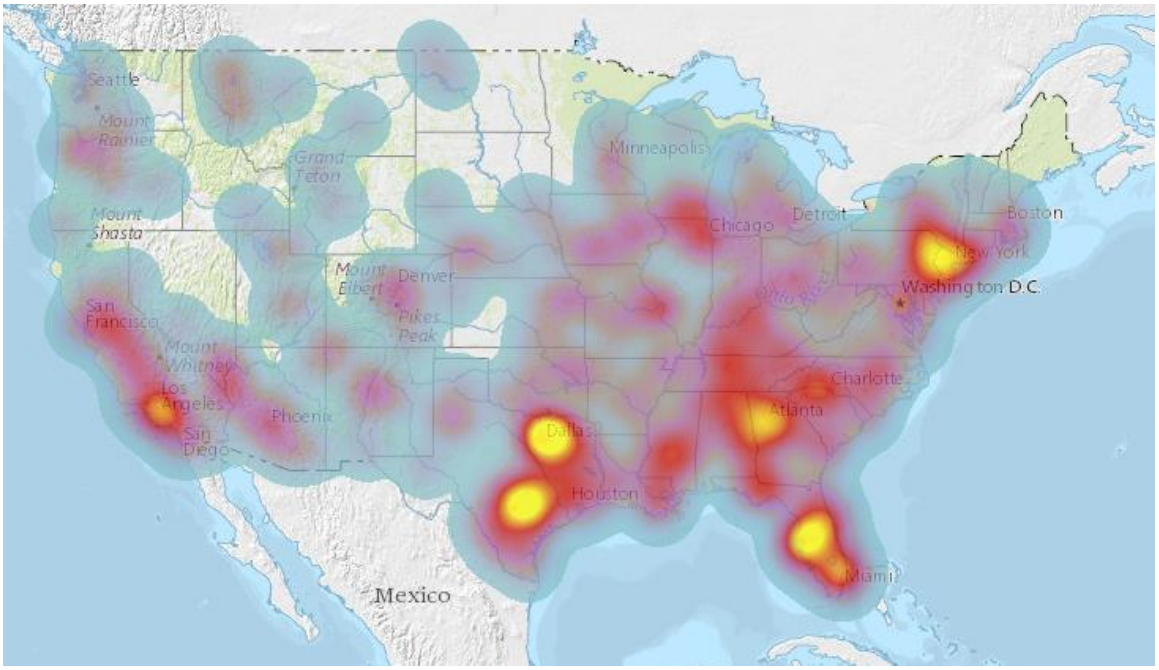

FIGURE 3.3 Locations of the large-fatality crashes within the U.S. mainland.

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TABLE 3.10 Model Estimations of the 4-level Mixed-effects Logistic Regression Model

Description		Coef.	SE	Z	P-value
Case level	Crash case number - level effect	0.219	0.115	---	---
	Constant	0.574	0.231	2.48	0.013
Crash Characteristics	Total number of vehicles involved - level effect	0.078	0.052	---	---
	Vehicle body type - Van	-0.437	0.136	-3.21	0.001
	Vehicle body type - Truck	-1.824	0.295	-6.18	0.000
	Vehicle body type - Other	0.676	0.632	1.07	0.285
	Fire	1.434	0.218	6.59	0.000
	Crash location - Intersection	-0.233	0.178	-1.31	0.189
	Crash location - Ramp	-0.554	0.654	-0.85	0.397
	Crash location - Railway	1.577	0.734	2.15	0.032
	Crash location - Other location	-0.518	0.311	-1.67	0.096
	location of crash on traffic way - outside roadway	0.836	0.217	3.85	0.000
	location of crash on traffic way - other	0.871	0.462	1.88	0.060
	Air bag deployed	0.466	0.164	2.84	0.004
	Air bag deployment - Unknown	0.065	0.18	0.36	0.719
	Manner of collision – level effect	0.078	0.052	---	---
Person Characteristics	AGE	-0.002	0.001	-0.39	0.002
	Seat position - second seat	-0.012	0.153	-0.08	0.938
	Seat position - third seat	-1.037	0.295	-6.18	0.001
	Seat position - other locations	-0.515	0.353	-1.46	0.145
	Seat position - Unknown	-0.708	0.263	-2.70	0.007
	Restraint equipment use - Shoulder belt only	0.147	0.904	0.16	0.870
	Restraint equipment use - Lap belt only	-0.463	0.703	-0.66	0.51
	Restraint equipment use - Lap and shoulder	-0.784	0.158	-4.96	0.000
	Restraint equipment use - Child safety seat	0.0387	0.364	0.11	0.915
	Restraint equipment use - Helmet	-0.429	1.01	-0.42	0.671

TABLE 3.10 Continued

Description		Coef.	SE	Z	P-value
	Restraint equipment use - Unknown	-0.273	0.193	-1.41	0.159
	Restraint equipment misuse	2.618	1.115	2.35	0.019
	Ejection path - Side door	4.762	1.947	2.45	0.014
	Ejection path - Side window	1.468	0.888	1.69	0.092
	Ejection path - Windshield	0.679	0.849	0.80	0.424
	Ejection path - Other	2.692	1.127	2.39	0.017
	Ejection path - Unknown	1.264	0.218	5.82	0.000
	Extrication - yes	1.439	0.159	9.00	0.000
	Extrication - Unknown	1.394	0.344	4.06	0.000
	Number of persons not in motor vehicles in transport	-0.387	0.159	-2.52	0.012
	Number of persons in motor vehicles in transport	-0.039	0.007	-5.10	0.000

likelihood ratio test between 4-level mixed-effects logistic regression model and the fixed-effect logistic regression model is: 19.41, with p-value, equals to 0.0001. Meaning adding the random effect to those levels will increase the modeling power to capture more heterogeneity in each group that can be clustered using each level. For those important variables, the discussions based on the results are presented.

- Age. This is a statistically significant variable in the model. It shows older people are less likely to be dead in a fatal crash.
- Fire. If the fire is involved in a fatal crash, then it will significantly increase the potential death probability for the people involved in the crash.

  Seat position. In terms of where are the people sitting in the vehicle. The results show that it is the safest when people sit in the third position in the vehicle, which is behind the driver's seat.
- Vehicle body type. If the trucks are involved in a crash, then it certainly increases the overall injury severity level of the crash, but in terms of each person, the person in the truck usually have lower potential to be dead when compared to passenger vehicles. Similarly, for other big vehicles (e.g. vans, pick-up trucks), the people in those vehicles received less potential to be dead. However, those driving motorcycles and smaller vehicles have a high potential to be dead in a fatal crash.
- Restraint system use. Similarly, if people use full restrain system with lap and shoulder belt on, then the chance of being dead in a fatal crash is significantly decreased. However, if the restraint system is being misused, then the potential for a people to be dead in a fatal crash is significantly increased, and such impact is even higher

- Air bag. If the air bag is deployed, then surely, the chance of being dead for a person is significantly higher (see Table 3.10). However, such a relationship is not causal. Contrarily, the installment purpose of air bags is used to protect the body from being seriously injured. But the presence of the deployment of the air bag indicates the severity of the crash is already very high. Then this indicates a higher potential of death in the crash.
- Ejection path. Compared to no injection of the body in the fatal crash, the presence of any type of ejection will increase the potential of death in a crash. Among those ejection paths, the most significant ejection paths are people ejected from side door, and people ejected from other strange positions other than side window, windshield. So, so to avoid being dead in the fatal crash, being well seated using the full restraint system is recommended.
- Equipment or other force to remove a person from the vehicle. It is a statistically significant variable. But it also does not reveal a causal relationship. If such operations are deployed, it usually means people cannot move, and most likely the people are dead already at the scene.
- Number of persons in motor vehicles in transport, and number of persons not in motor vehicles in transport. These two variables are statistically significant with a negative sign. It indicates, with more people involved in the crash, either in a motor vehicle or not in motor vehicles, the probability of being dead for a specific person is lower. It is also not a causal relationship. It just indicates that when the number of people is greater, then somebody else will have higher probability surviving the crash compared to the dead because not everybody is dead at the crash.

- In terms of geometric characteristics, if such crash happened near a junction (e.g. intersection, driveway, interchange area), then the potential for a person to the dead is much lower. This is probably due to the reason that when vehicles approach those areas, their speed is usually slower. However, if such a crash happened at a railway, the potential of the person dying in the fatal crash is much higher. Also, if the crash happened outside the roadway (e.g. shoulder, median), then it highly increases the potential of a person being dead in a crash.

To sum up, to avoid being dead in a fatal crash, people need to be extremely careful when driving close to bigger vehicles (e.g. trucks, vehicles with hazardous materials). Keeping a good distance is a good option. Also, be well seated with full restraint system correctly on, thus it is hard for people to be thrown out of the vehicles. When driving on the roadway, always keeps eyes on the road. Do not let the unintentional lane departure or roadway departure involve in the travel trips.

3.5.5 Time to Death Analysis using Heckman Selection Model

Given a person is fatal in a crash, how long they lived until death? Do they die at the scene or do they die en route or at the hospital? This analysis is investigating the impact of various factors on those people’s final times on the earth. Among those large-fatality crashes, a sample size of 1,377 crashes is selected for this analysis.

3.5.5.1 Heckman Selection Model

Like ordinal regression, the Heckman selection also assumes an underlying regression relationship between the dependent variable and other independent variables. It is often written as,

$$\boldsymbol{y_i = x_i + u_{1i}} \qquad \textbf{Eq. 3.14}$$

In addition to that, this model to indicate whether the dependent variable is observed or not. If observation i is observed for dependent variables, then a new equation should be satisfied,

$$\boldsymbol{z_i \gamma + u_{2i} > 0} \qquad \textbf{Eq. 3.15}$$

Where, $u_1 \sim N(0, \sigma)$, $u_2 \sim N(0,1)$, and $corr(u_1, u_2) = \rho$. z_i are the variables selected to determine whether the dependent variables are observed or unobserved.

Heckman selection model is advantageous in the sense that if $\rho \neq 0$, then it can solve the problem where standard regression technique applied to equation 3.14 yield biased results. Instead, it will provide consistent, asymptotically efficient estimates for all the parameters in the model. In order to have a more stable outcome, the two-step Heckman selection model is adopted. Lambda $\lambda = \rho\sigma$ is used to investigate the selectivity effect.

3.5.5.2 Modeling Results and Discussion

The data descriptive are shown in the following Table 3.11. The time to death information shows that if a person is involved in a fatal crash, then he/she will most likely die about 5.22 hours after the crash on average. The selected variables include DOA, ROLLOVER, EXTRICAT, WEATHER, REL_ROAD. The independent variables are HOSPITAL, LGT_COND, and PER_TYP. Over 81.5% of those people died at the scene, and only about 0.9% of those people died en route. The mode of transportation will impact the time to death when they do not die at the scene. About 63% of those people are passengers in the motor vehicle in transport.

The model estimations are presented in Table 3.12. The p-value for lambda is 0.017,

TABLE 3.11 Descriptive Statistics for Explanatory Variables

Description		Obs.	Mean	Std. Dev.	Min	Max
Dependent	TTD (Time to death after crash)	1,296	5.226	33.78	0	667.9
Independent Variables	Mode of transportation to hospital, base - not transported	1,377	0.815	0.389	0	1
	Mode of transportation - EMS Air	1,377	0.033	0.178	0	1
	Mode of transportation - EMS Ground	1,377	0.144	0.351	0	1
	Mode of transportation -Transported, Unknown source	1,377	0.003	0.054	0	1
	Mode of transportation - Unknown	1,377	0.006	0.076	0	1
	Light condition, base - unknown	1,377	0.033	0.179	0	1
	Light condition - Daylight	1,377	0.464	0.498	0	1
	Light condition - Dark not lighted	1,377	0.351	0.477	0	1
	Light condition - Dark lighted	1,377	0.152	0.359	0	1
	Role of person involved in a crash, base - driver)	1,377	0.354	0.478	0	1
	Role of person - Passenger of a motor vehicle in transport)	1,377	0.629	0.483	0	1
	Role of person - Other	1,377	0.017	0.131	0	1
Selection Variables	Die at scene or en route, base - not applicable)	1,377	0.176	0.381	0	1
	Die at scene	1,377	0.815	0.389	0	1
	Die en route	1,377	0.009	0.097	0	1
	Rollover in a crash, base - no)	1,377	0.713	0.452	0	1
	ROLLOVER - Frist event tripped by object	1,377	0.234	0.423	0	1
	ROLLOVER - Subsequent event untripped	1,377	0.039	0.196	0	1
	ROLLOVER - unknown type	1,377	0.013	0.114	0	1
	Extrication, base – no	1,377	0.643	0.479	0	1
	Extrication - Yes	1,377	0.314	0.464	0	1

TABLE 3.11 Continued

Description		Obs.	Mean	Std. Dev.	Min	Max
	Extrication - Unknown	1,377	0.042	0.203	0	1
	Location of crash related to traffic way, base - on roadway	1,377	0.693	0.461	0	1
	Location of crash - Off road	1,377	0.278	0.448	0	1
	Location of crash - Other	1,377	0.029	0.168	0	1
	Weather condition, base - clear	1,377	0.696	0.459	0	1
	Weather condition - Rain	1,377	0.083	0.276	0	1
	Weather condition - Other	1,377	0.181	0.385	0	1
	Weather condition - Unknown	1,377	0.039	0.196	0	1

TABLE 3.12 Model Estimations of the Two-step Heckman Selection Model

Description		Coef.	SE	Z	P-value
Independent Variables	Constant	16.282	11.66	3.06	0.002
	Mode of transportation - EMS Air	42.292	2.179	8.17	0.000
	EMS Ground	29.943	2.957	10.13	0.000
	Transported, Unknown source	100.865	21.719	4.64	0.000
	Unknown	7.954	11.647	0.68	0.495
	Light condition - Daylight	-11.063	5.29	-2.09	0.037
	Dark not lighted	-11.079	5.358	-2.07	0.039
	Dark lighted	-9.789	5.598	-1.75	0.080
	Role of person - Passenger of a motor vehicle in transport)	-5.302	1.851	-2.86	0.004
	Other	-9.28	6.755	-1.37	0.170
Selection Variables	Constant	1.132	0.159	7.10	0.000
	Crash case number	6.93e-07	3.63e-07	1.91	0.056
	Die at scene	0.700	0.131	5.33	0.000
	Die en route	0.396	0.532	0.74	0.457
	ROLLOVER - Frist event tripped by object	0.087	0.150	0.58	0.561
	Subsequent event untripped	-0.544	0.241	-2.26	0.024
	Unknown type	-1.034	0.330	-3.13	0.002
	Extrication - Yes	-0.265	0.127	-2.09	0.037
	Extrication - Unknown	-0.748	0.220	-3.39	0.001
	Location of crash - Off road	-0.451	0.132	-3.43	0.001
	Other	-0.015	0.367	-0.04	0.968
	Weather condition - Rain	0.606	0.287	2.11	0.035
	Other	0.305	0.175	1.75	0.081
	Unknown	-0.173	0.278	-0.62	0.534

TABLE 3.12 Continued

Description		Coef.	SE	Z	p-value
	Lambda	-23.238	9.767	-2.38	0.017
	Rho	-0.705			
	Sigma	32.967			

value for the Wald chi-square test is 0.0000, indicating the power of this regression model. In terms of the effect of those selected and independent variables, the discussions are listed as follows:

- The mode of transport will increase the time until death. Especially, the EMS air transport, it has a high potential to increase the time to death.
- Lighting condition also plays an important role in reducing the time to death when compared to the unknown type of light conditions.
- As for passengers in a motor vehicle fatal crash, their time to death is significantly reduced. This is probably due to the passengers are not well seated and restrained. As for the selection variables, they all show their effect in grouping those observations. For example, the group of people died at the scene is totally different from people die en route. If a rollover vehicle is involved in a crash, then the certainly the potential to die soon is much higher than non-rollover crashes. Also, if people need to be taken out of the vehicle, then it has a higher potential the people will die soon due to the trap in the vehicle. This also applied to different roadway geometrics (on roadway compared to roadway departure).

3.6 LIMITATIONS

This study focuses on truck-involved crashes by matching the two separate databases (crash and incident) by date/ time, location, and incident type. Due to two different databases with two different reporting systems may report slightly different, the time of the accident occurred cannot be strictly matched from the two databases, so the matching requirements are relaxed to less than 1 hour of time difference. The sample size is not large enough, leading to a smaller number of the severely injured accidents, but that is what we can obtain, and analyze right now.

3.7 CONCLUSIONS

This study aims at identifying the association between injury severity and incident duration in truck-involved accidents, and how they are correlated with other factors. To achieve this goal, data have been collected and matched through E-TRIMS for crash data and TDOT region 1 TMC for incident data, and 442 truck-involved crashes have been finally collected. Injury severity is a categorical variable, and incident duration has been categorized into three levels. Based on this, a suitable recursive bivariate ordered probit model was applied.

Descriptive statistics show both incident duration and injury severity are normally distributed. Though most of the incidents can be cleared in 120 minutes, the duration being more than 120 minutes is worthy of attention. It indicates that the probability of severer injury accidents' duration being more than 120 minutes is higher than that of minor injury accidents.

Several modeling findings have been presented in the modeling section, and the most interesting finding is that there is a strong correlation between injury severity and incident duration, the more severe the injury level is, the longer the incident duration will be. As expected, the incident duration is much longer for incapacitating or fatal crashes. There is a 0.8807 increase, and a 0.8931 increase in the probability of incident duration is more than 120 minutes for incapacitating injury and fatal injury level, respectively.

From an operations perspective, this study reveals the recursive relationship between injury severity and incident duration. Operational countermeasures to shorten lane block duration, and the response time for reducing the incident duration could be adopted.

Given that injury severity robustly affects the incident duration, more severe accidents are more likely to associate with longer duration. Preventive actionable countermeasures for decreasing the injury severity should be researched such as educating drivers (especially non-truck drivers) the dangerous driver actions, conditions, and distractions, which affect the injury severity while they in the vicinity of trucks. Moreover, more attention should be given by practitioners like city traffic engineers while traveling on snowy days with the icy roads, since it is more likely to associate with a severe injury that also may result in longer incident duration. Further research is worthy and needed for how to integrate the preventive countermeasures with operational measures effectively.

From the methodological perspective, this study creates a unique database by matching two databases (Tennessee crash database and incident database) through the date, time, route, direction, and incident type to obtain information of both injury severity and incident duration, which previous studies seldom did. In addition, a recursive bivariate ordered probit model is adopted for analyzing the injury severity and duration simultaneously, which previous studies often only focused on one of injury severity and incident duration or analyzed them by two separately models. The unique database created, and the methodology presented in this study are technically sound and would be helpful to the researchers.

CHAPTER 4
LARGE-SCALE INCIDENT-INDUCED CONGESTION: EN ROUTE DIVERSIONS OF COMMERCIAL AND NON-COMMERCIAL TRAFFIC

4.1 ABSTRACT

When large-scale incidents occur on freeways, en route diversion of traffic is among the effective strategies to reduce the impact of incident-induced congestion. In corridors with substantial commercial traffic, especially large trucks, route diversion is complex compared with non-commercial vehicular traffic, for several reasons. Large trucks may not be able to navigate through the alternate routes (narrower streets and small turning radii), and they may be more likely to be associated with a safety risk, e.g., at intersections on the alternate route. To address the issue of commercial and non-commercial diversions to alternate routes in response to large-scale incidents, this paper identifies truck traffic corridors and establishes a methodology for analyzing the impacts of commercial (truck) and non-commercial en route diversion. A microscopic simulation model is used to analyze en route diversion strategies in real-life corridors for single-unit and multi-unit trucks and passenger vehicles under different incident scenarios. The results show that in addition to incident duration and lane blockage, important factors such as the availability of incident information and number of intersections and AADT on the freeway, alternate routes, as well as CAV, impact en route truck diversions and hence the resulting delays. In the future practice of traffic diversion operations, a strategy to consider is separately customizing incident information to truck drivers and passenger vehicles, especially in urban areas.

Keywords: Truck en route diversion, Incident-induced congestion, Simulation, CAVs

4.2 INTRODUCTION

Under an incident-induced congestion along the freeways, upstream traffic may react in different ways in response to this situation. From the perspective of drivers, either be patient, stay in the traffic queue or wait for the incident to be cleared or divert to alternative routes and return to the freeway to continue their trips. In corridors with substantial commercial traffic, especially large trucks, route diversion is far complex compared with non-commercial vehicular traffic when considering the travel time, traffic violations, lane changing movements, turning movement, etc. Therefore, commercial trucks, among all traffic, are a special group of vehicles that need special traffic operations in such situations, due to vehicle weight, traffic impact, road infrastructure, safety, energy, and value of travel time, etc. To make good decisions in terms of en route diversion, truck drivers need to access some critical and timely traffic information such as incident duration, lane blockage, current travel time on the freeway and predicted travel time on the alternate route if any, etc. From the perspectives of Traffic Management Center (TMC)'s operations, quick clearance of the incident site is their priority, but under large-scale incident-induced congestion situations, proper traffic management such as en route diversion will also be activated. In extreme cases, law enforcements are implemented to ensure detour operations' effectiveness.

However, the benefits of applying the en route diversion strategies for commercial trucks are not well understood in many of studies, especially under a large-scale incident scenario. Therefore, this paper intends to study the regime about the benefits of applying truck en route traffic diversions under large-scale incident-induced congestion scenarios. All these scenarios are based on realistic locations along Interstate freeway (I-40) corridor in Knoxville area, Tennessee (TN). To be specific, this study will firstly, construct a microscopic simulation model to analyze en route diversion strategies in I-40 corridors for single-unit and multi-unit trucks and passenger vehicles under different incident scenarios. Secondly, estimate benefits obtained from each scenario by using different traffic information penetration ratio, the value of travel time (VOT), incident duration, etc. Suggestions based on the simulation results will be provided towards to TN State Department of Transportations (TDOT).

4.3 LITERATURE REVIEW

A technical report from Federal Highway Administration (FHWA) defines an alternative route as a route begins from one point on the primary route and terminates at another point on the primary route (P. E. Dunn Engineering Associates, Consulting Services, 2006). According to the definitions, the alternative route for a freeway will start from an exit to alternative routes and then return to the freeway on another ramp. However, due to the weight, height, width, and other truck attributes, most of the alternative routes are not intended to be used by trucks. In TN state, the alternative routes for trucks along major freeway and highways in metropolitan areas are defined such that trucks will take certain alternative routes upon a large-scale incident-induced congestion on the freeway (TDOT, 2012). Upon incident-related congestion, unreliable travel time is identified as the most problematic outcomes of congestion, and it is a significant factor for long-haul truck drivers in making route choices as they navigate through the U.S. highway network (Golob & Regan, 2001; Knorring et al., 2005). Various factors that impact the en route diversion decision are evaluated, such as incident duration, number of blocked lanes, flow rate on routes, number of signals on detour route, etc., and generally, under incident scenarios with long duration, considerable diversion rates can be observed (Liu et al., 2011; Liu et al., 2012; Yin, Murray-Tuite, & Wernstedt, 2012). However, detour operations under non-recurrent congestion can also cause problems on alternative routes. Even though system delay in vehicle-hours is reduced, the delay on the detour route went up by about 64%, causing an unexpected congestion in the detour route (Cragg & Demetsky, 1995), so estimations should be done for both routes. In terms of traffic operations, traffic information systems, as well as the dynamic route guidance systems are found to be effective in travel time savings for passenger vehicles as well as public buses and trucks, especially during morning or afternoon peak hours upon non-recurrent incidents (Ng et al., 2006; Pan & Khattak, 2008; Sundaram, Koutsopoulos, Ben-Akiva, Antoniou, & Balakrishna, 2011).

When estimating the benefits of activating the en route diversion, VOT should be emphasized in freight transportation. Due to the heterogeneity and uncertainty of truck industry categories, estimating the value of travel time for each individual truck on the road is complex and unrealistic. According to the previous research papers, commercial trucks usually have much higher VOT than passenger vehicles, so it deserves much attention to incorporate VOT in the analysis for truck en route diversions (Belenky, 2011; Pan & Khattak, 2008). Upon reviewing previous research papers, seldom has focused on the truck en route diversion upon a non-recurrent large-scale incident scenario along the freeways. According to Li, et al (2017), when a large-scale incident happens, it usually lasts longer than 2 hours and blocks at least one lane on the freeway. In extreme cases, all the lanes are blocked (Xiaobing Li, Asad J. Khattak, & Behram Wali, 2017). Therefore, such incident characteristics, as well as the existing detour route characteristics (such as the number of lanes, existing AADT, number of intersections, signal timing plans, etc.), may eventually impact the operational decisions made by TMC managers. Figure 4.1 conceptually shows how TMC operations look like for implementing the diversion strategy upon an incident occurrence on the freeway.

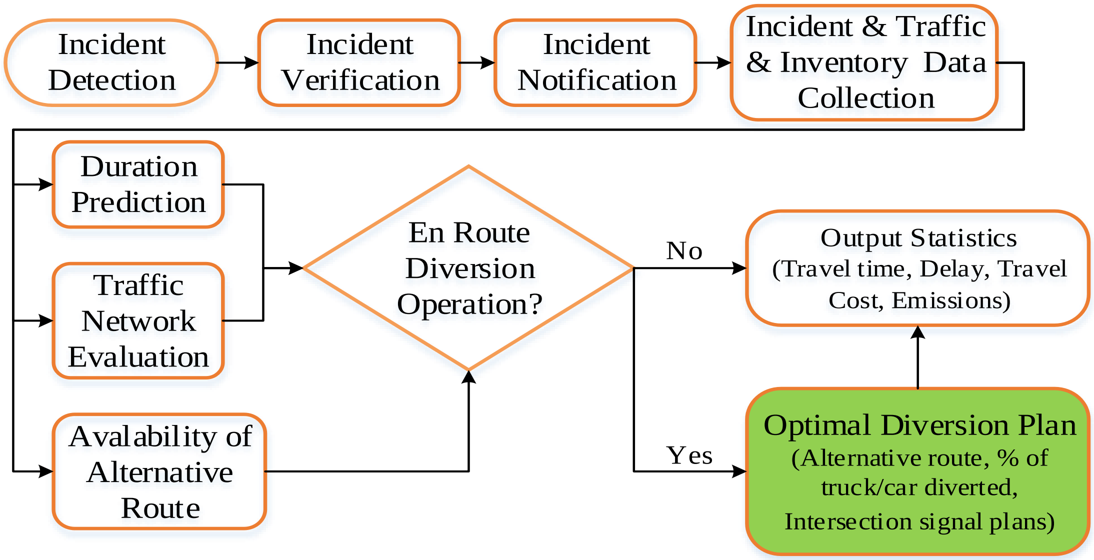


FIGURE 4.1 En route traffic diversion operations system flowchart under the incident situation.

To sum up, there is a gap in studying the en route diversion strategies for trucks under large-scale incident scenarios, because, under such scenarios, the benefits will be totally different, and more diversions will cause the alternative route to be very congested. To address the above mentioned critical issue, this paper aims to focus on this area by using simulation analysis to evaluate the benefits by diverting the truck traffic as well as the passenger vehicles. Interstate freeway I-40 and arterial Kinston Pike in Knoxville Tennessee will be the main study area for this study. Also, this study is timely and original in the sense that truck flow grows significantly in Tennessee State, and estimating the benefits in diverting the commercial trucks to alternate route upon a large-scale incident is very important in freight traffic management.

4.4 METHODOLOGY

4.4.1 Network and Experimental Design

This study uses TransModeler to run the simulation analysis. TransModeler is a traffic simulation package applicable to a wide array of traffic planning and modeling tasks (Corporation, Accessed July 71, 2017). It employs advanced methodological techniques and software technology to simulate all kinds of road networks, from freeways to downtown areas and can analyze wide area multimodal networks in great detail and with high fidelity. It can also model and visualize the behavior of complex traffic systems in a 2-dimensional or 3-dimensional GIS environment to illustrate and evaluate traffic flow dynamics, traffic signal and ITS operations, and overall network performance. It simulates public transportation as well as car and truck traffic and handles a wide variety of ITS features such as electronic toll collection, route guidance, and traffic detection and surveillance.

Currently, Connected and Automated Vehicle technology has penetrated the vehicle market, and under such environment, the driving behaviors will be somewhat different from current driving style. Therefore, in designing the simulation experiments, different levels of automation will be added. The details of levels of automation provided by National Highway Traffic Safety Administration (NHTSA) are listed as follows (Administration, 2016):

- Level 0, the human driver does everything;
- Level 1, an automated system on the vehicle can sometimes assist the human driver to conduct some parts of the driving task;
- Level 2, an automated system on the vehicle can actually conduct some parts of the driving task, while the human continues to monitor the driving environment and performs the rest of the driving task;
- Level 3, an automated system can both actually conduct some parts of the driving task and monitor the driving environment in some instances, but the human driver must be ready to take back control when the automated system requests;
- Level 4, an automated system can conduct the driving task and monitor the driving environment, and the human need not take back control, but the automated system can operate only in certain environments and under certain conditions; and
- Level 5, the automated system can perform all driving tasks, under all conditions that a human driver could perform them.

As for dynamic route choices of drivers, it models such behavior based upon historical or simulated time dependent travel times, and it models trips based on OD (Origination-Destination) trip tables or turning movement volumes at intersections.

Therefore, to properly run the simulation analysis and keep high fidelity of the simulation model, the OD matrix should be obtained and built into the simulation models. To achieve such purpose and realistically reflect the real-world operational characteristics for this study network, the Annual average daily traffic (AADT) information is obtained through an Enhanced Tennessee Roadway Information Management System (E-TRIMS). Within such roadway inventory and traffic archiving system, other key variables associated with the experimental scenarios are also extracted, they are grouped as follows (for more details on each variable, see Table 4.1):

- Freeway-related variables: number of lanes on freeway mainline, AADT, percentage of passenger vehicles/single-unit (SU) trucks/multi-unit (MU) trucks;
- Incident-related variables: number of lanes blocked, block duration, the travel speed on unblocked lanes, total length of the blockage; and
- Alternative/detour route-related variables: AADT on two collector road connecting freeway and arterial road (one way from the freeway and arterial road, and the other one back to the freeway), and on the arterial road such as Kingston Pike in our study. Also, the number of lanes, the number of intersections, and signal timing plans on these roads.

As we can see from above Table 4.1, there are thousands of combinations of the experimental designs. In order to limit the number of scenarios and also keep the experimental designs somewhat realistic, 8 diversion locations are chosen along I-40 in Knox County, Tennessee. These locations include: exits 369, 373, 374, 376, 378, 379, 380, and 383.

TABLE 4.1 Key Variables in the Experimental Design for the En route Diversion Strategy

Variables	Description	Range of Values
Fr_Ln	Number of main lanes each direction on the freeway	3, 4, 5
Fr_AADT	AADT on freeway	105,970, 119,300, 136,250, 179,910, 188,060, 196,210, 196,710
Fr_PerPC	Percentage of passenger vehicles on freeway	70%, 72%, 74%, 76%, 77%, 78%, 80%, 81%, 83%, 84%, 87%, 88%, 89%
Fr_PerSU	Percentage of single-unit trucks on freeway	2%, 3%, 4%, 5%, 6%
Fr_PerMU	Percentage of multi-unit trucks on freeway	8%, 9%, 10%, 11%, 12%, 14%, 15%, 16%, 17%, 18%, 21%, 25%, 27%
Inc_Ln	Number of lanes blocked during the incident	3, 4, 5
Inc_BlcDur	Incident blockage duration	≥ 2 hours
Inc_Speed	Travel speed on available travel lane on the freeway	10 mph, 15mph
Inc_length	Total length of the blockage during incident	200, 300, 400, 500, 600
Alt_Col1AADT	AADT on collector road 1 from freeway to arterial	10,740, 27,840, 41,820, 63,990, 19,500, 11,420, 19,450, 27,284
Alt_Col2AADT	AADT on collector road 2 from arterial to freeway	27,840, 41,820, 63,990, 19,500, 11,420, 12,550, 14,360, 77,420
Alt_AADT	AADT on alternative arterial	22,570, 29,340, 28,760, 31,090, 19,170, 24749
Alt_Col1Ln	Number of lanes each direction on collector road 1 from the freeway to arterial	1, 2, 3, 4
Alt_Col2Ln	Number of lanes each direction on collector road 2 from arterial to freeway	1, 2, 3, 4
Alt_Ln	Number of lanes each direction on alternative arterial	2, 3, 4, 5
Alt_Int	Number of signalized intersections on the alternative route	2, 3, 4, 5

To investigate various outcomes from these simulation runs, a conceptual study network is firstly introduced as shown in Figure 4.2. This diagram shows when a traffic incident happens on a freeway by blocking, then traffic might take an alternative route (e.g. arterial) to bypass the congested area by entering the freeway system in a downstream ramp.

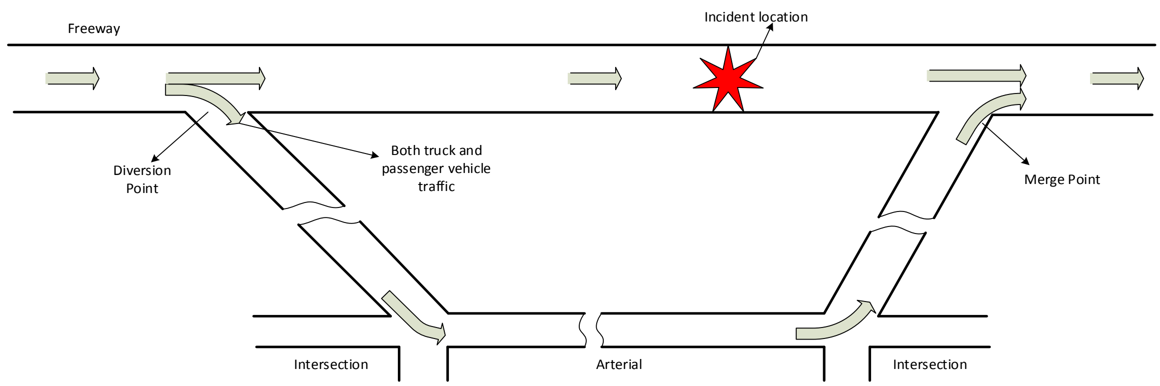


FIGURE 4.2 En route diversion scheme along the freeway.

The diverted traffic from freeway include both passenger vehicles and trucks (SU and MU). In TransModeler, if an incident happened along the freeway and if drivers are not informed of the updated travel for the freeway, then they will stay on the current freeway without any diversion. In this sense, not all the drivers are informed of the updated travel time, and information communication devices become very important in delivering these information (travel time/delay on freeway, and travel time on alternative route, etc.), also in changing drivers' en route choice behaviors as having mentioned by Sundaram, et al (2011), and Pan, and Khattak (2008). In other words, the travel time related information penetration ratio will make a difference in the diversion strategies and benefit estimations thereafter. Such variations in travel time related information penetration (from 0% to

100%) will be incorporated in the simulations scenarios, so do other key variables listed above.

All these diversion strategies are based on the east direction, and all the simulation runs are based on these locations. Within each simulation scenario, there are also variations in incident characteristics, the percentage of drivers receiving updated travel information, and value of travel time for trucks as well as for passenger vehicles. The initial configurations for these 8 diversion locations are listed in Table 4.2 as shown below.

4.4.2 Origination-Destination Estimation

In estimating the OD matrix for the simulation analysis, 8 nodes are set up for simplicity as originations and destinations in the conceptual network as can be seen in following Figure 4.3.

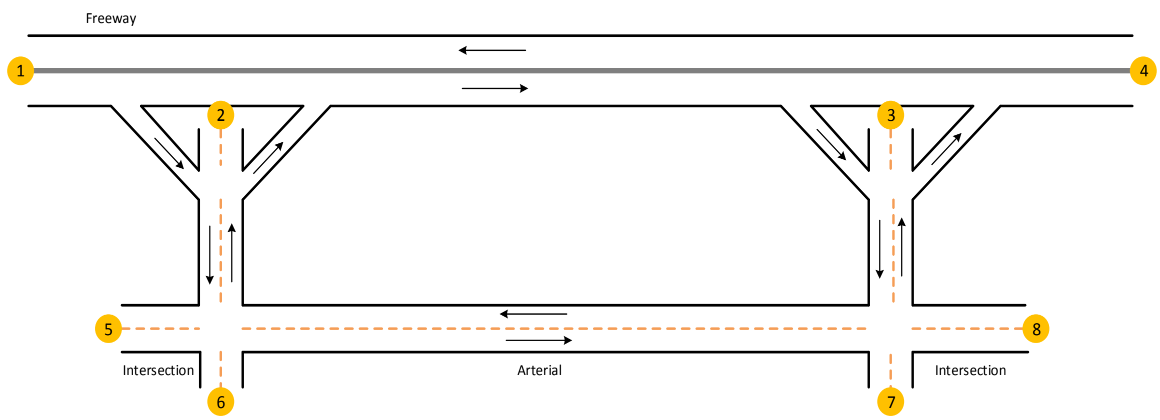


FIGURE 4.3 Originations and destinations for the study network.

The simplified network here does not include many intersections, they will be revealed in the simulation models in TransModeler, but to simplify our analysis, only 8 nodes will be considered as either originations or destinations. Trip productions and

TABLE 4.2 Initial Configurations for 8 Diversion Locations

No	Location 1	Location 2	Location 3	Location 4	Location 5	Location 6	Location 7	Location 8
Freeway number of lanes	3	3	4	5	5	4	5	4
Freeway AADT	150,970	119,300	136,250	179,910	188,060	196,210	196,710	196,410
Freeway PC %	78%	81%	83%	87%	88%	88%	81%	81%
Freeway SU %	4%	3%	3%	2%	2%	2%	3%	3%
Freeway MU %	18%	16%	14%	11%	10%	10%	16%	16%
Collector 1 AADT	10,740	27,840	41,820	63,990	19,500	11,420	19,450	27,284
Collector 2 AADT	27,840	41,820	63,990	19,500	11,420	12,550	14,360	77,420
Arterial AADT	22,570	29,340	29,340	28,760	31,090	31,090	31,090	21,960
Collector 1 number of lanes	1	2	2	2	3	2	2	2
Collector 2 number of lanes	2	2	2	3	2	2	2	3
Arterial number of lanes	2	2	2	2	2	3	2	2
Number of signalized intersections	11	12	7	11	11	9	10	15

Note: Location 1 is from I-40 to Watt Rd to Kingston Pike to Everett Rd, then to I-40;
Location 2 is from I-40 to Everett Rd to Kingston Pike to N Champbell Rd, then to I-40;
Location 3 is from I-40 to N Champbell Rd to Kingston Pike to Lovell Rd, then to I-40;
Location 4 is from I-40 to Lovell Rd to Kingston Pike to Pellissippi Pkwy, then to I-40;
Location 5 is from I-40 to Pellissippi Pkwy to Kingston Pike to N Cedar Bluff Rd, then to I-40;
Location 6 is from I-40 to N Cedar Bluff Rd to Kingston Pike to Bridgewater Rd, then to I-40;
Location 7 is from I-40 to Bridgewater Rd to Kingston Pike to Buckingham Dr, then to I-40;
Location 8 is from I-40 to Northshore Dr to Kingston Pike to Alcoa Hwy, then to I-40.

attractions (PAs) are the starting point for generating future OD matrix. Main data from Table 4.2 will be utilized as the input data. However, it's not enough to only use that data, other data from E-TRIMS will also be utilized including directional distributions of AADT, peak hour traffic direction, AADT on each node if they are different from the AADT on the segment in Table 4.2. The data are error checked and validated. All these factors need to be considered in the final calculation of the trip productions and attractions for each node in the study network. For example, for diversion location 1, the peak hour directional distribution of AADT on freeway is 60% (east direction) vs. 40% (west direction), so the calculated traffic demand or traffic productions for node 1 is 105,970 * 0.6 = 63,582 trips, and attractions will be 105,970 * 0.4 = 42,388. Similar operations can be done for each location. After getting the PAs for each location, the next step is to convert the PAs to ODs. This can be easily done using the TransCAD software through applying its own internal gravity models, which are well known in the traffic demand forecasting community, so details about that are not specified here.

4.4.3 Traffic Composition

Trucks (SU and MU) are our focus in this paper, so by separating the traffic flows into passenger vehicles and trucks (SU and MU) are necessary. Again, E-TRIMS provides us information about the percentage of these three vehicle types (PC – Passenger Cars, SU – Single-Unit trucks, and MU – Multi-Unit trucks), and they will be dealt with individually in the simulation models. More information about the setup of these variables is shown in the previous Table 4.1 and Table 4.2.

4.4.4 Traveler Information and VOT

In evaluating the impact of traveler information on implementing the en route diversion strategies, the information penetration rate for drivers is set up to vary from 0% to 100%. So, for each group of drivers (PC, SU, and MU), they either receive the updated travel time information or not. For those who do not receive the updated travel time information, they will stay in the current traffic flow without changing the route in the TransModeler simulation models; while for those who receive the information, they either stay on original route or take the designated alternative route based on the threshold value of the difference between travel times on freeway and alternative route. In the simulations, 5% difference of the travel time between the freeway and the alternative route is used as the threshold value.

As for the impact of VOT on the diversion strategies, Pan, and Khattak (2008) finds an interesting result where higher VOT are associated with lower percentage of savings in total travel cost when applying the diversion strategy. But in large-scale incident situations, will this relationship change? The results will be explained in later sections. In saying so, we will apply what we have prepared so far in previous sections into the simulation models, and results are shown in detail in the next section.

4.4.5 En Route Choice Model

Stochastic shortest path method is adopted in this study. This method is all based on path costs. Compared to the deterministic shortest path, this method takes account the variations in each individual drivers' perception and behavior on pre- and en- route choice. Thus, the path costs are randomized and there is not one, but many, shortest paths between a given O-D pair. TransModeler is a path-based simulation model (Caliper, 2014). In TransModeler, each vehicle has an assigned path before it departs it origin and enters the network, and drivers will consider alternative paths en route if they experience delay on a link that far exceeds their expected delay which is usually obtained though dynamic traffic assignment using the stochastic user equilibrium method computed by the method of successive averages (MSA). The threshold at which link delay is considered excessive is determined by each drivers' route choice parameters (such as different from current path, choice set threshold, update delay threshold, reroute threshold, etc.), and those parameters usually vary among the driving population, such as passenger vehicles, single-unit trucks, and multi-unit trucks as mentioned in our study. Eventually, these parameters will determine whether the drivers will take the alternative new paths en route or not. Descriptions of some of the key parameters are presented as following:

- Informed – drivers in the model have access to updated travel time information. If uninformed, drivers will make all route choice decision solely based on historical travel time information. Depends on the information penetration rate, and the vehicle fleet proportions, the proportions of the informed and uninformed drivers vary among each scenario.
- Update delay threshold – expressed as the percent difference in experienced travel time on a line relative to the expected or historical travel time. When the experienced travel time exceeds this threshold, a driver will consider alternative paths, which may or may not lead to a new route, depending on the alternatives. In this study, 20% update threshold is used to let drivers reconsider current path and alternative paths.
- Reroute threshold – it represents the percentage reduction in travel time relative to the current path (freeway in our study) that is required in order for a driver to decide to switch to the alternative route. 5% is chosen as the criterion for this threshold. For trucks, 10% is the chosen criterion since truck drivers' inertial preference for

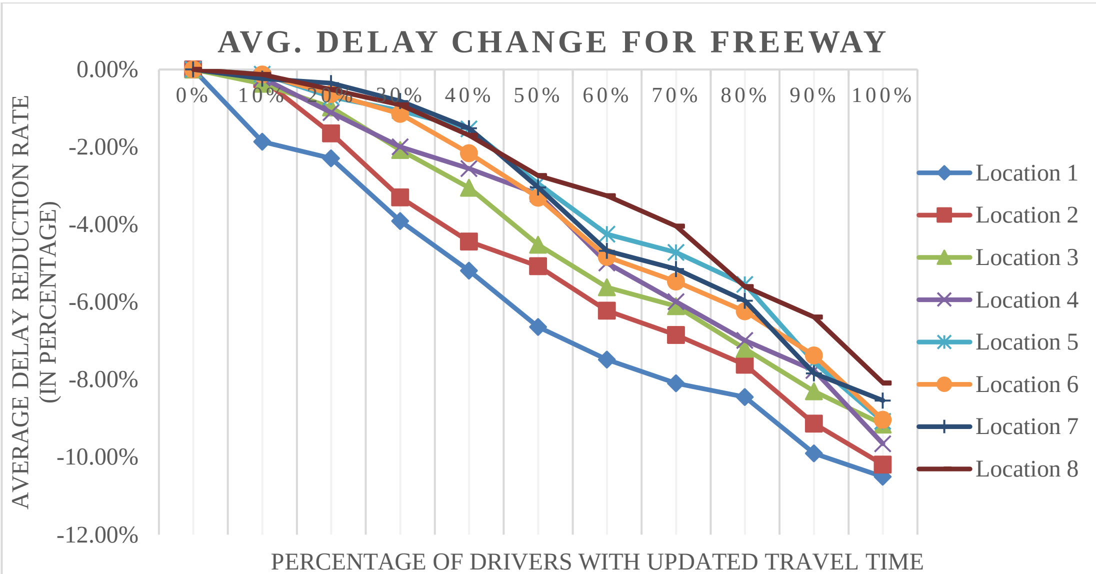
the current path is usually freeway instead of other local arterials.

4.5 SIMULATION ANALYSIS RESULTS

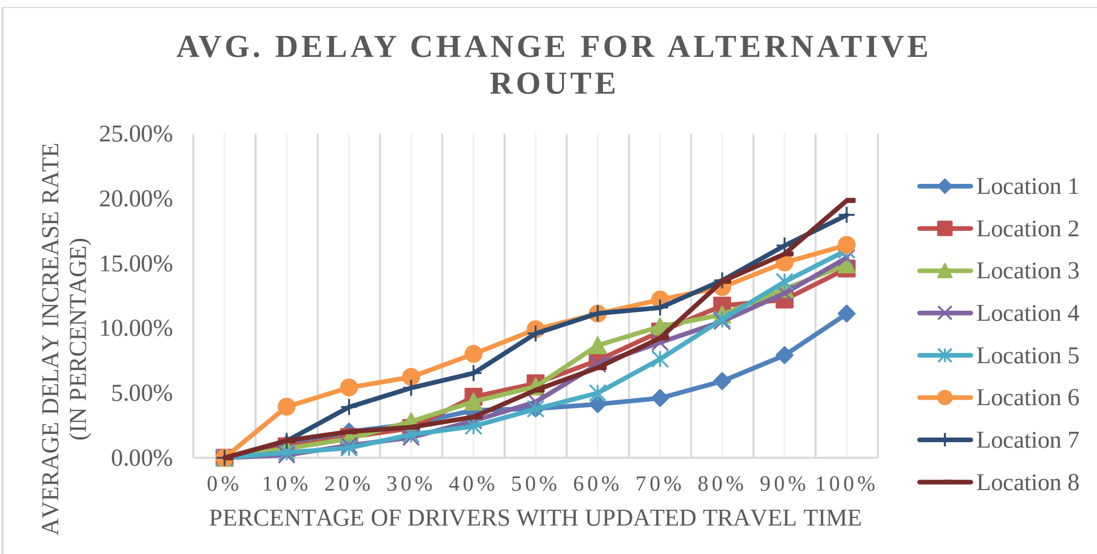
There are many traffic network performance evaluation criteria that can be used to evaluate the en route diversion traffic operations strategy. Those criteria include travel time on the freeway and alternative route, Level of Service on the alternative routes, and intersections, delay by freeway and alternative routes, queue length on the freeway and near intersections, etc.(P. E. Dunn Engineering Associates, Consulting Services, 2006; Knorring et al., 2005; Liu et al., 2011; Liu et al., 2012; Ng et al., 2006; Pan & Khattak, 2008; Yin et al., 2012). Delay statistics is most used among all these criteria. In other words, delay reductions can be treated as travel time saving for both freeway and alternative routes, and then delay reductions of trucks and passenger vehicles can be converted to savings in dollars, emissions, fuel. The simulation runs are based on a daily basis which means each simulation starts at 00:00:00 and end at 23:59:59, and the incident is assumed to block all other lanes except one lane on the left side of the freeway, and the travel speed is assumed to be 10 mph for this available travel lane. The incident is set up during morning peak hours from 7 AM to 9 AM for preliminary analysis. Other scenarios are presented afterwards.

4.5.1 Delay Reductions

Figure 4.4 presents the delay statistics for freeway and alternative routes at 8 locations under different traffic information penetration rate. Figure 4.4 (a) shows the delay statistics for the freeway. Compared to normal traffic situation (no incident occurrence), when an incident occurs along the freeway and 0% of the drivers in each fleet group are informed of the updated travel time, the total delay increased about 6.1 to 12.5 times for freeway diversion points at 8 locations, while the average delay increased about 4.6 to 8.7 times for



(a)



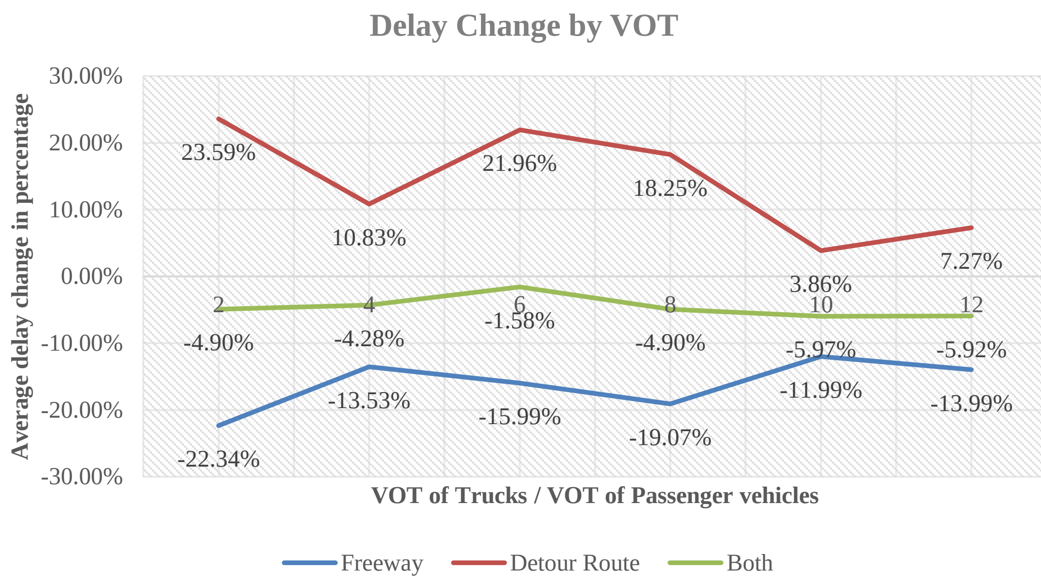
(b)

FIGURE 4.4 (a) Average delay reductions for freeway at 8 locations; (b) Average delay reductions for the alternative route at 8 locations.

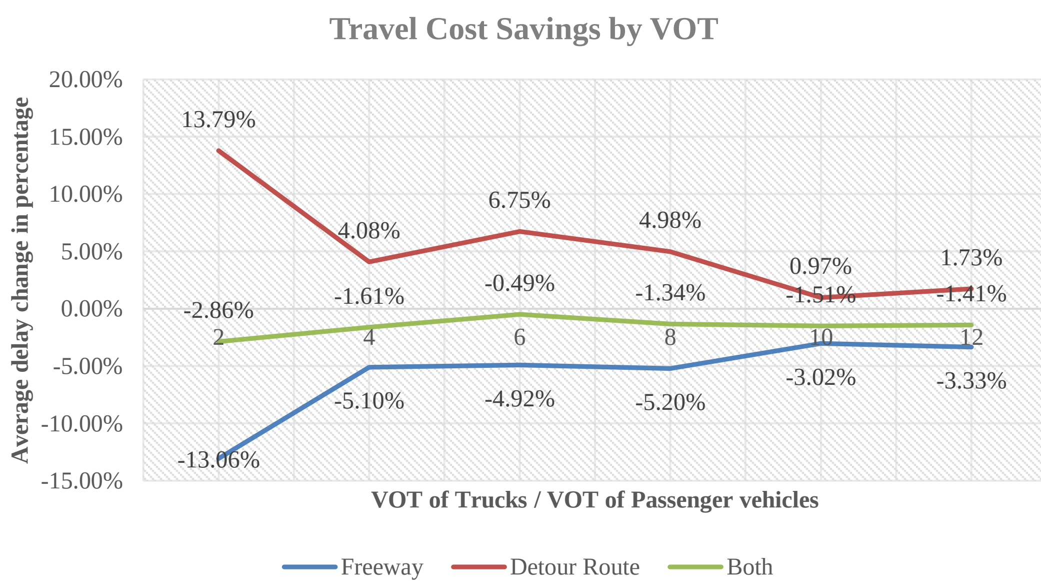
freeway diversion points at 8 locations. These statistics indicate a driver will spend 20 – 45 minutes to get through the freeway segment when normally 5 minutes is used to travel through it. When traffic information is available to travelers, based on the percentage of drivers in each fleet group, Figure 4.4 (a) presents how delay reductions look like for the freeway. Those 8 locations (from location 1 to location 8) are located from rural to urban. Similar to what has been found before, Figure 4.4 (a) shows that with more and more traffic information delivered to drivers, the en route diversion rate will increase, and the travel delay will be reduced. Additionally, under dynamic traffic environment, our simulation results show that, generally, traffic on the freeway, if taking en route diversions from the freeway to alternative arterials at rural locations can receive more benefits of saving travel time. Also, the preliminary analysis graphs do reveal a monotonic increasing benefit from the average delay reductions for freeway (up to 8% - 10% at various locations) and a monotonic average delay increment for an alternative route (up to 10% - 20% at various locations, see Figure 4.4 (b)). This interesting result indicates that with more and more traffic related information delivered to the drivers, their response to the incident and the en route diversion operations are generally contributing the overall congestion relief and improving the overall performance of the traffic network. Notice that in Figure 4.4 (a), compared to rural locations (such as location 1 and 2), average relay reductions at urban locations are less. One reason to explain this is that drivers prefer to stay on the freeway since the alternative routes at urban locations are also very congested at morning peak hour. Due to the number of intersections and a high chance of long intersection delays, drivers, especially truck drivers may still consider the freeway as their primary route choice. While in rural areas, fewer intersections are observed, that could be another reason for gaining more benefit in delay reductions for rural areas. This implies that under heavily congested areas such as urban areas, downtown area, even though traffic information is available to most drivers, the freeway is still their primary choice due to high congestion in peak hour because there might be no lane change, merging, diverging, and turning movement on the freeway. Therefore, en route diversion strategy applied in rural areas is more effective and beneficial in saving travel time and reducing the negative impact of the incident on travelers.

4.5.2 VOT Impact

Assuming 50% of the drivers can get updated traffic information, then we tested the impact of VOT on the delay reduction for the freeway. The base VOT for passenger vehicles is assumed to be $15 (for illustration purpose, true values need to be verified for each region), and the VOT for trucks (both single-unit and multi-unit) are set up as 2, 4, 6, 8, 10, and 12 times larger compared to passenger vehicles. Previous studies show that with higher VOT, the savings in travel time and cost decreased for the whole network. However, if we only consider the freeway and detour route separately, then our simulation analysis results (shown in Figure 4.5 (a)) show that the delay reductions/increments for freeway and detour route are not very stable. But if we take both of them together, then there is not much variation in delay reduction. Higher VOT means higher risk in increasing travel cost if not taking a proper alternative route, so most truck drivers prefer to remain on the freeway. However, if law enforcement is deployed altogether with real-time information of incident to travelers, especially with detailed instructions to trucks, then the benefit of implementing the en route diversion traffic operations need to be further investigated in future. If converting travel time saving into dollars (fleet composition is 81% / 3% / 16% for PC,



(a)



(b)

FIGURE 4.5 (a) Delay changes, and (b) travel cost savings for freeway and alternative route under different VOT for trucks.

SU, and MU) using conversion factors in Table 4.3, the results shown in Figure 4.5 (b) indicate that compared to the based case ($15 VOT for all vehicles), when the VOT of trucks are 2, 4, 6, 8, 10, and 12 times larger than that of passenger vehicles, the overall travel cost savings in percentage declines, even though the total amount of travel cost savings increases, but the magnitude is decreased. This result implies that when en route diversion operations are implemented, diverting trucks as well as passenger vehicles is necessary because trucks usually have higher VOT, which contributes to higher total cost savings, but in terms of percentage savings, it is reduced, implying the huge negative impact of large-scale traffic incidents.

4.5.3 Impact of Incident Durations

Location 8 is selected specifically to study in detail as shown in Figure 4.6. The east bound direction is chosen as the peak hour direction for I-40 and the alternative en route diversion route starts from I-40 Exit 383 to Northshore Dr. to Kingston Pike to State Route 129, then back to I-40 at 386B.

Under normal traffic conditions, the travel time on the freeway is 4 minutes for 4.3 miles, and it becomes 13 minutes for 5.6 miles if taking the alternative route since there are 15 signalized intersections along this route. The network in simulation is shown in Figure 4.6. Assuming 50% of the travelers are updated with traffic information. The impact of incident duration is evaluated. It will start from 7 AM and last from 2 to 6 hours. Only one lane is assumed to be available during the incident. Figure 4.7 presents the delay reduction information for the whole study network under large-scale incident scenarios lasting from 2 – 6 hours. The delay reductions are increasing as the incident duration lasts longer. The scenarios are simulated around morning peak hours.

TABLE 4.3 Conversion Factors and Their Sources

Conversion Factor	Value	Source
Delay to HC	13.073 g/h	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)
Delay to CO	146.831 g/h	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)
Delay to NO	6.261 g/h	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)
Delay to CO_2	0.156 gal/h of passenger cars 0.85 gal/h of trucks	Ohio Air Quality Development Authority; Lutsey et al. (2004) (Lutsey et al., 2004)
CO_2	19.56 lbs/gal of gasoline 22.38 lbs/gal of diesel	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)
Delay Cost	$27.37/h	U.S. Census Bureau 2009
Fuel Cost	$2.264/gal of gasoline (East Coast) $2.546 gal of diesel (East Coast)	Energy Information Administration
HC cost	$6,700/ton ($6.7/kg)	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)
CO cost	$6,360/ton ($6.36/kg)	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)
NO cost	$12,875/ton ($12.875/kg)	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)
CO_2 cost	$23/metric ton ($0.023/kg)	Chang and Raqib (2013) (G.-L. Chang & Raqib, 2013)

FIGURE 4.6 I-40 and Kingston Pike en route diversion network.

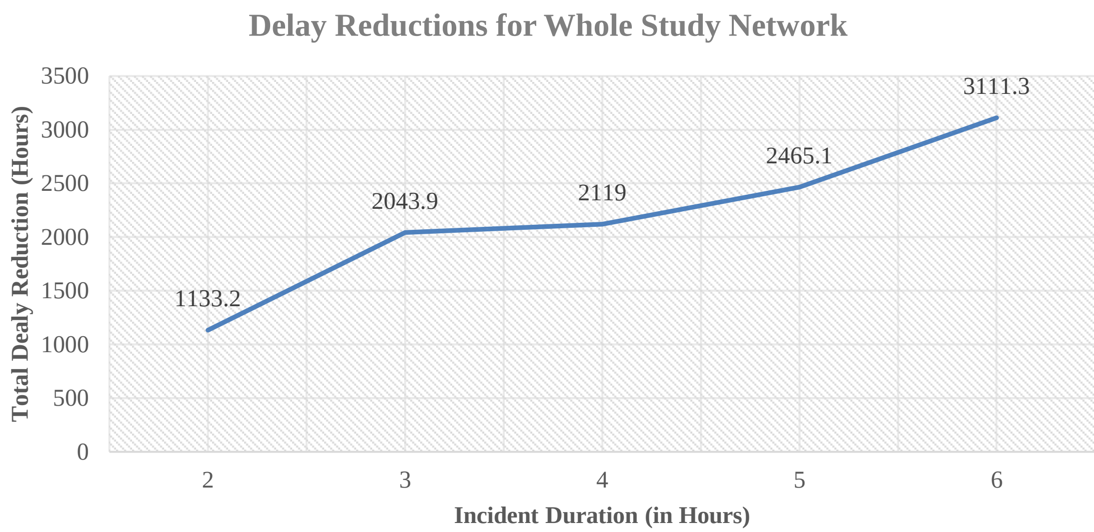


FIGURE 4.7 Total delay with and without updated traffic information for the case study under large-scale incident scenarios lasting 2 to 6 hours.

4.5.4 Benefit Estimation

Along with reductions in delay, the benefits in terms of emission, and fuel reduction can also be estimated. Then the savings can be converted to monetary values using the conversion factors in Table 4.3.

Using the conversion factors in Table 4.3, the cost savings are obtained for the incident scenarios lasting from 2 hours to 6 hours, which are shown in Table 4.4. Column 2 – 8 in Table 4.4 represents the cost savings by taking account of one of the incident-related characteristics – incident duration. Results clearly show that with longer incident durations, the benefit of cost savings (in delay, emissions, and fuel) is greater. This result is in accordance with other studies (G.-L. Chang & Raqib, 2013; Liu et al., 2012; Lutsey et al., 2004), but under such large-scale incident scenarios, the magnitude of the cost savings is much higher than non-large incident scenarios.

TABLE 4.4 Cost Saving for Large-Scale Incident Scenarios

Incident Duration (in hours)	Delay Cost Saving	Fuel Cost Saving	HC Cost Saving	CO Cost Saving	NO Cost Saving	CO_2 Cost Saving	Total Cost Savings
2	$31,015	$790	$99	$1,058	$91	$71	$33,126
3	$55,941	$1,425	$179	$1,908	$164	$129	$59,748
4	$57,997	$1,477	$185	$1,978	$170	$134	$61,944
5	$67,469	$1,718	$215	$2,302	$198	$156	$72,061
6	$85,156	$2,169	$272	$2,905	$250	$197	$90,952

4.5.5 Impact of CAV on Network Performance

Vehicle automation has made the progress in improving the surface transportation in terms of mobility and safety. However, seldom has the current existing studies focused their attention on estimating the benefits under the en route traffic diversion under large-scale traffic incident on the freeways. Thus, the impact analysis of CAVs on network performance in terms of travel delay reductions and other performance indicators (e.g. number of stops, stop time, average speed), is done to compare the difference between the benefit estimations under various vehicle automation levels and under normal driving conditions with drivers fully controlling the vehicles.

Traditionally, the traffic is modeled in the TransModeler using General Motors (GM) car-following models, and its formulation based on TransModeler User's Guide version 5.0 is written as follows:

$$\boldsymbol{A_i^{\pm}[t+\Delta t] = \alpha^{\pm} \frac{V_i^{\beta^{\pm}}[t]}{D_{i,i-1}^{\beta^{\pm}}[t]} (V_{i-1}[t] - V_i[t])^{\theta^{\pm}} + \varepsilon_i^{CF}} \qquad \textbf{Eq. 4.1}$$

Where:

$A_i^{\pm}[t+\Delta t]$ = Acceleration rate of vehicle i at time t + reaction time Δt;

$V_i[t]$ = Speed of subject vehicle i at time t;

$V_{i-1}[t]$ = Speed of front vehicle $i-1$ at time t;

$D_{i,i-1}[t]$ = Distance between the vehicle i and front vehicle $i-1$ at time t;

$\alpha^{\pm}$, $\beta^{\pm}$, $\gamma^{\pm}$, $\theta^{\pm}$ = Model Parameters; + means acceleration, and – means deceleration.

ε_i^{CF} = Vehicle-specific error term for the car-following regime.

The acceleration of the subject vehicles happens when its speed is less than the speed of the front vehicle. Otherwise, the subject vehicle will remain constant or decelerate.

Lower bound and upper bound of headways are set to limit the vehicles running above the emergency regime and under the free flow regime.

However, under the CAV environment, it is suggested to run the Constant Time Gap car-following model (CTG) to achieve the goal of improving transportation mobility by increasing roadway capacity and travel speed. It follows the concept that drivers seek to maintain a constant, desired following headway with the front vehicle. It is more like a simplified algorithm representing an on-board computer's operating policy, thus it can be used to approximate the behaviors of connected vehicles in a cooperative adaptive cruise control environment. Its formulation based on TransModeler User's Guide version 5.0 is written as,

$$\boldsymbol{A_i[t] = -\frac{1}{h}(V_i[t] - V_{i-1}[t] + \lambda\delta_i)} \qquad \textbf{Eq. 4.2}$$

$$\boldsymbol{\delta_i[t] = D_{i,i-1}[t] + hV_i[t] + D_{i,i-1}^{desire}} \qquad \textbf{Eq. 4.3}$$

Where:

$A_i[t]$ = Acceleration rate of vehicle i at time t;

h = Desired following time headway (in seconds);

$V_i[t]$ = Speed of subject vehicle i at time t;

$V_{i-1}[t]$ = Speed of front vehicle $i-1$ at time t;

δ_i = Spacing error for vehicle i requiring correction to achieve the desired headway h;

$D_{i,i-1}[t]$ = Distance between vehicle i and vehicle $i-1$ at time t;

λ = Model parameter for control purpose.

4.5.5.1 Simulation Results with No Incident

Various scenarios are also created to evaluate the impact of CAV on the network performance based on the location 8. Firstly, one of the roadway segments in the simulations models are extracted to compare the simulated traffic flows and realistic traffic flows. By doing this, the simulation model is validated to have represented more realistically about the I-40 and Kingston Pike traffic flow conditions. The segment where traffic entered through the freeway network is used. The hourly volume for realistic traffic on this segment is shown to be 4918/hour. Using the Mean Absolute Percentage Error (MAPE) measurement, the averaged value of MAPE for simulated traffic volume and realistic traffic volume is 3.55% based on 70 simulations without any incident. It is an acceptance value because 5% is usually used for the gap acceptance in TransModeler.

Figure 4.8 and Figure 4.9 presents the simulation outcomes in terms of total network delay and average travel speed. A huge jump in all these statistics from no automation to level 1 automation. 1.5% - 13% reduction in total delay with incident durations ranging from 675 minutes to no incident. 0.96% - 5.16% increase in average travel speed for incident durations ranging from 675 minutes to no incident. By adjusting the headway (1.1, 1.0, 0.9, 0.7, 0.6, and 0.5) in the 5 automations levels, the scenarios present a monotonically decreasing (total delay) or increasing (average travel speed) trends for those statistics. Such phenomenon can be explained by the headway setup. With shorter headways between vehicles, the roadway has more capacity, so vehicles will use less time in the system. Automation level 3 is probably the watershed that distinguishes among those automation levels. Because we see a sharp decrease in total network delay percentage reductions, and share increase in term of the percentage increase in average travel speed.

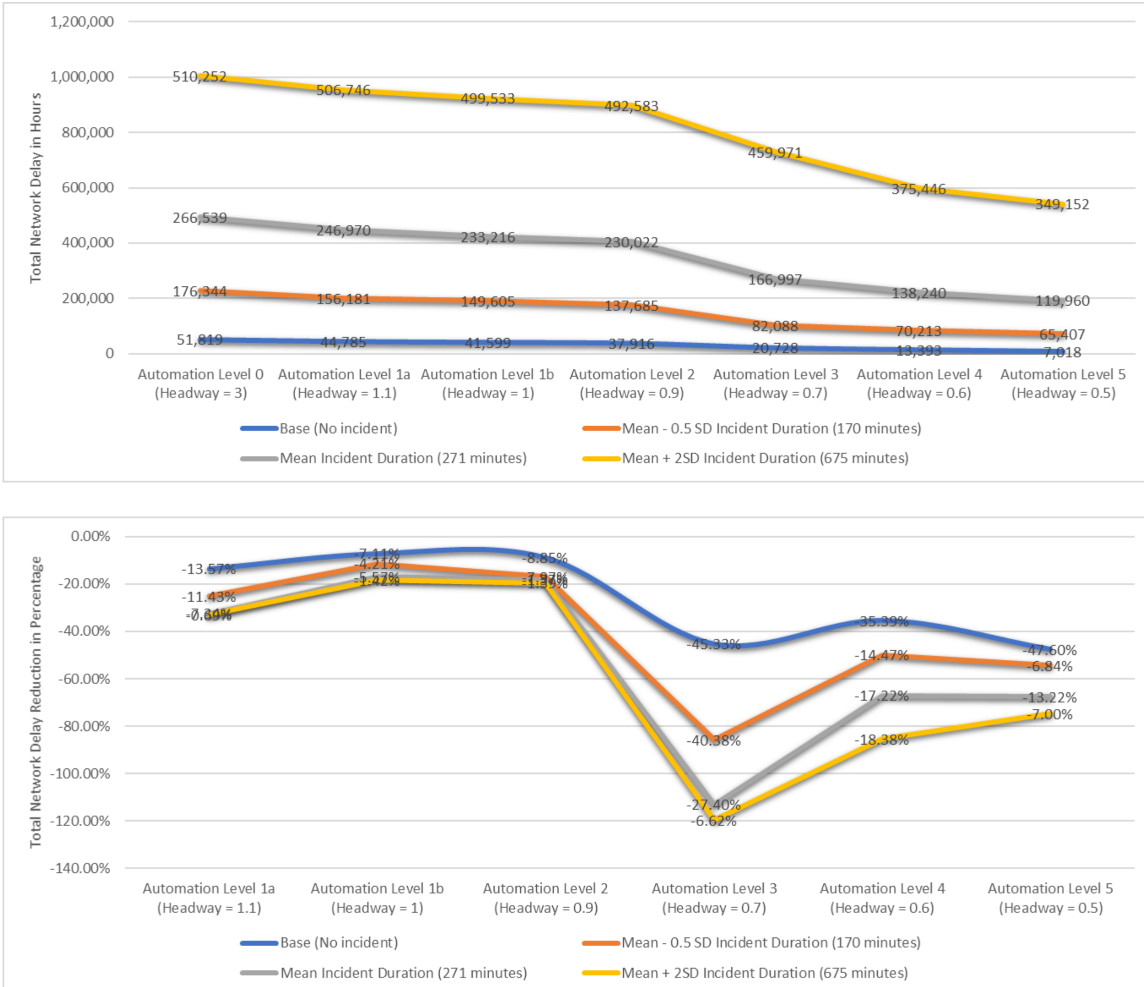


FIGURE 4.8 Simulation outcomes of total delay in hours and percentage reduction, with no incidents & various incident scenarios under 5 levels of automation.

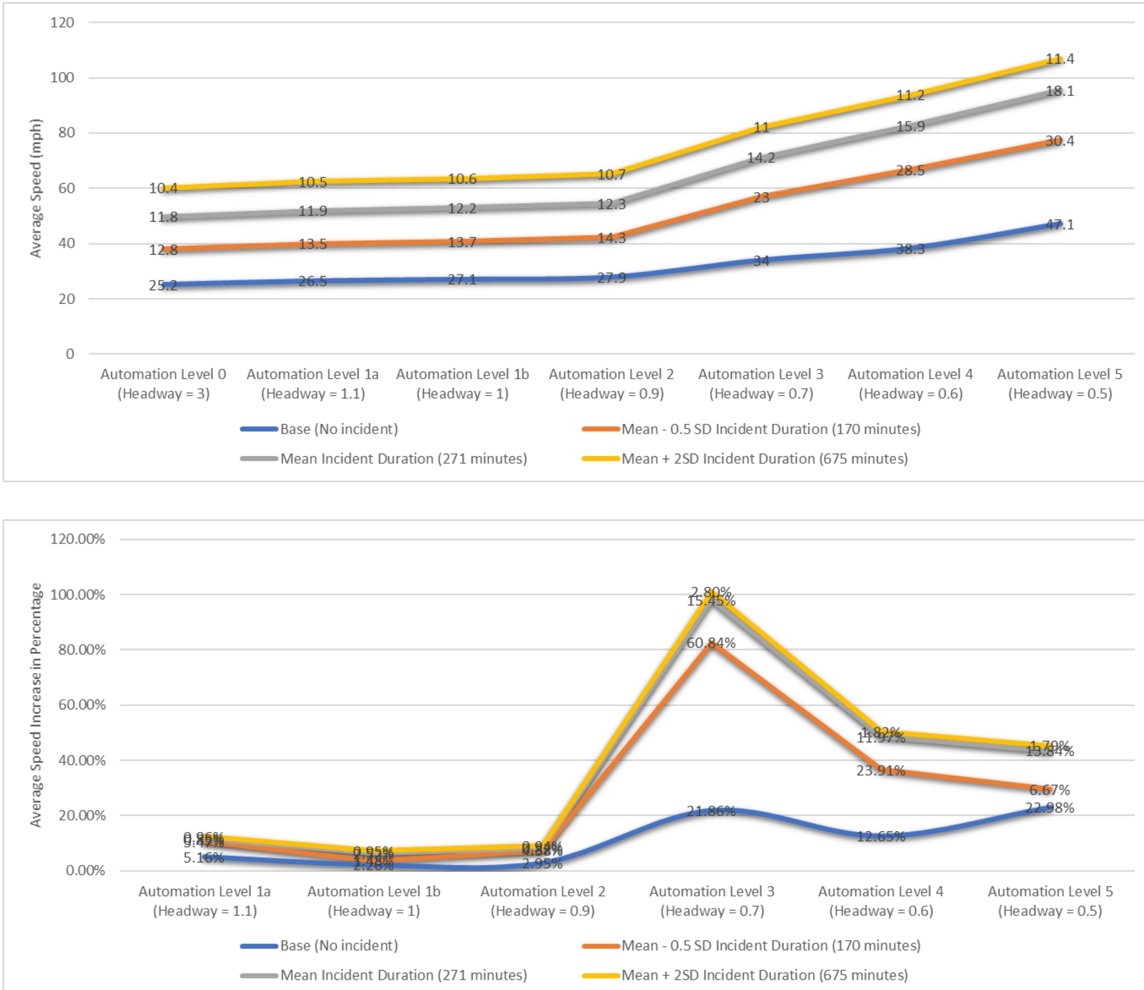


FIGURE 4.9 Simulation outcomes of average speed in mph and percentage increase with no incidents & various incident scenarios under 5 levels of automation.

However, after that, the improvement in gaining those benefits is less when compared to previous automation levels. But still, the benefit can be seen from those Figures 4.8 and 4.9. Overall, introduce of vehicle automation into the transportation will benefit the society in saving more travel time. With more and more real traffic operations data collected, more analytical results will prove the benefits of deploying those CAV vehicles.

4.5.5.2 Impact of Vehicle Performance on the Traffic Network

If the performance of the commercial vehicles (e.g. trucks) can be improved by a certain amount of percentage, how the delay in the traffic network will look like. This part is analyzing the impact of the performance of truck on the traffic network. Following Figures 4.10 and 4.11 presents the results of truck performance under different levels of automation. As can be seen from these two figures, the network performance can also be increased by introducing higher performance trucks, as well as other vehicles. The largest change in terms of percentage often happens at level 3 automation when compared with level 2 automation. Such a result is in accordance with the conclusion in the last part. Maximum percentage reduction in delays can be as large as 25.97% when the vehicle performance increases by 10% at level 3 automation. A similar trend can be seen in the average speed of the traffic network. A sharp increase can also be seen at the watershed level 3 automation. However, the largest percentage increase happens where the vehicle performance increases by 15% at level 5 automation when compared to level 4 automation with same vehicle performance. Therefore, to sum, both CAV and vehicle performance play important roles, and the impact of CAV is much higher in saving more travel time.

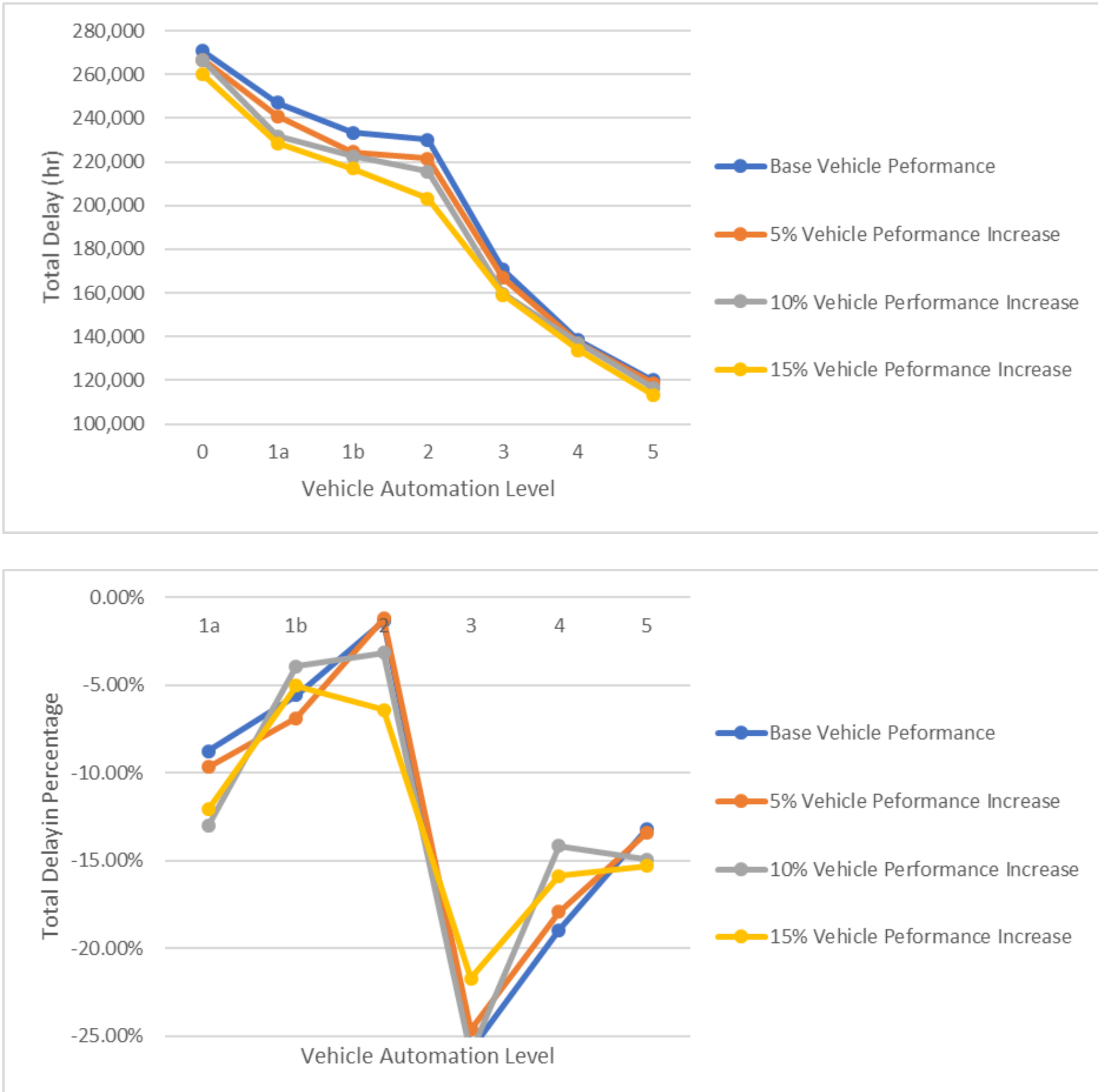
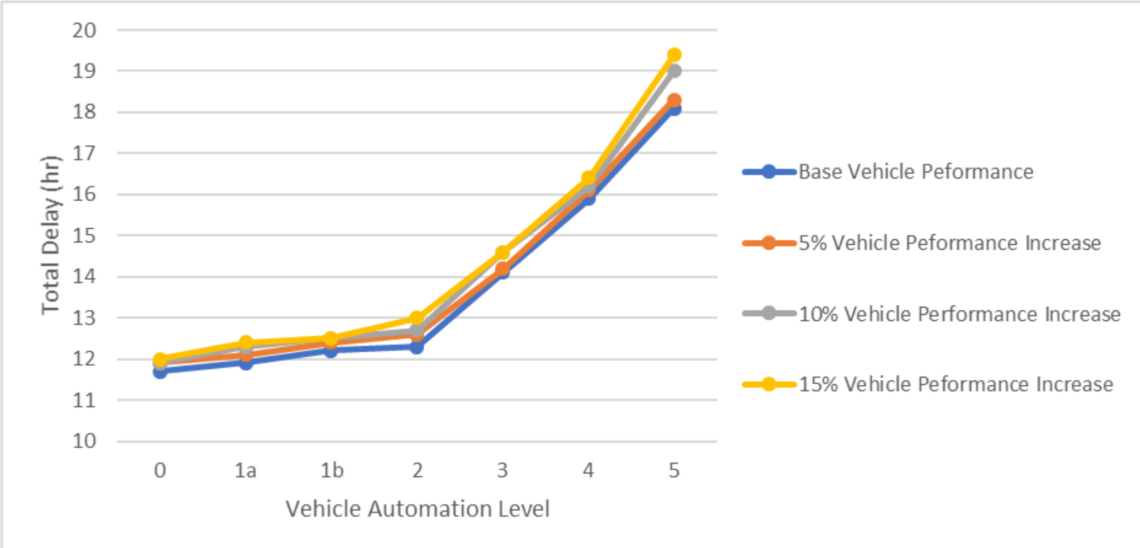


FIGURE 4.10 Traffic network total delay (in hours and percentage reductions) based on vehicle performance under 5 levels of automation.



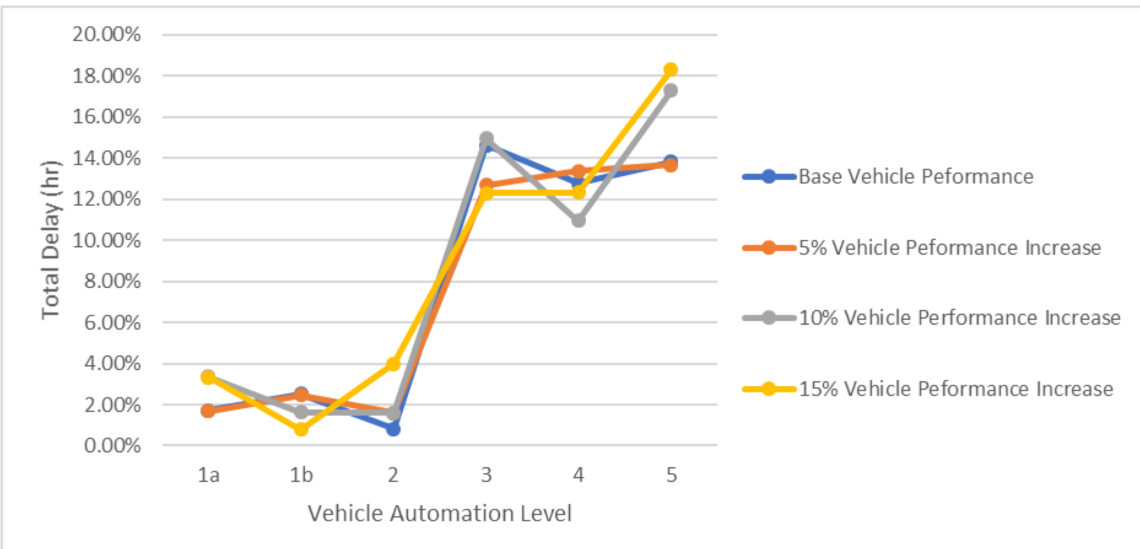


FIGURE 4.11 Traffic network average speed (in mph and percentage increase) based on vehicle performance under 5 levels of automation.

4.6 CONCLUSIONS

Upon an incident occurring along the freeway in urban or rural areas, one of the traffic calming strategies is to implement the en route diversion traffic operation to divert both trucks (SU and MU) and passenger cars to nearby alternative routes. However, seldom research has been done to specifically talking about such situations under non-recurrent large-scale incident situations. Large-scale incidents usually last longer and block more lanes than non-large-scale incident situations. And for our study, TransModeler simulation models are applied to analyze the delay reductions and cost savings for both trucks and passenger vehicles for such situations. The simulation models are based on real-life data. For studying a small network with the only freeway, alternative arterial and a few local roads, the biggest problem is to calculate or obtain a relatively realistic OD matrix for the trips allocated to the network. AADT data from E-TRIMS is extracted and error checked to calculate such OD matrix for the traffic network using the TransCAD. Then the OD matrix from TransCAD is incorporated in the simulations models to obtain traffic network performance statistics such as travel time, delay, etc. Some key findings from the simulation analysis results are:

- Delay reductions for the trucks as well as passenger vehicles are larger in rural areas than in urban area by implementing the en route diversion, because AADT is smaller in rural areas, and also there are fewer intersections in rural areas, which might attract more travelers to take the alternative route upon a large-scale incident on the freeway;
- The increase in the average delay for alternate route is huge if a lot of traffic is diverted to this route, especially when diverted traffic includes a lot of trucks since

they will spend more time in maneuvering. The percentage increase of average delay is even higher compared to average delay reduction for freeway traffic.

- The percentage of travelers accessing the updated travel time has a significant effect on persuading truck drivers as well as passenger vehicle drivers to take the alternative route;
- Cost savings in implementing the en route diversion strategy is huge for large-scale incidents occurring on the freeway when the incident duration is long. This indicates that the longer the incidents, the urgent the implementation of the diversion operations will be; and
- The CAV technology penetration will help improve the traffic detour operations better in terms of reducing delays and increasing travel speed. Similarly, this is true for truck performance increase.

In the long term, this research will be useful in helping practitioners in evaluating the alternative routes by comparing the benefit estimations. This study highlights the necessity and importance of the customization of en route diversion information to trucks for traffic management because truck drivers' primary choice is a freeway and if not well informed and guided, the chance of diverting from the freeway is very low for them. Such customized information includes the availability of alternate routes for trucks and travel time for trucks on the current freeway and alternate routes. This study is limited to a certain number of scenarios and study network. Future research direction will be the signal timing plans to accommodate diverted traffic on alternative routes. Another research direction would be comparing different alternative routes if there are multiple detour routes available to trucks. Truck drivers' en route diversion behavior is another research question left to be answered, and the survey work in undergoing. Drivers' en route diversion behaviors can be used to explain some of the results concluded above, such as why drivers prefer to remain in freeways in urban areas, and this is our next step in the truck en route diversion analysis for truck drivers' behaviors.

CHAPTER 5
SIGNAL PHASE TIMING IMPACT ON TRAFFIC DELAY AND QUEUE LENGTH-AN INTERSECTION CASE STUDY

A version of this chapter was originally written by Xiaobing Li, Asad J. Khattak, Airton G. Kohls. This chapter presents a revised version of this research paper by adding additional arterial signal control analysis under the Connected and Automated Vehicle environment. This paper was presented at the Winter Simulation Conference (WSC) 2016 in Arlington, Virginia at the Crystal Gateway Marriott on December 12, 2016.

Xiaobing Li's effort on idea formation, model construction, interpretation and paper writing, Asad Khattak's effort on instructions, as well as the instructions of Airton Kohls's are all recognized.

5.1 ABSTRACT

Traditional intersection traffic signal control strategy is a pre-determined signal with certain phase timing length for each circle. Studies focusing on adaptive traffic signal strategy have somewhat achieved the goal of reducing traffic system delay to some extent. However, few of them capture the benefit of using the queue length as the criteria under the connected vehicle environment, and this paper focuses on firstly identifying the potential saving of average system delay with agent-based simulation modeling, and secondly finding out the relationship between average system delay and average queue length for traffic approaching the signalized intersections. Through applying the agent-based simulation modeling approach in AnyLogic, findings show that average system delay could be reduced using optimized parameters (e.g. arrival rate, signal phase length, etc.), specifically, 5.29% saving of total average system time, 4%-28% traffic queue reduction for different traffic lanes, and a positive relationship between average system delay and the average traffic queue length is detected.

5.2 INTRODUCTION

An intersection is a junction at grade two or more roads either meeting or crossing and they are used to guide the traffic to make the right choice for a vehicle maneuver, such as turning right, left or simply going straight. Types of intersections controls include: stop signs, signalized, roundabouts, etc. specifically by using the number of road segments, there are 3-way, 4-way, 5-way, and 6-way intersections. Main goals for setting up those intersections are to satisfy the traffic demand with an efficient and safest way to control the traffic. Some of these intersections have a better way to manage the traffic and keep them moving in a smooth and safe flow, while others are not so well managed. But for safety and operational purposes, it is necessary and even required, to some extend to control the traffic arriving the intersections either in an automatic way or a manual way, thus creating an environment for the traffic to safely go across intersections efficiently. However, in a real situation, traffic queue will form at intersections, thus creating a lengthy delay when approaching intersections, and sometimes causing traffic incidents on the congested road. Therefore, achieving a more efficient and safer intersection is necessary and important not just for traffic planners, but truly matters to the drivers.

Current situation of the traffic control strategies at the intersection has evolved and improved through applying the advanced technologies during the last decades, especially for the signalized intersection in the urban area. It has evolved from the fixed time signal to the actuated signal according to the traffic demand, which is the traditional solution to solve the safety and congestion problem at intersections. Even though some achievements were achieved in the past, that doesn’t mean there is no space to improve the efficiency of traffic operations even further at intersections. Under the vehicle-connected environment, many areas could be researched, and the intersection is one of those areas that could be deeply studied. Recent improvements of the connected vehicle technologies include dedicated short-range communication (DSRC), global positioning system, etc. All these advanced technologies are developed to keep maintaining the goal of the efficient and safe traffic flow on the road. How can these advanced techniques be used at intersections to relieve the situation that people have to be delayed by the signals, where sometimes it is not necessary to stay that long at that intersection? Since queuing is an unavoidable situation at intersections when the traffic demand is high, it is necessary to conduct an in-depth analysis about how different techniques could be applied and finally improve the overall efficiency and safety conditions at intersections. Therefore, this paper is intended to present an in-depth analysis about how to use the information from the connected vehicle, then by simulating the real-world situation, we can properly propose the optimal solution to traffic signal control at intersections, and final results and suggested intersection traffic control strategies can be documented and delivered to traffic planners and managers, which will eventually benefit largely traffic flow.

Several objectives are to be achieved through the study in this area:

- Critically evaluate previous researchers' methods in studying the intersections;
- Evaluate the impact of Signal phase and timing, arrival patterns on the queue length approaching the intersections in this study;
- Simulation modeling on intersection performance: the average system delay and the average queue length at intersections using the data from the world congress research database; Give out recommendation regarding the intersection traffic control policy.

Following Figure 5.1 shows the framework that is used for this study of the impacts of traffic signal phase and timing on the intersection operational efficiency. We are going to test the hypothesis that under the optimized traffic signal environment, the operational efficiency will go up and the queue length will be reduced, more specifically how much percentage improvement will the simulation modeling technology help achieve the goals.

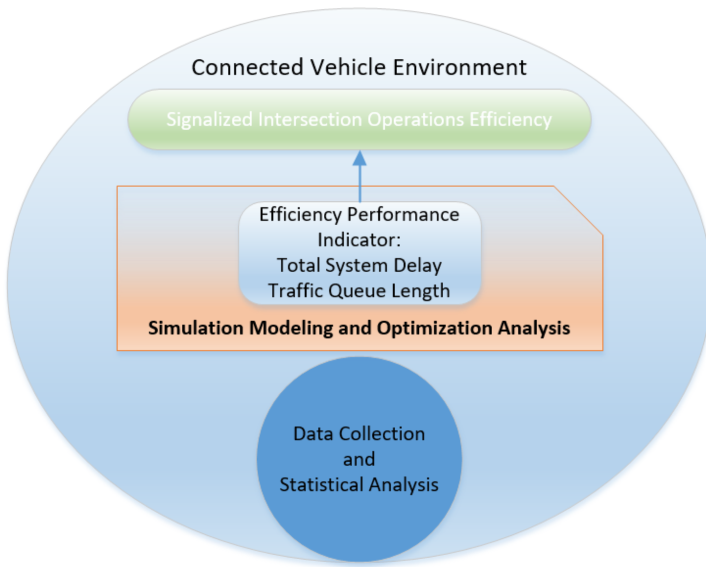


FIGURE 5.1 Conceptual framework of the study on intersection operational efficiency and safety.

5.3 LITERATURE REVIEW

Connect vehicle (CV) technology has been identified by many researchers to be one important role-playing in increasing the operations efficiency of signalized intersections. Some of the researchers, such as (Lin, Lo, & Xiao, 2011), are focusing on managing the queues approaching the intersection. They proposed a quasi-dynamic scheme to keep a balanced queue length for all approaches at the intersection in their study. In this way, the traffic queue would vanish at the same time. By testing the queue proportion line slope, the width of two regions, the proposed method can reduce the average delay about 15% when comparing to fixed time planning. Zhang, et al mainly focused on the queue length and control delay for field data and simulated data. By using the video image processors with virtual loops, they were able to get a higher accuracy of the estimation algorithm in their study when compared with traditional *Highway Capacity Manual* (HCM)-based intersection performance calculation methods. (Zheng, Ma, Wu, & Wang, 2013). Their effectiveness needs to be further explored with the real-time queue length data and connected vehicle technology can help provide more information about the traffic queue.

Other methods are still studied to increase the intersection operational efficiency in terms of delays or stops. El-Tantawy, et al investigated several ways including Reinforcement Learning (RL) method, traffic state representation, and action selection method, traffic signal phasing scheme, reward definition and variability of flow arrivals to the intersection. Simulation runs showed that RL-based adaptive traffic signal control outperforms other strategies in terms of average delay in many cases, especially in high traffic demand level.(El-Tantawy, Abdulhai, & Abdelgawad, 2014). Prashanth and Bhatnagar used a threshold-tuning algorithm for graded signal control. When compared with traditional traffic light control schemes, their approach showed a significant gain in system performance. (Prashanth & Bhatnagar, 2012). Coordination between intersections is also covered. Girianna and Benekohal formulated a discrete-time signal-coordnation model as a dynamic optimization problem and solved it using Genetic Algorithms (GA). The algorithm is applied to a one-way arterial network with 20 signalized intersections. Depending on the traffic demand's variation and the position of critical signals along the roadway, the algorithm intelligently generates optimal signal timing (offsets) along with individual arterials. (Girianna & Benekohal, 2004).

Another group of research is intersection studies under the CV environment. Goodall, et al. proposed a novel technique to estimate the positions of non-communicating vehicles based on the behaviors of communicating vehicles along a signalized arterial. Using this location estimation of unequipped vehicles, it achieved some improvement in delay, and speed when compared to using the equipped vehicle data only (Goodall, Park, & Smith, 2014). He, et al was trying to investigate the multimodal traffic signal control under the connected vehicle environment. They proposed a request-based mixed integer linear programming approach to accommodate multiple requests from different modes of vehicles and pedestrians. By comparing with state-of-practice transit signal priority in simulation, they were able to show 14%-25.9% reduction in average delay for different travel modes. (He, Head, & Ding, 2014). Girianna and Benekohal investigated the effectivesness of car-car communication based adaptive traffic signal intersection. A cluster-based data dissmination protocal is proposed and simulation of 7 intersections with the implementation of this approach showed a collision free result. (Maslekar, Mouzna, Boussedjra, & Labiod, 2013). Guler, et al used information from connected vehicles to better adapt the traffic signal. With different penetration rate ranging from 0% to 60%, the decrease in delay is up to 60% in low demand scenarios, and if the penetration rate is extremely low, the value of running this minimization delay algorithm is limited. 20-40% penetration rate seems to be a resonable range according to their study. (Guler, Menendez, & Meier, 2014)

However, few researchers are studying the safety issues at intersections. Li, et al talked about how to apply Markov Process to develop a stochastic dilemma zone protection algorithm, which made the end-green criterion be more updated in order to avoid vehicles trapping in dilemma zone. (P. Li, Abbas, & Pasupathy, 2015). Girianna and Benekohal achieved an intersection collision free result under the car-to-car communiation environment using simulaiton. Also, lack of the trajectory information of the vehicles may have a negative impact on the intersection performance and cooperative signal intersections are seldom covered in the literature. To raise the question whether it is safer to cross the intersections under CV environment becomes a valuable research area, which can be also found in Table 5.1. However, due to the reason that the intersection safety data is not obtainable, we focus on efficiency part in this study and later research on safety is continued.

5.4 METHODOLOGY

5.4.1 Data

The data to be used in this study comes from the Research Data Exchange website, which can be downloaded from (Transportation). The data is from the City of Detroit Connected vehicle data environment, which was collected during a queue length estimation field test being conducted in the Southeast Michigan test bed, during the 2014 Intelligent Transportation Systems World Congress. The primary goal of this field test is to use connected vehicles, in a connected environment, to support a queue estimation algorithm. Additionally, this field test demonstrated a real-world implementation of a connected vehicle environment, while showcasing the operation of its Data Warehouse and Data Clearinghouse, which are intended to support connected vehicle research. Nine

TABLE 5.1 Summary of Studies on Intersection Operational Efficiency in Literature

Authors	Relationship investigated with Connect Vehicle		Study Approach		Study Quality
	Operational efficiency	Safety	Method	Location and Sample Size	
Lin, Lo et al. 2011	Not CV related; Based on the selection of parameter *s*, which is the queue proportion.	N/A	Quasi-dynamic robust control; Queueing theory; Simulation; Cell transmission model.	N/A. Estimation.	Medium
Li, Abbas et al. 2015	N/A	Reduce the number of vehicles in dilemma zone	Markov Process; stochastic dilemma zone protection algorithm.	Peppers Ferry Road and North Franklin Street in Christiansburg, VA; 9 hour period traffic with 3 lanes and 4 approahces. Around 22,000 in volume.	Very High
Maslekar, Mouzna et al. 2013	Car-to-car communication reduces cars approaching intersection by up to almst 20%.	Collisin-free system	Density estimation; Clustering algorithm.	Simulation of a topology 3000m by 3000m with 7 intersections.	High
El-Tantawy, Abdulhai et al. 2014	Not quite related to CV; 27%, 28%, 28% reduction in average delay; queue length and emissions seperately.	N/A	Reinforment learning based adaptive traffic signal control;	downtown Toronto, Front Street, and Bay Street; 4660.	Very High

TABLE 5.1 Continued

Authors	Relationship investigated with Connect Vehicle		Study Approach		Study Quality
	Operational efficiency	Safety	Method	Location and Sample Size	
(Zheng, Ma et al. 2013	Queue length and Control delay estimated work well with the proposed algorithm. But not quite related to CV.	N/A	Video image processing; Queue length estimation algorithm;	Northbound approach of the intersection of SR 99 and 200th Street SW, Lynnwood, WA; VISSIM simulation; 1788	High
Goodall, Park et al. 2014	Low penetration rate; A small improvement in delays, speeds and stopped delay.	N/A	Location estimation algorithm; Predictive microscopic simulation algorithm;	U.S. 50, a four-intersection arterial corridor in Chantilly, Virginia, Data collected in 2003 between 3:00 p.m. and 4:00 p.m. on weekdays.	High
He, Head et al. 2014	Vehicle-to-infrastructure communication; Reduce average bus/pedestrian/passenger car delay.	N/A	Request-based mixed-integer linear program.	VISSIM simulation; N/A	Very High

TABLE 5.1 Continued

Authors	Relationship investigated with Connect Vehicle		Study Approach		Study Quality
	Operational efficiency	**Safety**	**Method**	**Location and Sample Size**	
Prashanth and Bhatnagar 2012	Not CV realted; Comparions of fours algorithms in terms of avarage trip waiting time;	N/A	Traffic light control algorithm (TCL); Three threshold-based TCLs, PTCL, QTCL-SA, and QTCL-FA-NFS; Stochastic optimization.	a network of nine signalized junctions with 24 roads around the Indian Institute of Science campus in Bangalore Simulation with 25,000 cycles and 1500 vehicles.	High
Girianna and Benekohal 2004	Not CV related; Coordinated signal intersections; Computing time efficiency increased;	N/A	Genetic algorithm; Simple genetic algorithm.	N/A	High
Guler, Menendez et al. 2014	Car-to-infrastructure; Significant reduction of avarage delay;	N/A	Minimizing delay; Minimizin stops.	Simulation.	High

Notes: 1) N/A represents it is not available in the study;
2) Study quality ranges from very low, low, medium, high to very high, totally 5 levels

instrumented vehicles were a part of this field test. Their data, along with data from instrumented intersections in the test bed and number of travel information messages were obtained via subscriptions to the Data Warehouse and Clearinghouse. As for the queue length data, those were collected by researchers in the field, with the aid of video recordings during the field test. This Data Environment includes 4 data sets: 1) Vehicle Situation Data, 2) Intersection Situational Data, Traveler Situation Data and the Queue Length Data sets.

5.4.2 Analysis Method

By using this dataset, our focus is on the testing of the efficiency of intersection operations, which is, to some extent, related to the queuing length. Longer length means more waiting time and system delay. Also, by studying traveler's and vehicles situational data, we may find out whether drivers are taking the proper actions or not.

Simulation is the chosen method towards studying the traffic flow at intersections. By investigating the performance of each indicator, a general clue of how and to what extent the connected vehicle will impact on the intersection operations is obtained. Statistical data analysis is another fundamental analysis method toward analyzing the basic distribution information of the traffic and such information will be used as the input into the simulation model, the result will finally affect the outcome of the simulation model.

5.5 RESULTS

5.5.1 Descriptive Statistics

The vehicle situational data from the ITS world congress data is used to study the arrival pattern, with speed data and vehicle length data. Based on the fundamental traffic flow theory, we have the relationship between flow, speed and density, which is,

$$\boldsymbol{q = k \times v} \qquad \textbf{Eq. 5.1}$$

Where q = flow, v/h/l; k = density, v/m/l; and v = speed, m/h.

In order to determine the arrival rate, which is flow rate, we need to determine the density and speed. Through doing the statistical analysis, the results show most of the time the vehicle length is 500 cm, which is equal to 16.4 feet. Without gap between vehicles, the jam density is estimated to be ${}^{5,280}/{}_{16.4} = 321$ vechiles/mi/lane. By considering the space between vehicles as 10 feet, also the variance of the vehicle length, finally the value of 170 is assumed for the jam density. The Greenshield's linear model is used, and its formulation is shown as below:

$$\boldsymbol{v = v_f\left(1 - \frac{k}{k_j}\right) \; or \; k = k_j\left(1 - \frac{v}{v_f}\right)} \qquad \textbf{Eq. 5.2}$$

Where v_f =free-flow speed and the posted speed limit is 25mph, and k_j = jam density.

Then,

$$\boldsymbol{q = k_j\left(1 - \frac{v}{v_f}\right) \times v = 170\left(v - \frac{v^2}{25}\right)} \qquad \textbf{Eq. 5.3}$$

The speed data we analyzed is as follows. Based on this data, the speed of vehicles approaching the intersection has the minimum value 0, maximum value 42.94 m/s, and the mean 3.5425 m/s shown in Table 5.2. Assume using the triangle distribution for speed, so the arrival rate is also calculated as Triangle (0, 517, and 1,063) representing number of vehicles coming to this intersection per hour with minimum value 0, maximum value 1,063 and the mean value 517.

TABLE 5.2 Speed Data Descriptive Statistics (m/s)

	N	Minimum	Maximum	Mean	Std. Deviation
bundle_fundamental_speed_metersPerSecond	930,215	.00	42.94	3.543	4.637

Signal phase and timing (SPAT) are also very important to determine the queue length, and the SPAT data is analyzed to describe the general statistics and is shown in Table 5.3. Where current state 1 means green ball, 2 means yellow ball, 4 means red ball, and 16 means left arrow.

TABLE 5.3 Signal Phase and Timing Descriptive Statistics

		Time to change(s)			
Current state	**Frequency**	**Min**	**Max**	**Mean**	**Std. Deviation**
0	195,788	0.1	63.7	25.291	24.2264
1 / green	969,970	0.1	48	8.616	10.1704
2 / yellow	260,459	0.1	75	7.638	14.0866
4 / red	1,418,919	0.1	93.2	15.313	15.104
16 / left arrow	25,253	7	50	45.97	2.8865

5.5.2 Simulation

The simulation is based on one two of the intersections, with a horizontal road named Shelby and two vertical roads named W Congress and Larned. The vehicle's direction is shown in Figure 5.2 below.

While in Figure 5.3, it is showing the traffic flow logic representing the arrival rate, traffic separation, traffic queue, exiting choice, etc, and the traffic signal control. Because

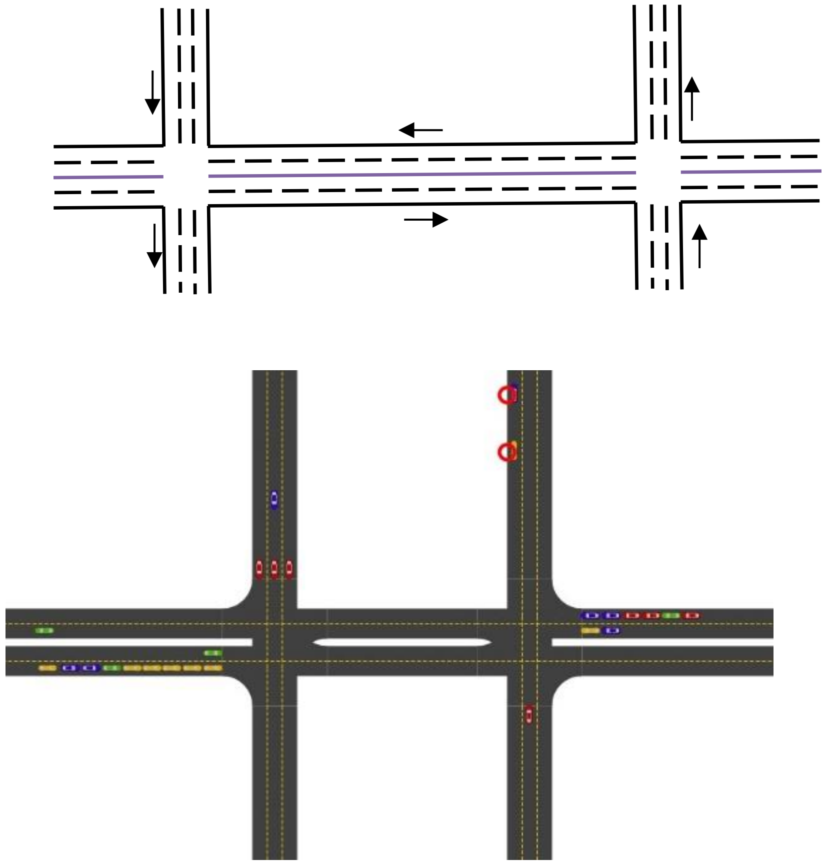
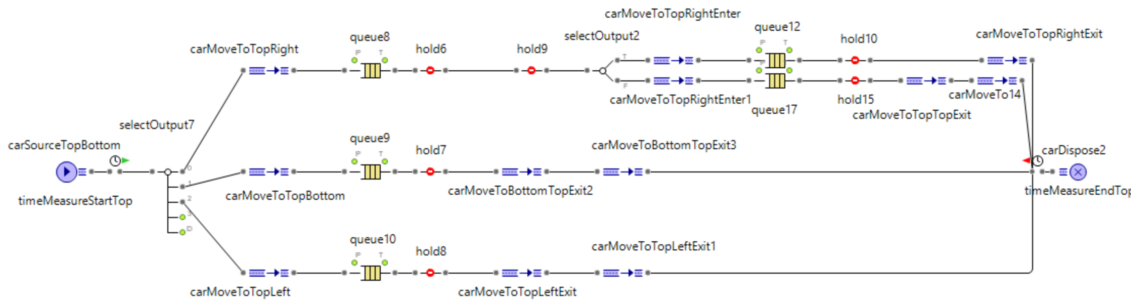


FIGURE 5.2 Road configuration for two intersections modeling and simulation.



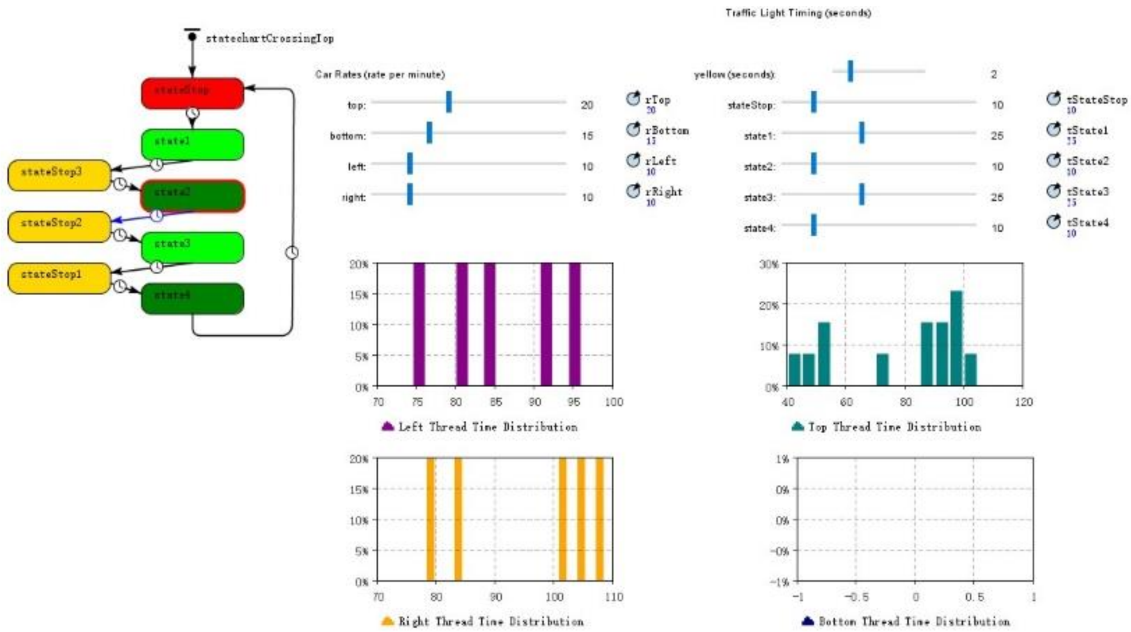


FIGURE 5.3 Traffic flow logic and signal control.

of the limitations of the personal learning edition of Anylogic, which is a multi-method simulation modeling tool developed by The AnyLogic Company supporting agent-based, discrete event, and system dynamics simulation methodologies, some of the information cannot be built into the simulation model, but still some of the findings can be obtained to show how traffic flow rate near the intersections, lane choice, and the signal phase and timing affect the whole system. We are especially interested in one of the intersections, with Larned and Shelby's roadway involved. Optimization procedures are based on the total system average delay for the traffic in this small modeling two intersections, and to simplify the optimization process, we initially set the traffic arrival rate as 15/min, 15/min, 20/min and 6/min from the top, bottom, left and right entrance into the system. Some of the simulation results are shown in the following Figure 5.4.

5.5.3 Queue Statistics based on Simulation

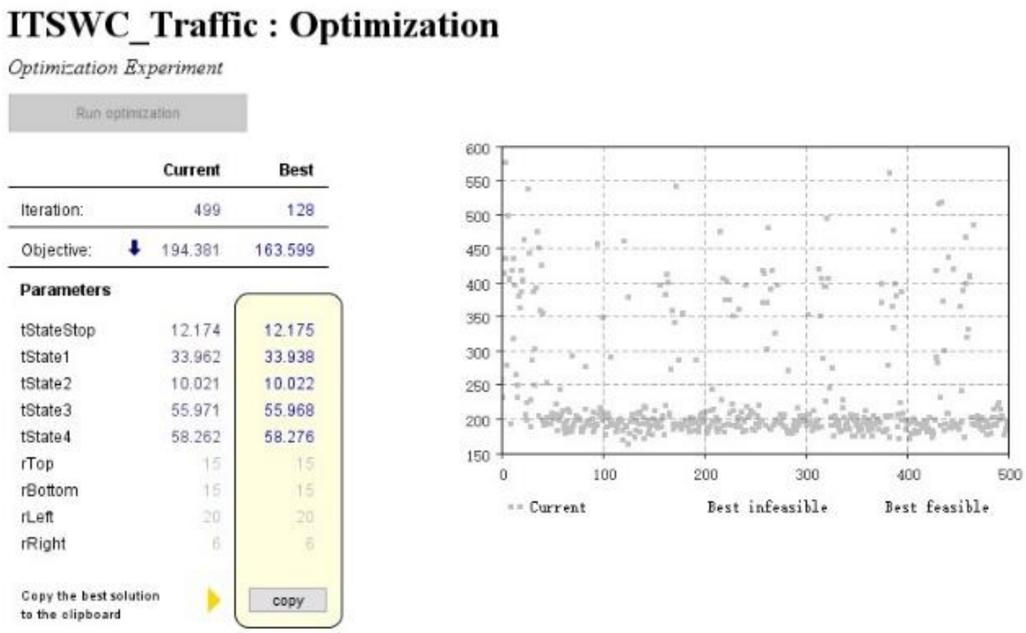
Based on the parameters given above, the queue statistics of the chosen intersection are summarized in the following Table 5.4. The original setting is 10 seconds for red, 25 seconds for the green on Larned road and 10 seconds for the green on Shelby road.

Through the optimization procedure with 500 runs, we have the new values for those parameters, which is shown as below (see Figure 5.5 for example).

$tStateStop = 12.175, tState1 = 33.938, tState2 = 10.022$

$tState3 = 55.968, tState4 = 58.276, and\ yellow\ time = 7.6$

Total average time saving is 163.599 - 154.943 = 8.656 seconds and the total percentage reduction with the optimized parameters is $\frac{163.599-154.943}{163.599} \times 100\% = 5.29\%$, which shows that adjusting the signal timing according to the incoming traffic is a



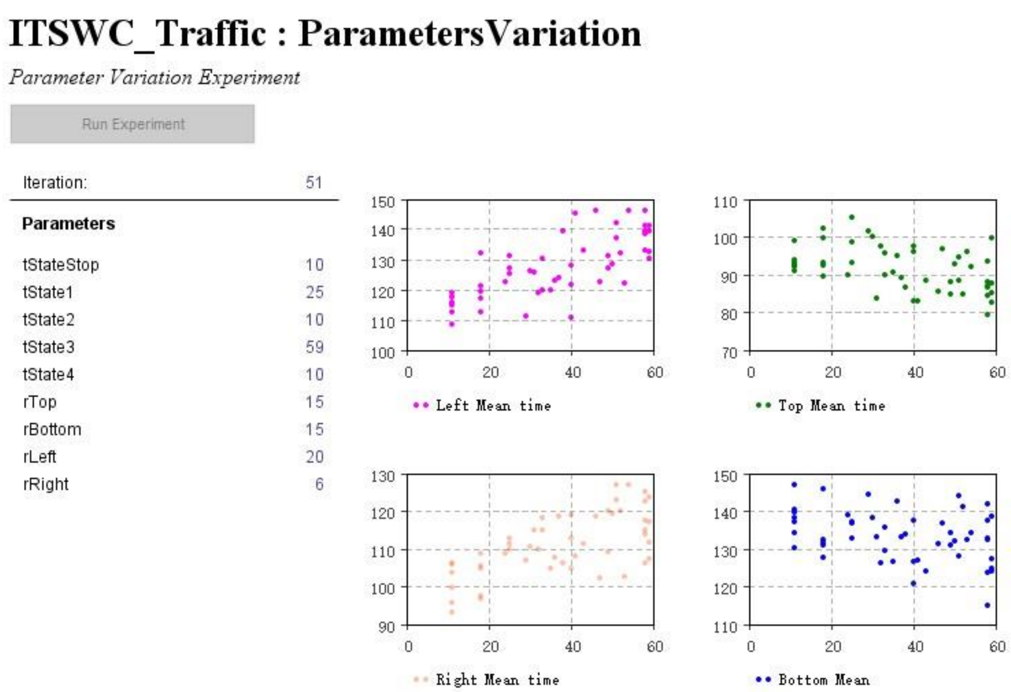


FIGURE 5.4 Optimization and Parameter selections.

TABLE 5.4 Queue statistics from simulation

		Time to change (in Seconds)		
Direction	**Simulation time**	**Min**	**Max**	**Mean**
Bottomtoleft	3 hours	0	9	1.69
Bottomtotop		0	35	12.905
Bottomtoright		0	13	3.24
Lefttoright		0	15	2.727
Lefttotop		0	7	1.158
Righttotop		0	8	1.931
Righttoleft		0	19	7.145

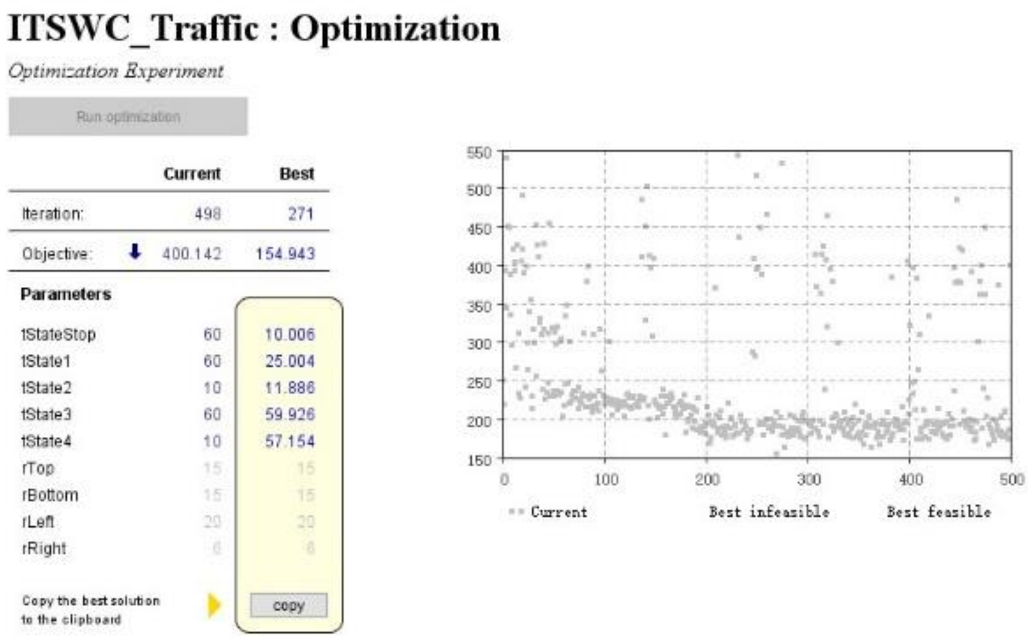


FIGURE 5.5 Optimization of parameters.

promising time saving strategy for the total traffic system. Also, the queue approaching the intersection is shown in the following Table 5.5 Based on the output from the model, it is found that the queue length is also reduced with 4% - 28% range.

TABLE 5.5 Queue statistics after simulation optimization

		Time to change (in Seconds)		
Direction	**Simulation time**	**Min**	**Max**	**Mean**
Bottomtoleft	3 hours	0	8	1.561
Bottomtotop		0	33	10.384
Bottomtoright		0	11	2.874
Lefttoright		0	15	2.065
Lefttotop		0	7	0.828
Righttotop		0	8	1.708
Righttoleft		0	18	6.854

5.6 LIMITATIONS

One of the disadvantages of the personal learning edition AnyLogic simulation model is that is cannot dynamically update the parameters in the agent-based model, so the traffic arrival rate is not dynamically updated according to the real traffic, by just analyzing the traffic data using world congress data, we have the distribution of the traffic arrival rate and then use that as the input of the simulation. However, with limited data being analyzed, it may not represent the real traffic pattern, and also lane choice (preference to take left, middle, or right lane) is also another important factor that will impact the overall length of the traffic queue. Further, a study on the lane choice is a promising research direction. Even though this study two nearby intersections are modeled, we focused on just one of them. How the other intersection impacts the overall system performance is not included in this study, so future intersection coordination is another step forward to better understand the traffic characters at the intersection.

5.7 CONCLUSIONS

In this study, the traffic flow, and signal control operations at the intersections are investigated. Several factors will impact the queue length approaching the intersection and the performance of the intersection. The traffic demand, traffic arrival pattern, drivers' behavior, drivers' lane preference when approaching the intersection, signal phase and timing, infrastructure, etc. Particularly, in this study, the impact of traffic signal phase and timing on the queue length and the total system delay are evaluated based on the traffic demand analyzed from the world congress data. By simulating the intersection and optimizing the traffic signal parameters, it is found that there is still potential travel time savings according to the traffic coming to this intersection, and the percentage reduction in this paper is approximately 5.29% in time saving, and the queue length reduction percentage is even as high as 28%. However, this study is limited to one configuration of demand pattern. While in other cases, such as highly congested traffic intersection, the benefit of running the optimization model maybe not so obvious. This pilot study of intersection performance will provide more insights how to integrate the agent-based model into traffic engineering research. One suggestion for traffic planning and control practitioners is to adjust the traffic signal control according to the traffic queue length approaching the intersection for medium traffic demand where small traffic queues (e.g. 10 vehicles in a queue) are forming frequently during the daytime. Even though max queue length data is collected in the world congress dataset, it is not related to the signal phase and timing, so it is hard for us to find valuable information through that dataset, so future connected vehicle research is suggested in order to fully optimize the traffic signal system, where queue length data is quickly obtained and dynamically transmitted to the centralized intersection signal controller, and one future possible implementation is to install the camera-based queue detection system instead of the now most popular used conventional electromagnetic induction loop detectors. The detector can detect the presence of vehicles, but it cannot detect the traffic queue at the intersection. Another potential focus area for future work is the development of road network topologies of varying size and configuration to investigate under what conditions the various signal control strategies, as well as the types of detection equipment, are most, and least effective.

CHAPTER 6
CONCLUSION

By integrating and mining traffic incident and crash data, the dissertation aims to explore the characteristics associated with large-scale traffic incident and how they can be used to evaluate the effectiveness of the en route diversion strategy. First, this research starts by extracting data from multiple databases including LOCATE/IM incident data; E-TRIMS crash data; RDE signal timing data; and other data source such as weather history. The research constructs new datasets for each study by integrating some of these databases through powerful programming software. After data integration and preparation, the first study applies data mining techniques and statistical modeling approaches to identify large-scale traffic incidents and predict incident duration both empirically and in real-time. This dissertation research study is timely given that there is an increasing trend of large-scale traffic incidents occurring in the state of Tennessee in recent years, and there is a strong need for methods designed specifically for dealing with large-scale traffic incidents.

The research contributes to the state-of-art of incident management strategies by demonstrating how to identify a large-scale incident by using advanced data mining techniques. The en route traffic diversion strategy under large-scale incidents has the potential to be incorporated in an ATIS application, e.g. display of travel timing savings by taking alternative routes, especially under the CAV environment. This dissertation study demonstrates a methodology framework to analyze large-scale incidents and en route diversion strategy. The results indicate huge benefits when applying en route traffic diversion regarding under large-scale traffic incidents. Future research would be integrating signal timing operations under CAV to further improve traffic network savings.

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VITA

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Mr. Li has always been active in research as well as in social activities. He received several scholarships and awards including First-class Academic Scholarship, Graduate Student Senate Travel Award. He served as a reviewer for a couple of journals and conferences. He is a member of the ITE and served as a social director in UTK student chapter. He also served as a vice president of Chinese Students & Scholars Association at The University of Tennessee, Knoxville from May 2014 to May 2016.