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FINAL REPORT
FREIGHT FLOWS AND INCIDENT MANAGEMENT

Authored by:
Asad Khattak, Ph.D. Xiaobing Li, Ph.D., Sevin Mohammadi, Mohsen Kamrani, Ph.D., Mark Burton, Ph.D., and David Clarke, Ph.D. P.E.

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16. Abstract

This study models and simulates vehicle behaviors based on large-scale traffic-incident congestion and the availability of Advanced Traveler Information Systems (ATIS). The study examines how well detours can help truck and passenger vehicle drivers avoid unexpected congestion and associated delay costs. En-route diversions could also decrease secondary incidents and speed up traffic incident management processes. This study reviewed candidate incident management strategies from the USDOT and various states, including communication protocols and en-route diversion assistance. The study found, analyzed, and verified easily accessible ATIS data sources and used the data to develop a freight en-route diversion analysis approach. To verify the accuracy of driver behavior in this study, researchers conducted a small survey of truck driver diversion behavior. A synthesis of this survey and surveys conducted by previous studies revealed that truck drivers are interested in improving safety through en-route diversion. Truck drivers value familiarity, incident information, and notification through smart or cell phone when making en-route diversion decisions. Besides accurately depicting diversions and outcomes under the status quo, the underlying simulation model accounts for behaviors and outcomes under improved conditions linked to infrastructure betterments, improved information delivery, or automation. Through these simulations, the study found that increased traffic information penetration and connected and automated technology can increase speeds and decrease overall travel delay and costs. This research indicates that ATIS and other emerging technologies could result in fewer delays and secondary incidents.

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Executive Summary

Large-scale traffic incidents can cause significant delays, especially if a roadway has to be closed for many hours. Such incidents, e.g., those involving multiple vehicles, not only delay passenger vehicle drivers, but also impose significant costs on truck drivers/carriers. Incident management, traffic congestion and subsequent delays are a national problem, with annual costs estimated at $120 Billion in 2011 (Wilmot 2015). Traffic-Incident Management (TIM) is a program typically coordinated through State Departments of Transportation (DOTs) and is focused on detecting, responding, and clearing traffic incidents as quickly and as safely as possible. A significant part of a TIM program is providing traveler information or alerting other vehicle drivers about the incident so that they can find alternative routes. This report provides a review of the USDOT traffic incident management guidelines and best practices, and highlights selected state practices. The report also includes an in depth look at TDOT's incident management practices and a literature review of large-scale incidents and truck en-route diversion strategies.

The research objective is to explore the occurrence of various large-scale incidents and simulate the effects of notifying drivers in time for them to take alternative routes. Advanced Traveler Information System (ATIS) can divert trucks and passenger vehicles so that they can effectively avoid incident-induced congestion and associated delay costs. The efficient diversion of trucks to alternate routes in response to a roadway incident rests on several elements: expected incident duration, available alternatives, trip time or distance remaining, and diversion-induced congestion on alternative routes. The speed and accuracy with which information is conveyed to drivers further influences the effects of these factors. Consequently, the research analyzes information describing truck driver en-route diversion behaviors and correlates these behaviors with incident, roadway, and trip characteristics.

In order to develop the simulations, this study found, analyzed, and verified appropriate data sources and attributes of easily accessible relevant data. Researchers utilized the data in a newly developed freight en-route diversion analysis approach (simulation) that is based on an ATIS framework that quickly disseminates pertinent information to trucks and other vehicles. The study analyzes the impacts of potential truck en-route diversions in response to large-scale incidents. To verify the accuracy of truck en-route diversion behavior in simulations, the study also conducted a survey of truck driver diversion behavior. This survey, along with others conducted by various federal and state agencies/departments, provides insight into what information drivers prefer during en-route diversion decisions. Driver survey data was combined with secondary data describing large-scale incidents and other attributes. The data includes information on truck flows in the network that can be used in models and simulations to identify likely truck diversion choices and their outcomes under various disruption scenarios.

Beyond accurately depicting diversions and outcomes under the status quo, the underlying simulation models mimic behaviors and outcomes under improved conditions through infrastructure betterments or improved information delivery and emerging technologies. The modeling and simulation undertaken in this study can help guide TDOT policies and the predicted reductions in freight delay costs can be an important element in project evaluation. This report provides recommendations to appropriate TDOT divisions. The project has leveraged opportunities provided by Intelligent Transportation Systems (ITS), such as ATIS and automation technologies, to effectively manage truck-involved incidents. The researchers have analyzed the current situation regarding large-scale incidents in Tennessee, modeled and simulated likely truck en-route diversions and consequent outcomes under various disruption scenarios, and quantified the benefits from appropriate truck diversion schemes. Results indicate that the implementation of customized travel update information is the key for better incident-induced congestion management through passenger vehicle and truck traffic diversion. Survey results suggest that different truck drivers have different preferences depending on their contract, value of time, and familiarity with available diversion routes. Simulation indicate that strategies such as increasing traffic information penetration and connected and automated technology can increase speeds and decrease overall travel delay and costs. Diverting traffic during large-scale incidents can reduce delays and secondary incident occurrence.

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1.0 INTRODUCTION

The Freight Flows and Incident Management Project provided researchers at the University of Tennessee Center for Transportation Research an opportunity to model large-scale incidents and simulate en-route traffic diversions and Advanced Traveler Information System (ATIS). Such advanced information can give travelers the opportunity to choose alternative routes if they are comfortable with the available detour routes. This research performed a review of incident management practices as well as a literature review of large-scale incidents and truck route diversion strategies. The study gives specific focus to the role of the Tennessee Department of Transportation in Traffic Incident Management (TIM) and to the development of an ATIS framework for dissemination of information to truck drivers. The simulations used a number of verifiable data sources. Researchers used simulations to study and develop a freight en-route diversion analysis approach, and to estimate the impacts of truck en-route diversions in response to large-scale incidents. Finally, the report makes recommendations for TDOT Divisions.

Traffic congestion is a major problem on US roadways, but in the case of incident-induced congestion, procedures to enhance the timeliness of ATIS can reduce travel time uncertainty and prove beneficial for road users. According to the USDOT Bureau of Transportation Statistics, Tennessee is ranked ninth in the nation for major truck freight flows to, from and within the state. The geographic location of Tennessee can explain a substantial amount of through truck traffic, as it is surrounded by eight states. Trucks transport nearly a trillion dollars of cargo annually in Tennessee. Because of its growing population, the state needs to address traffic congestion. According to The Road Information Program (TRIP), 43 percent of Tennessee's major urban highways are congested. Total traffic congestion costs Tennessee motorists a total of $2.8 billion each year in the form of lost time and wasted fuel (TRIP 2017). Annual time wasted from congestion ranges from 28 hours per capita in Chattanooga to 45 hours per capita in Nashville (TRIP 2017). Incidents cause some of the congestion, and the costs of such highway incidents, particularly crashes, are substantial. Furthermore, the Highway Fatality Rate for fatalities per 100 million vehicle miles travelled is 1.40 in Tennessee versus 1.09 for the United States (USDOT 2015). Notably, advanced traveler information penetration can reduce traffic congestion, improve TIM response times, and diminish secondary incidents. However, the extent of potential benefits from route diversions and improvements through intelligent technologies not clear.

Traffic incident management is a program typically coordinated through Tennessee's Department of Transportation and focuses on detecting, responding, and clearing traffic incidents as quickly and as safely as possible. TDOT's TIM program utilizes available tools through Intelligent Transportation Systems (ITS) and established lines of interagency communication from a series of communication centers, as well as public notifications that provide a strategic standpoint to reduce impacts of traffic incidents. TDOT's strategy also incorporates tactical policies and procedures such as an incident command structure, removal laws, and quick clearance incentives.

The purpose of this research was to examine how different rates of ATIS penetration impact en-route diversion choices, and how this diversion mitigates the impact of major incidents on Interstate freeways. The study applied a percentage of information penetration to different vehicle types on freeways to simulate traffic under various conditions. One research objective explores the potential of early ATIS traveler information penetration on congestion delay reductions. Early ATIS warnings can divert trucks and passenger vehicles so that they can more effectively avoid incident-induced congestion and associated delay costs. Diversion efficiency depends on several elements including expected incident duration, available alternatives, trip time or distance remaining, and diversion-induced congestion on alternative routes. The effects of these factors are further influenced by the speed and accuracy with which information is conveyed to drivers. Consequently, the research analyzes information describing truck driver en-route diversion behaviors and correlates these behaviors with incident, roadway, and trip characteristics.

The scope of this study is limited to large-scale traffic incidents on major highways. Incident costs include the value of time lost by passenger vehicle drivers and commercial vehicle operators. The estimates for the cost of delay caused by an incident assume that the vehicles have access to one cleared lane, and that each vehicle will have varying rates of incident duration delay based on information penetration rates; delay also includes the time it takes for accumulated traffic to dissipate after the incident is cleared. Thus, the total delay time is calculated based on the delay for each vehicle in the simulation. Some vehicles may deviate to other routes and others may decide to remain on the same route. While this may reduce the overall delay, each simulation run will allow drivers to be given information on delays to be expected on the main route (due to the incident) and the potential delay on the alternate route/s. Therefore, those leaving the main route (typically freeway) will likely experience less delays than if they had stayed on the main road. The simulations also assume that traffic is flowing on at least one unblocked lane, but does not account for "rubber-necking." That is, vehicles in the opposite direction are assumed to be not affected by the incident even though experience shows that an incident almost always has an effect on adjoining lanes, driven by the curiosity of drivers. This issue is beyond the scope of this study.

The investigations in this study include the following. To review national and state practices and laws as documented in the literature, review practices in Tennessee, develop a procedure to estimate the cost of crash incidents dependent on their time of occurrence and duration, and use this procedure to evaluate simulation variations that calculate delay reductions due to traveler information penetration and en-route diversion. Individual aspects of the methodology are addressed in the following chapters.

2.0 LITERATURE REVIEW

Traffic Incident Management (TIM) consists of planned and coordinated multi-disciplinary processes that detect, respond to, and clear traffic incidents in order to restore normal traffic flow as safely and as quickly as possible. Effective TIM can reduce the duration and impacts of traffic incidents and improve the safety of motorists, crash victims and emergency responders (USDOT 2018). Publications by the US Department of Transportation (USDOT) provide guidance regarding traffic incident management, including information about local, state and national efforts for TIM efficiencies and planning. This literature review presents incident management practices that are currently in place by the U.S. Department of Transportation (USDOT) and various State DOTs. TIM processes conducted by the Tennessee Department of Transportation (TDOT) are found in Chapter 3.0.

This review covers traveler information strategies that departments use to alert motorists of potential congestion and suggest en-route diversion practices, specifically those issued by Advanced Traveler Information Systems (ATIS). Traveler information is the communication of various incident-related information (e.g. location and severity of incident, estimated clearance time, alternative routes, etc.) to motorists at all stages in their journey, including motorists who are at or approaching the scene of the incident, or those who have not yet departed for the trip. This information serves to reduce traffic demand and improve responder safety, reduce the potential for secondary incidents and allow motorists to alter their routes. The various tools and strategies that have proven effective in providing traveler information include 5-1-1 systems, used in more than 30 states; traveler information websites, used in more than 40 states; media partnerships, used in about 55 metropolitan areas; dynamic message signs (DMS), used in about 80 metropolitan areas; and DMS with standardized messages, used in about 75 metropolitan areas (USDOT 2010).

Motor vehicle traffic accidents have several characteristics that responders use to identify the accident's type. These characteristics are varied and, depending on the first responder, can include the number and types of injuries, the number and types of vehicles involved, and whether there are secondary considerations such as hazardous materials spill or fire. The goal of TIM is to secure the area and resume traffic flow as quickly as possible. Large scale incidents are those that involve multiple vehicles and generally happen on high-capacity and high-speed roadways. These incidents can cause hours of delay and may require various command teams to secure the area and clear the roadway. When large-scale incidents involve semi-trailer trucks (either single unit or multi-unit), it can be much more hazardous and time-consuming to clear them. Truck-involved crashes are often disruptive, costly and can be deadly. Large scale accidents may also cause secondary events, compounding existing safety concerns. As freeway demand increases, both for freight transport and personal vehicles, it will become harder to address the safety concerns of drivers, travelers, and traffic operations managers.

En-route traffic diversion is one possible solution to safety concerns and exorbitant delay costs. Generally, when there is unexpected congestion on the freeway, drivers must patiently wait for TIM responders to complete their tasks. However, if advanced congestion warnings are provided, drivers can potentially take an alternative route. Researchers involved in this study have reviewed literature regarding en-route diversion practices in order to understand attributes that influence alternative route selection. En-route diversion behavior is often influenced by available traffic information, expected length of delay versus regular travel time, available alternate routes, and perceived safety/congestion level on alternate routes. Notably, real-time traffic information can influence diversion behavior. Providing clearer information on delays and congestion sooner may help truck drivers make more informed en-route diversion decisions.

2.1 Traffic Incident Management (TIM) Practices

Traffic Incident Management is a prearranged and strategic process involving coordinated efforts between a variety of public and private sector partners including local police, firefighters, emergency medical services, towing and recovery services, as well as state DOT personnel, public safety personnel, hazardous material contractors and various media (USDOT 2018). Traffic incidents are a major contributor to increased congestion. USDOT estimates that traffic incidents are the cause of about one-quarter of congestion on US roadways. They also estimate that for every minute a freeway lane is blocked due to an incident, four minutes of travel delay time are added. Based on wasted time (approximately 4.2 billion hours) and wasted fuel (about 2.8 billion gallons), the congestion cost is about $87.2 billion per year (USDOT 2010).

Over time, various tools and strategies have been developed and implemented to improve overall TIM efficiencies. However, the nature and extent of these tools and strategies in use are highly variable across the United States, reflecting different priorities, congestion effects, levels of program maturity, and investment. This study has collected information on different aspects of incident management practices of the federal government and state Departments of Transportation (DOT) from their websites and online publications. This includes TIM strategies outlined by the United States Department of Transportation (USDOT), and the DOTs of Arizona, Colorado, California, Florida, Georgia, Indiana, Iowa, Louisiana, New Jersey, New Mexico, New York, North Carolina, Ohio, Texas, Utah, Washington, and Wisconsin. Chapter 3.0 explores Tennessee TIM and Advanced Traveler Information System (ATIS) protocols.

2.1.1 U.S. Department of Transportation

The USDOT provides guidance and best practice suggestions regarding elements of traffic incident management. Various publications provide information on statewide TIM assessment, performance measurement, the critical role of TIM in national preparedness, effective communication such as ATIS, and various program elements. Best practices include information on TIM planning and training, on-scene operations, technology use, and program management and administration. The USDOT's goal is to promote, develop, and sustain effective TIM programs that can operated locally, regionally, sitewide, across jurisdictional boundaries, and federally. USDOT stresses the importance of formal TIM programs and training. USDOT analyzed important elements of TIM programs and determined several characteristics associated with high-performing programs.

USDOT publications outline various TIM components that can provide consistency and interoperability across geographic areas. The list of these components is complex and includes legislative initiatives, multidisciplinary education, performance measurements and all-inclusive communication. The components used to completely achieve all objectives include training, policies and laws, partnerships, communications, and the creation of operating standards and measurement. The aim is to have constant and reliable availability of traffic incident responders and equipment throughout each day and in every location.

Traffic Incident Management training includes multidisciplinary TIM training that ensures incident responders are cross-trained regarding on-scene roles and responsibilities, and have a thorough understanding of the Incident Command System. Multidisciplinary TIM education encourages widespread adoption of procedures for quickly clearing incident-involved vehicles, cargo, and debris. Also, driver training and awareness programs can teach drivers how to prevent secondary incidents. Policies and laws include Move Over/Slow Down laws that ensure motorists provide a safe buffer for responders; and state TIM policies that support TIM goals including responder safety, safe and quick clearance, and interoperable communications. Partnerships, both public and private, encourage participation in TIM programs at the state, multi-state, regional, and local levels, as well as develop awareness through education opportunities that educate motorists on the shared responsibilities in safe and quick incident clearance. ATIS is one of the ways incident responders and motorist can engage in the communication that must take place. On that note, practitioners need guidelines for standardized multidisciplinary communications practices and procedures. These communications include prompt, reliable responder notifications to ensure the speed and accuracy of incident information to incident responders. Communication involves interoperable voice and data networks that link incident responder information and communications systems, as well as broadband emergency communications systems that integrate broadband networks linking emergency service providers. Prompt, reliable traveler information systems, as well as partnerships with news media and information providers should be established (by state DOTs), including specific practices for working with news media and information service providers to deliver timely and reliable traveler information. Finally, DOTs use operating standards and measurements in conjunction with the creation of goals for performance and progress, including response and clearance time goals, which ensure the development of systematic approaches for measuring TIM program performance at various levels. This includes the promotion of affordable and useful new TIM technologies, as well as the development of recommended best practices for responder safety.

The USDOT publications include best practices that incorporate many of the components mentioned above. TIM task-specific activities are categorized into five overlapping and broad functional areas: Detection and Verification, Traveler Information, Response, Scene Management and Traffic Control which includes planning alternative routes, and Quick Clearance and Recovery. These task-specific pursuits are found in state-and county-level areas as well as a variety of metropolitan areas. Comprehensive descriptions of each task-specific activity, as well as the number of metropolitan areas engaged in task-specific activities are found below:

1. <u>Detection and Verification</u>. This task determines that an incident has occurred and can be confirmed as a specific type of incident at a specific location. Incidents can be detected

by motorists, response personnel or technology (e.g. electronic loop detectors and associated incident detection algorithms). Official response personnel or Closed-Circuity Television (CCTV) can report the severity and location of incidents (USDOT 2010). Rapid incident detection and verification can improve access to the scene for incident responders, support personnel and equipment, improve clearance time and reduce secondary incidents. The various tools and strategies used in detection and verification differ based on where the tools are used (urban or rural). For example, motorist aid call boxes and automated collision notification systems may work best in rural areas; whereas CCTV cameras may be more cost-efficient in urban areas. The tools and strategies most frequently used for detection and verification include field verification by on-site responders; CCTV, used by more than 75 metropolitan areas; frequent and enhanced roadway reference markers; enhanced 9-1-1 and automated positioning systems; motorist aid call boxes, used by approximately 30 metropolitan areas; and automated collision notification systems, used in about 15 metropolitan areas (USDOT 2010).

2. Traveler Information. Traveler information is provided based on the communication of various incident-related information (e.g. location and severity of incident, estimated clearance time, and alternative routes) to motorists at all stages in their journey, including those who are at or approaching the scene of the incident, or not yet departed for their trip. This information serves to reduce traffic demand and improve responder safety, reduce the potential for secondary incidents, and allow motorists to alter their routes. The various tools and strategies that have proven effective in providing traveler information include 5-1-1 systems, used in more than 30 states; traveler information websites, used in more than 40 states; media partnerships, used in about 55 metropolitan areas; dynamic message signs (DMS), used in about 80 metropolitan areas; and DMS with standardized messages, used in about 75 metropolitan areas (USDOT 2010).

3. Response. Incident response is the activation of the preplanned strategy for the safe and rapid deployment of personnel and resources to the incident scene. Information management plays a critical role in the speed of the response, and subsequent clearance time. Accurate information about an incident (e.g. location, traffic impacts, vehicle types, injury, and presence of hazardous material) is essential. There are several strategies that facilitate rapid and accurate response. These include personnel and equipment resource lists that include geographic or jurisdictional response areas, telephone, cell phone and fax numbers, procedures for radio contact, alternative contacts, available equipment, supplies and materials, and anticipated response times. Currently, there are more than 75 metropolitan areas that use resource lists. Other strategies to facilitate rapid response include towing and recovery vehicle identification guides, instant tow dispatch procedures, and towing and recovery zone-based contacts. Enhanced Computer-aided dispatch is used by about 45 metropolitan areas, others use dual/optimized dispatch procedures. Nearly all metropolitan areas have motorcycle patrols. Finally, two states utilize equipment staging areas that include pre-positioned emergency responder equipment (USDOT 2010).

4. Scene Management and Traffic Control. Scene management involves the coordination and management of resources and activities at or near the incident scene. Scene

management and traffic control occurs after the initial responding agencies have arrived and injured persons have been helped. At this point in the TIM process, the incident scene is protected, and plans are formulated for scene documentation and wreckage or debris clearance. This task involves a wide variety of scene management and traffic control strategies based on the severity of the incident. These include incident command systems, used by nearly 60 metropolitan areas; response vehicle parking plans, including high-visibility safety apparel, vehicle markings and on-scene emergency lighting procedures; the enactment of safe, quick clearance laws practiced by 48 states (not New York or Hawaii); effective traffic control through on-site traffic management teams; end-of-queue advance warning systems; and alternative route plans, used by more than 60 metropolitan areas (USDOT 2010).

5. Quick Clearance and Recovery. Clearance and recovery are the final steps in the TIM process. Clearance refers to the safe and timely removal of any wreckage, debris, or spilled material from the roadway. Recovery refers to the restoration of the roadway to its full capacity, including clearing the vehicle backup. Effective incident clearance relies on efficient equipment utilization and an awareness of the legal authority to accelerate clearance. Strategies for quick clearance and recovery include 1) abandoned vehicle legislation practiced by more than 20 metropolitan areas, 2) quick clearance laws for driver removal, in the case of non-injury crashes, and 3) clearance laws that give authorization to a predesignated set of public agencies to remove or have removed damaged or disabled vehicles and spilled cargo. More than 130 metropolitan areas use service patrols, and more than 16 metropolitan areas use incident investigation sites, which provide a safe refuge off the main roadway where further investigation or documentation can take place. More than 90 metropolitan areas use expediated crash investigation techniques as a strategy for quick clearance and recovery. Furthermore, more than 30 metropolitan areas use quick clearance or open roads policies. These policies bind agencies to quick clearance consensus by setting implied or explicit goals for clearing traffic incidents from the roadway. Other quick clearance and recovery strategies include vehicle-mounted push bumpers, non-cargo vehicle fluid discharge policies, fatality certification and removal policies, quick clearance using fire apparatus, towing and recovery quick clearance incentives, and major incident response teams.

USDOT has provided significant guidance in the elements of a traffic incident management program, and has specified tasks and activities involved in incident processing from verification through recovery. However, a review of strategies put in place at the state and local levels provides insight into the actual use of federal guidelines and best practices. Researchers reviewed TIM strategies in the United States and have highlighted the outstanding strategies of 18 states, including Tennessee.

2.1.2 State Departments of Transportation

The review examined each state in the U.S. for its traffic incident management strategies. 18 states have unique TIM strategies that engaged personnel in non-standard collaborative ways, utilized unique technologies or created legislative policies or exceptional procedures for traffic incident management. The review includes the states of Arizona, Colorado, California, Florida, Georgia, Indiana, Iowa, Louisiana, New Jersey, New Mexico, New York, North Carolina, Ohio, Texas, Utah, Washington, and Wisconsin. Tennessee has its own section.

Table 1 identifies the five overlapping and broad functional areas of TIM: Detection and Verification; Traveler Information; Response; Scene Management and Traffic Control, and Quick Clearance and Recovery. These table identifies each strategy type, provides the number of metropolitan areas engaged in each strategy type, and then lists the states uniquely engaged in the strategy. Details of each strategy types as well as benefits are highlighted in Table 1.

Table 1: TIM Processes and Strategy Types

TIM Process	Strategy Type	Metro. Areas	State
Detection and Verification	Field Verification by On-Site Responders		NY (Hudson Valley Region)
	Closed-Circuit Television Cameras	76+	MD
	Frequent/Enhanced Roadway Reference Markers		FL, NJ, OH, PA (Delaware Valley Region), TN
	Enhanced 9-1-1/Automated Positioning		TX (San Antonio)
	Motorist Aid Call Boxes	27+	GA
	Automated Collision Notification	16+	NY (Erie Co.)
Traveler Information	5-1-1 Systems		33+
	Traveler Information Websites		39+
	Media Partnerships	53+	
	Dynamic Message Signs (DMS)	81+	CA (Stockton)
	DMS with Standardized Messages	73+	TX (Austin and San Antonio)
Response	Personnel/Equipment Resource Lists	75+	
	Towing and Recovery Vehicle Identification Guides		NJ/PA (Delaware Valley Region), TX (Austin)
	Instant Tow Dispatch Procedures		WA (Seattle)
	Towing and Recovery Zone-Based Contracts		TX (Houston)
	Enhanced Computer-Aided Dispatch	43+	CA (Los Angeles), NM (Albuquerque), TN (Sequatchie Co.)
	Dual/Optimized Dispatch Procedures		NJ
	Motorcycle Patrols	~ All	
	Equipment Staging Areas/ Pre-positioned		TN, WI
Scene Management and Traffic Control	Incident Command System	58+	WA
	Response Vehicle Parking Plans		AZ (Phoenix), CO (Lakewood), IA, MI (Farmington), TX (Lancaster)
	High-Visibility Safety Apparel/Vehicle Markings		CO (Eagle)
	On-Scene emergency Lighting procedures		TX (Austin and San Antonio)
	Safe, Quick Clearance Laws – Move Over		48 States (Not NY or HI)
	Effective Traffic Control Through On-Site Traffic Management Teams		CA (Stockton), FL (Southeast), NJ

	End-of-Queue Advance Warning Systems		CA (Bishop, Los Angeles, Redding, Stockton), NJ (Camden), TN (Chattanooga), UT (Salt Lake City)
	Alternative Route Plans	62+	CA (Anaheim), FL (Northeast), ME, NH, NJ, PA (Delaware Valley Region), WI
Quick Clearance and Recovery	Abandoned Vehicle Legislation/Policy	21+	IN, NC
	Safe, Quick Clearance Laws—Driver Removal		~25 states, including FL, GA, MD, NC, OH, SC, TN, TX, VA, WI
	Service Patrols	130+	AZ (Phoenix), CA, FL, GA (Atlanta), IN, MD, MI, NM (Albuquerque), OR, TN, UT (Salt Lake City)
	Vehicle-Mounted Push Bumpers		CA (Redding, Stockton), MD (Baltimore), NJ/PA (Delaware Valley Region), OH (Cincinnati), TN (Chattanooga), TX (Austin), UT (Salt Lake City)
	Incident Investigation Sites	16+	Texas (Houston)
	Safe, Quick Clearance Laws—Authority Removal		AZ, CA, CO, FL, GA, IL, IN, KY, MO, NM, NC, OH, OR, SC, TN, TX, VA, WA
	Quick Clearance/Open Roads Policy	35+	CA, FL, GA, ID, IN, LA, MD, NV, NH, TN, UT, WA, WI
	Non-cargo Vehicle Fluid Discharge Policy		FL, MN
	Fatality Certification/Removal Policy		PA, TN, TX (Austin), WA
	Expedited Crash Investigation	93+	FL, IN, TX (North Central Region), UT
	Quick Clearance Using Fire Apparatus		TX (Austin)
	Towing and Recovery Quick Clearance Incentives		FL, GA, WA
	Major Incident Response Teams		DE, FL, IL (Chicago), LA, MD, NJ, OH (Cincinnati, Columbus), NY, TX (Dallas Co.), WA

In reviewing other states' traffic diversion management strategies, several state-of-the-art strategies have been identified. Examples of how these state DOTs are implementing their TIM and traffic diversion strategies are examined. Seventeen of the states engage in at least one notable traffic incident management strategy or program, while many states, such as California, Florida, New Jersey, Texas and Tennessee, engaged in more than one notable strategy.

Arizona (AZ). In Phoenix, Arizona, the response vehicle parking plan allows fire and rescue personnel to position apparatus between oncoming traffic and response personnel to protect the scene but must avoid unnecessarily blocking traffic lanes to permit law enforcement to move traffic and relieve congestion.

Colorado (CO). Eagle County, Colorado has instituted high-visibility safety vehicle markings and safety apparel based on European models. The county's ambulances feature distinctive reflective yellow and blue chevron stripes across the back, yellow and blue horizontal stripes along each side, and white contour lines outlining the profile of the vehicle. Ambulance doors are equipped with blinking lights, and ambulance personnel wears the same reflective colors on their jackets.

California (CA). As a quality assurance measure for Dynamic Message Sign in Stockton, California, on-site responders verify the appropriateness of posted DMS messages and provide requests for updated messages as the TIM process evolves. Also, the Loma Linda University Medical Center in Los Angeles, California uses Advanced Emergency Geographic Information System (AEGIS) for ambulances equipped with GPS. Agreements were established to patch streaming data feeds from area police and fire and rescue agencies, patient-capacity information from other area hospitals, and weather data and traffic images from the California Department of Transportation. The system supports routing and staff decisions, as well as uploads incident images prior to departing or en route to the scene.

Florida (FL). In Florida, TIM practitioners develop alternate route plans and distribute these plans, in electronic format, to all TIM agencies. The maps include local routing scenarios with officer locations, barricades, bridge closures, and detour signs for all major highways within their jurisdictions. Also, Florida has adopted procedures or policies that exempt non-cargo vehicle fluid spills from hazardous materials response procedures, providing the spill has been contained on the pavement. Florida's Guidelines for the Mitigation of Accidental Discharges of Motor Vehicle Fluids (Non-cargo) encourages the mitigation of such spills and speed the clearance of minor incidents. Under these guidelines, the Florida Department of Transportation and other incident response personnel may apply absorbents and sweep off travel lanes regardless of spill quantity. Additionally, Florida uses towing and recovery quick clearance incentives to expedite clearance. Under this program, contract towing, and recovery operators are required to respond to major incidents with two certified heavy-duty wreckers and a support vehicle carrying cleanup and traffic control equipment. Contractors earn a $2,500 bonus if they respond to the incident site within 60 minutes and clear the roadway to traffic within 90 minutes. If the contractor fails to open the roadway within three hours, the contractor is penalized $10 for each minute over.

Georgia (GA). Motorist aid call boxes installed along 39 miles of rural I-85 in Georgia were estimated to yield a cost savings of $329,820 (USDOT 2010).

Indiana (IN). Indiana passed a law that reduced the amount of time that an abandoned vehicle can remain in the right-of-way from 72 hours to 24 hours. Also, Indiana passed a law that includes "hold harmless" (not liable) language allowing enforcement personnel to safely and quickly remove vehicles or debris from the roadway and reopen the impacted traffic lanes. The "hold harmless" clauses protect against liability for responder actions as authorities are not held responsible for any damages or claims.

Iowa (IA). In Iowa, fire and rescue personnel utilize a Roadway Incident "Cue Card," that reminds response personnel of proper vehicle placement and encourages aggressive termination of incidents, noting that a faster return to normal traffic flow reduces the potential risk of secondary incident and response personnel exposure.

Louisiana (LA). Louisiana passed the first ever open roads law that mandates keeping roads open whenever possible, requiring TIM training for all law enforcement officers, establishing improved towing procedures, and requiring open roads agreements between key agencies. The inclusion of explicit performance goals in quick clearance policies helps to ensure continued focus on quick clearance and improvement in operations.

New Jersey (NJ). In the Delaware Valley region in New Jersey and Pennsylvania, TIM personnel rely on ramp reference markers at complex intersections for accurate identification of incident locations. A corresponding map is provided to dispatchers for reference. Also, TIM personnel in New Jersey participate in dual optimized dispatch procedures to minimize the crossovers required under dual dispatch procedures. New Jersey TIM personnel dispatch according to predetermined, mutually agreed-upon “response box” areas for limited access highways based on an agency’s proximity to an incident rather than its jurisdictional boundaries. Furthermore, New Jersey Incident Management Response Teams respond to major highway incidents or planned events and direct the response and use of resources in the most efficient fashion. These specially trained teams provide technical, logistical, and incident management support to the incident commander by establishing necessary traffic control and diversion routes. Finally, the Delaware Regional Planning Commission has developed a web-based Interactive Detour Route Mapping application (www.idrum.us) that includes regional emergency route plans for New Jersey and Pennsylvania. The application is available both online and offline.

New Mexico (NM). Albuquerque Ambulance in New Mexico uses a map-based Enhanced Computer-Aided Dispatch (E-CAD) system that allows the dispatcher to provide en-route ambulance drivers with the exact location of an emergency and guidance on appropriate routes, which has resulted in an increase in efficiency of 15 percent (USDOT 2010).

New York (NY). In Erie County, NY, Automated Collision Notification Systems (ACNS) reduced incident detection time from an average of three minutes to less than one minute. Maximum detection times for vehicles equipped with ACNS was two minutes, while the maximum detection times for unequipped vehicles was as 46 minutes (USDOT 2010).

North Carolina (NC). Under the abandoned vehicle legislation, North Carolina law enforcement personnel can typically expedite the removal of abandoned vehicles that are deemed a hazard. Before the legislation was passed, North Carolina’s research found that a total of 1,300 abandoned vehicles were struck, resulting in 47 fatality crashes and over 500 injuries.

Ohio (OH). Roadway reference markers, provided every 0.2 miles along urban freeways in Ohio, help motorists quickly and accurately identify the location of an incident. Dispatchers are trained to direct motorists to look for and report these roadway identifiers.

Texas (TX). Next Generation 9-1-1 (NG 9-1-1) systems are designed to respond to text messaging, voice-over-Internet, data, phone images, and video, which can be captured and broadcast by smartphone technology. The Texas counties of Bexar, Comal, and Guadalupe are using the NG 9-1-1 system, which cost $24 million, provided through telephone customer fees of $0.22 per month for landline telephone accounts and $0.50 per month for cellular telephone accounts (USDOT 2010). Also, Texas has priority criteria for standardized messages displayed on Dynamic Message Signs. As part of a recently developed multi-agency incident response plan for the I-35 corridor between Austin and San Antonio, a hierarchy of DMS use was defined to reflect the following priority: safety, roadway closures, delay information, emergency messages (including AMBER alerts), test messages, and public service announcements. Furthermore, in Austin, Texas, the Texas Department of Transportation and the Austin Towing Association jointly sponsored a new provision in the Towing and Recovery Vehicle Identification Guide for law enforcement, fire and rescue, and transportation agency response vehicles in the metropolitan area. Additionally, Houston, Texas has enacted the Safe Clear Program, which requires contracted towing and recovery companies to respond within an average of six minutes to incidents on a designated section of State-owned freeways. Currently, tow operators responded to more than 60,000 stalls and collisions, response times were under six minutes about 90 percent of the time. The Safe Clear program's expedited response and clearance times have resulted in savings of nearly $49 million per year (USDOT 2010). Moreover, in Austin and San Antonio, Texas on-scene emergency lighting procedures were developed as part of a multi-agency incident response plan for the I-35 corridor to promote the phased use of emergency lighting on-scene (i.e., use emergency lighting in the initial stages of an incident but reduce emergency lighting as soon as sufficient traffic control is in place), the preferred types of lighting, and the appropriate times and circumstances for use. Finally, in Houston, Texas uses a public service awareness video describing the State's Steer It, Clear It law to direct motorists to relocate their vehicle, if possible, to a designated incident investigation site or other safe location to minimize interference with existing freeway traffic.

Utah (UT). The most frequently used performance metric for TIM programs is average or maximum incident clearance time, defined as the time between the first recordable awareness and the time at which the last responder has left the scene. Utah's performance goals are based on incident severity: 20 minutes for fender benders, 60 minutes for injury crashes, and 90 minutes for fatalities. Also, Utah uses aerial photogrammetry to take crash scene photos with a camera mounted on a low-flying, remote-controlled helicopter. Photogrammetry captures the necessary data through the process of analyzing and interpreting photos taken at the incident scene. Photogrammetry systems have been credited with significantly reducing the amount of time it takes to perform incident investigation while increasing the number of measurements able to be captured.

Washington (WA). In Seattle, Washington, instant tow dispatch procedures are credited with saving an average of 15 minutes of lane-blocking congestion each time it is used, with associated cost savings for each instant tow deployment of approximately $35,000 per year.

Wisconsin (WI). Wisconsin Department of Transportation uses pre-positioned equipment staging areas to store portable roadway barriers near key freeway access ramps to expedite necessary road closures during major incidents or weather events.

2.2 Vehicle Incidents

Motor vehicle traffic accidents have several characteristics that are used to identify the type of accident. These characteristics include occurrences of injury or property damage, the number and types of vehicles involved, whether the vehicles were moving or stationary, and a description of the situation. Large scale incidents are those that involve multiple vehicles, generally happening on a high-capacity and high-speed roadway. Examples of large-scale accidents in Tennessee include a greyhound bus and freight lines truck collision on US Route 11 in Bean Station (1972); multiple vehicle collisions and fire during limited visibility on I-75 in Calhoun (1990); a semi-trailer's loss of control on the downgrade in Dunlap (2002); a fire involving the transport of lithium-ion batteries in Memphis (2005), and a multi-vehicle work zone crash on I-75 near Chattanooga in 2016 (NTSB 2019). These accidents caused substantial delays, property damage, and fatalities. In each incident, Traffic Incident Management procedures were employed to clear the roadway as soon as possible.

2.2.1 Large-Scale Incidents

Another example of a major incident involved a potato spill on I-40. In December 2011, a tractor-trailer hauling potatoes crashed on Interstate-40 in Tennessee between Nashville and Knoxville, closing that Interstate for 12 hours. Officials said the truck was carrying about 40,000 pounds of potatoes when it lost control and overturned. The truck's driver was arrested and charged with Driving Under the Influence, reckless endangerment, and drug possession (Russell 2011). This widely publicized event prompted an aggressive initiative aimed at improved incident management conducted jointly by the Tennessee Department of Transportation and Tennessee's Department of Safety and Homeland Security (TDOS). In 2012, the Open Roads Policy signed by TDOT and TDOS to promote TIMS training and promote Quick Clearance Principles. 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 the Texas Transportation Institute (TTI) analyzed mobility data from 1982 to 2014 and described the nation's congestion problem as "very large" (Schrank 2015). The data 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, totaling $121 billion in annual congestion costs nationally (Schrank 2015). Conservatively, traffic incidents account for approximately 25 percent of traffic congestion and are a leading cause of unexpected delay (USDOT 2015). While incidents of short to medium duration can affect traffic operations and mobility, large-scale incidents can substantially disrupt traffic flow by blocking lanes for long periods of time (Zhang 2012). Specifically, a 10-minute lane blockage can cause more than 40 minutes of extra travel delay (Schrank, Lomax, & Turner 2010). Furthermore, large-scale traffic incidents are more complex and require more response resources that require the practiced coordination between different agencies to secure and clear the incident scene to restore normal traffic flow (Zhang 2012). Additionally, large-scale incidents may require special arterial signal coordination to handle diverted traffic, detours, clean-up resources, and the dissemination of information to the public. Despite the 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.

A broad spectrum of studies has focused on analyzing incident duration modeling of traffic incidents to identify key factors that can be applied to incident management strategies (Chimba, Kutela, Ogletree, Horne, & Tugwell, 2013; Jones, Janssen, & Mannering, 1991; Nam & Mannering, 2000; Sullivan, 1997). From a methodological standpoint, incident durations and associated factors have been modeled successfully using diverse sets of rigorous statistical tools such as:

- Truncated and Quantile Regressions (Khattak 2016; 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
- Finite Mixture Models (Zou, Henrickson, Lord, Wang, & Xu, 2016).

Several factors, such as accidents and injuries, lane closures, number of vehicles, temporal/spatial factors, heavy truck involvement, and adverse weather, were found to be positively associated with longer incident durations (Boyles 2007; Khattak 2016; Nam & Mannering 2000; Stephen 2007). An article by Zhang and Khattak entitled "Analysis of large-scale incidents on urban freeways" published in the Journal of the Transportation Research Board can be referred to for a summary of findings from different studies (Zhang 2012). However, the aforementioned studies did not explicitly focus on identifying key correlates that are directly associated with durations of large-scale incidents. Large-scale incidents are different than small or medium incidents in that they require multi-agency coordination generally due to the prescience of multiple injuries, hazardous materials, etc. A thorough understanding of the important elements is needed to devise strategies for responding to such incidents effectively.

While there is considerable literature with general analysis on 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 2012). Large-scale incidents were found to take on average 216 minutes to clear, while non-large-scale incidents took 16 minutes to clear. Furthermore, Zhang and Khattak identified locations and times prone to large-scale incidents; large-scale incidents typically occur during morning and evening peak times (Zhang 2012). Empirically, large-scale incidents showed a significant positive association with work zones, the presence of road curvature, and the occurrence of secondary incidents (Zhang 2012). Similar results were obtained from analyzing cascading incident events on urban freeways (Zhang & Khattak 2010).

Previous studies have provided actionable strategies for large-scale incident management relating to clearance time but have not focused on multi-agency operational actions. Furthermore, studies have not applied new methods that can account for heterogeneity due to unobserved factors.

From a methodological perspective, fixed associations between large-scale incident durations and associated factors are assumed in most studies - these assumptions are restrictive given the presence of several unobserved factors in incident databases and considering the new methods that have emerged to deal with heterogeneity. Some 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).

Deeper 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 should be 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 are 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. The 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.

2.2.2 Semi-Trailer Truck Involved Incidents

Semi-trailer truck crashes can result in severe injuries and damage, as well as cause traffic congestion requiring long clearance and recovery times. Large-scale crashes can even lead to secondary incidents causing further disruptions. As freeway demand increases, for both freight transport and personal vehicles, safety becomes more of concern to drivers and travelers, as well as to traffic operations managers. Notably, truck-involved crashes are disruptive, costly and deadly. The Federal Motor Carrier Safety Administration reports that truck- and bus-involved crashes increased by five percent from 2014 to 2015 (USDOT 2018). Research has indicated that the involvement of trucks in an incident is directly related to an increase in fatalities and injuries (Duncan, Khattak, & Council 1998; Zong, Zhang, Xu, Zhu, & Wang 2013). When compared to single truck crashes, multiple vehicle truck-involved incidents are more likely to contribute to severe injury. Ideally, reducing the number of all truck-involved crashes would increase the safety of occupants in both trucks and other vehicles. As a result, identifying and analyzing risk factors associated with truck accidents and injury severity is essential for transportation safety. In addition, truck-involved highway accidents have a significant negative impact on traffic flow, as a series of accident management processes are needed to clear the incident. Traffic incident management (TIM) processes include incident detection, verification, and notification; as well as response and recovery, which contributes to incident duration. Improving TIM efficiency reduces the impact and duration of freeway congestion and the probability of secondary incidents. Reducing truck-involved crash rates and subsequent congestion is critical for improving highway traffic operations. By analyzing the risk factors that are associated with incident duration and understanding the links between these risk factors, researchers can discover methods for reducing incident duration. Previous research has been completed investigating the risk factors associated with incident duration, such as crash type, vehicle type, driver behavior, roadway conditions, and environmental factors as they are related to injury severity. Additionally, there are several other studies focusing on exploring the underlying factors correlated with incident duration such as response time, lane blockage, etc. However, these studies seldom focus on analyzing the simultaneous relationship *between injury severity and incident duration*.

One of the reasons for this disconnect is that injury severity and crash-related factors are often stored in an accident or crash factors database, while operations data, such as response time and incident duration are usually stored in an incident or response factors database. The databases are distinct, so that data from both sources are not combined. To better understand the correlation between injury severity and incident duration, this research links the two databases (crash database and incident database). Given that injury severity may, to some extent, affect incident duration, this analysis adopted a recursive bivariate ordered probit model to investigate such a relationship. Previously, the ordered probit model has been used to associate driver injury severity in car accidents to other factors (Wang and Kockelman, 2005; Eluru, Bhat and Hensher, 2008). When an accident occurs, injury severity and incident duration are two main indicators to measure the various aspects of accident outcome. Researchers have spent considerable efforts on uncovering the relationships between risk factors and injury severity, and the contributing variables that may be associated with incident duration. Table 2 summarizes previous studies with the focus on factors that are related to injury severity and duration, and the methodologies being used.

Table 2: Summary of Selected Studies for Injury Severity and Incident Duration

Author/ Year	**Study Focus Areas**			**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

The impact of various factors on injury severity has long been recognized and studied. A broad range of research has focused on the associations between injury severity and factors related to crash type, vehicle type, driver behavior, roadway conditions, and the environment. Factors involved in driver behavior include distractions, as well as physical and emotional impairments, which 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). Additionally, a correlation was found between females and older persons not using a seat belt with higher injury severity (Duncan 1998; Islam & Hernandez 2013; Lemp, Kockelman, & Unnikrishnan 2011). Regarding vehicle type, Zhu and Srinivasan claimed that truck-car crashes are estimated to be the most serious crashes (Zhu & Srinivasan 2011). Also, Duncan identified a higher likelihood of severe injuries with passenger car occupants if the vehicle was struck by a truck (Duncan 1998). Additionally, research by Chang and Mannering concluded that large trucks are significantly associated with injury severity of the most severely injured occupants (Chang & Mannering 1999). The researchers illustrated the association between occupancy and injury severity and found that more vehicles occupants resulted in higher probabilities of serious injury. With respect to incident duration, Khattak discovered that if trucks were involved in an accident, then the incident duration would be longer as trucks are more likely to interfere with incident clearance operations (Khattak 1995). Also, Garib found the importance of truck involvement in building an incident duration prediction model (Garib, Radwan, & Al-Deek 1997). Moreover, Nam and Mannering identified that detection and reporting, response time, and clearance time were significantly correlated with incident duration (Nam & Mannering 2000). Furthermore, Garib 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 (Garib 1997). Finally, Khattak identified a series of factors that affected the incident duration prediction (Khattak 1995). The results showed that the response time was positively associated with incident duration, which is slightly different from this research study, which links injury severity with incident durations.

Studies that focused on both injury severity and duration were quite rare. Nam and Mannering revealed a positive relationship between the presence of fatality or injury and incident detection/ reporting/ clearance times (Nam & Mannering 2000). Golob 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 (Golob, Recker, & Leonard 1987). Zong used the ordered probit model and hazard model to predict accident severity and incident duration, respectively (Zong et al., 2013). The results indicated the duration of truck-involved crashes to be 58 percent longer in duration than other accidents and identified the number of fatalities and injuries to be a critical factor related to duration. However, the research focused on how additional fatalities and injuries lead to longer accident duration, not on injury severity and incident duration. A gap exists in current research analyzing injury severity and incident duration within one model.

Previous studies have revealed the need to analyze injury severity and incident duration simultaneously. Studies that have remotely addressed injury severity and incident duration have used separate models for analysis. Studies have seldom integrated the accident crash and incident response databases. A gap remains for obtaining and researching injury severity and incident duration in a unique database and modeling them simultaneously. Furthermore, the risk factors influencing the truck-involved accidents are still underexplored, especially when taking a specific geographic factor into consideration. Such temporal and spatial characteristics make this research different from others. Therefore, this analysis mainly focuses on creating a unique database, exploring the association between injury severity and incident duration for a specific region in Tennessee, and analyzing the underlying factors related to injury severity and incident duration simultaneously.

2.3 En-Route Traffic Diversion

Generally, when there is unexpected congestion on the freeway, drivers must be patient waiting for TIM responders to complete their tasks. However, if advanced congestion warning is provided, drivers have the choice to take an alternative route. In corridors with substantial commercial traffic, especially large trucks, route diversion is complex compared with non-commercial vehicular traffic. Large truck drivers need to be concerned with travel time, traffic violations, lane changing movements, turning movements, low bridges, etc. As such, en-route diversions made by commercial trucks constitute a group of vehicles that need special guidance in such situations - due to their vehicle weight, traffic impact, road infrastructure, safety, energy, and value of travel time, etc. To make well-informed decisions in terms of en-route diversion, truck drivers need to access critical and timely traffic information such as incident duration, lane blockage, current travel time on freeway and predicted travel time on alternate routes, etc. From the perspective of the Traffic Management Center (TMC), quick clearance of the incident is a top priority. However, traffic management includes broadcasting en-route diversion routes to officials and the public, and in some cases, law enforcement is implemented to ensure detours are used.

Examples of TMC directed diversions are found in Kansas, Kentucky and New York. The Kansas Department of Transportation has a strategic diversion plan for all vehicles but does not have a clear plan the includes the special needs for freight movement. The K-7 Corridor Management Plan provides potential routes during freeway incidents as does the Traffic Incident Management Program Plan for the Topeka Metropolitan Area. Both plans are based on the guidelines found in the Manual on Uniform Traffic Control Devices (MUTCD). The Kentucky Transportation Cabinet TMC's provides incident management for the interstate and parkway. The emergency plan has route maps, control points for diversions, and a standardized setup for diversion traffic control, as well as pre-loaded message signs (i.e. permanent alternate, wayfinding signs, and flip-down detour signs). The diversion setup can be seen in Figure 1. Finally, in the Hudson Valley region, the New York HELP service patrol vehicles are equipped with a live video stream back to the traffic management center. Onboard dash cameras relay real-time incident information to dispatchers ensuring the proper and expedited dispatch of equipment. The use of streaming video was found to be extremely helpful for remote transportation and law enforcement personnel in determining the incident characteristics and subsequent response needs.

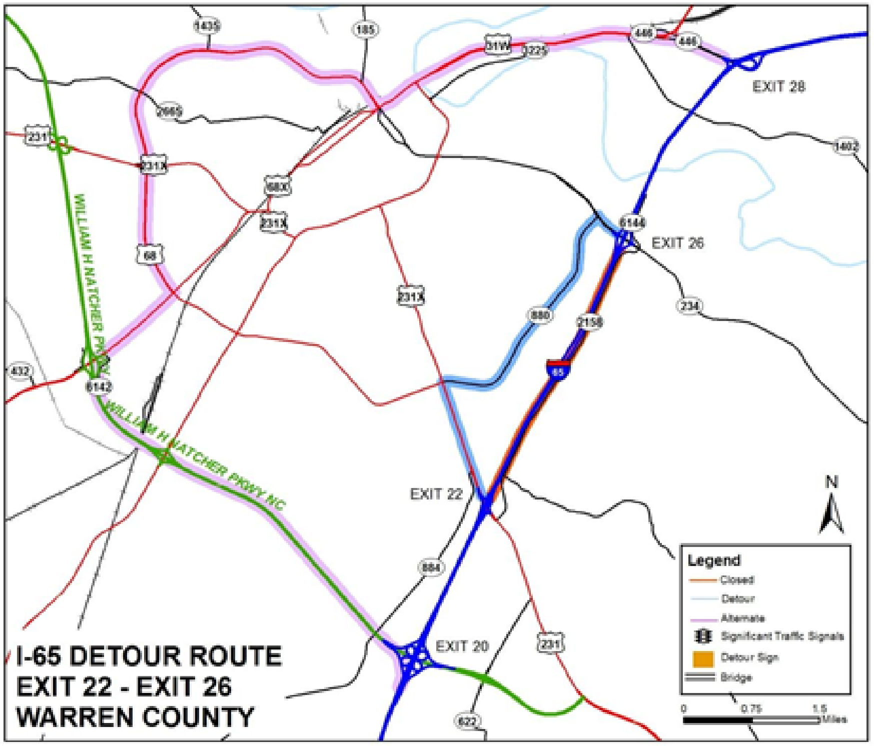

Figure 1: Diversion Scenario Examples in Kentucky

The literature review indicates the benefits of applying the en-route diversion strategies for commercial trucks are not well understood, especially under a large-scale incident scenario. Therefore, a part of the research involves the study of truck en-route traffic diversions under large-scale incident-induced congestion scenarios. Using simulation modeling, scenarios have been run based on realistic locations along the I-40 corridor in Knoxville, Tennessee. Specifically, the research study has constructed a microscopic simulation model to analyze en-route diversion strategies on the I-40 corridor for single-unit and multi-unit trucks, as well as passenger vehicles, under different incident scenarios. Additionally, the benefits of each scenario were obtained by evaluating different traffic information penetration ratios, values of travel time, incident durations, vehicle automation levels, truck performance, etc.

A technical report from Federal Highway Administration defines an alternative route as beginning at a fixed point on a primary route (exit) and terminating at a fixed point on the primary route (entrance) (Dunn 2006). According to the definitions, the alternative route for a freeway starts from an exit to an alternative route and then returns to the freeway. However, due to the weight, height, width, and other truck attributes, most of the alternative routes are not intended to be used by large trucks. In Tennessee, the alternative routes for trucks along major freeways and highways in metropolitan areas are defined such that trucks will take specified alternative routes upon large-scale incident-induced congestion on the freeway. Upon incident-related congestion, additional travel time is identified as the most problematic outcome. Costly additional travel time is s significant consideration that must be made by long-haul truck drivers in making route choices as they navigate through the U.S. highway network (Golob & Regan 2001; Knorring, He, & Kornhauser 2005). Various factors that impact the en-route diversion decision have been evaluated, such as incident duration, number of blocked lanes, flow rate on routes, number of signals on the detour route, etc. Generally, under incident scenarios with long duration, considerable diversion rates can be observed (Liu 2011; Liu 2012; Yin, Murray-Tuite & Wernstedt 2012). Also, detour operations under non-recurrent congestion can cause problems on alternative routes. For example, if en-route diversions are made, the delay on the detour routes can increase by about 64 percent, causing unexpected congestion in the detour route (Cragg & Demetsky 1995); therefore, time estimations should be calculated for both original and detour 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 & Lee 2006; Pan & Khattak 2008; Sundaram, Koutsopoulos, Ben-Akiva, Antoniou & Balakrishna 2011).

When estimating the benefits of activating the en-route diversion, value of time (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, commercial trucks usually have much higher VOT than passenger vehicles; therefore, VOT deserves to be incorporated into the analysis for truck en-route diversions (Belenky 2011; Pan & Khattak 2008). Furthermore, current research often fails to consider commercial truck en-route diversion choices in a large-scale freeway incident scenario. According to Li, when a large-scale incident happens, it usually lasts longer than two hours and blocks at least one lane on the freeway (Li 2017). In extreme cases, all the lanes are blocked (Li, Khattak & Wali 2017). Therefore, such incident characteristics, as well as existing detour route characteristics (e.g. number of lanes, annual average daily traffic, number of intersections, signal timing plans, etc.) may eventually impact the operational decisions made by Traffic Management Center (TMC) managers. Figure 2 conceptually illustrates how TMC operations are used to implement a diversion strategy upon an incident occurrence on the freeway.

After an incident is detected and verified, the TMC broadcasts a notice and information is collected regarding the incident, traffic, etc. The next steps involve predicting the duration of the incident, a network evaluation of the traffic and the availability of alternative routes. Only at this point, after all the data has been collected, is a decision about en-route diversion operations addressed. If it is decided that no en-route diversion operation will be used, then the output includes statistics on travel time, delay, travel cost, emissions, etc. However, if an en-route diversion operation is chosen, the elements of an optimal diversion plan are reviewed, including alternative routes, s, percent of trucks and cars diverted, intersection signal plans addressed, etc.

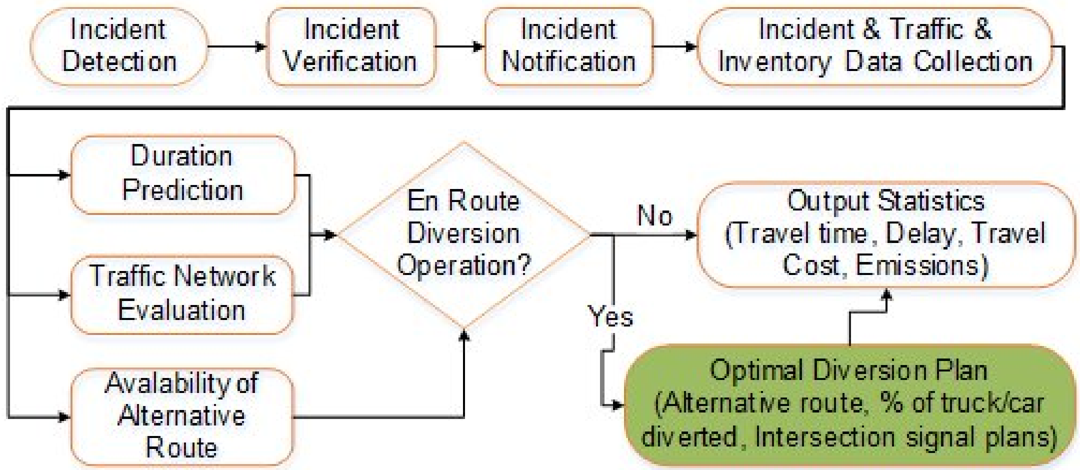

Figure 2: En-route Traffic Diversion Operations System Flowchart for Incident Situations

2.4 Summary

The literature review indicates a research gap in analyzing the en-route diversion strategies for trucks under large-scale incident scenarios. It is assumed that under such scenarios, the benefits will be largely different when compared to small-scale incidents as the diversions can cause the alternative route to become congested. To address this research question, this study aims to focus on analyzing the benefit of traffic en-route diversion scenarios under large-scale incidents by using simulation modeling. The study area will include I-40 and arterial roads along Kingston Pike in Knoxville Tennessee. This research topic is timely and original because the commercial truck flows in Tennessee are expected to grow significantly due to its geographic location (USDOT 2015). The estimation of benefits in diverting the commercial trucks to alternate routes upon a large-scale incident is very important in freight traffic management.

Based on the literature review of state DOT practices, as well as previous research efforts, some research regarding the unfinished work relating to truck-involved crashes, large-scale traffic incidents and en-route diversions under traffic incident-induced congestion should be conducted. Results from the analysis will provide actionable safety countermeasures, as well as viable operational traffic countermeasures in a timely manner for the Tennessee Department of Transportation. This research study will contribute by accomplishing the following tasks:

- Integration of the Tennessee crash database and incident response databases to create a unique database with the information of both injury severity and incident duration;
- Investigation of the injury severity and incident duration simultaneously within one modeling framework through using the recursive bivariate ordered probit model;

- Identification of large-scale traffic incidents using appropriate criteria and then the creation of a comprehensive database that can allow in-depth investigation of such crashes;
- Conceptualization and quantification of the associations between large-scale incident durations and multi-agency operational responses, especially their response and on-scene times;
- Investigation of unobserved heterogeneity in large-scale incident duration analysis by developing random-parameter hazard-based duration models, and
- Estimation of benefits obtained through en-route diversions strategies in response to large-scale traffic accidents or incidents by applying the microscopic simulations models.

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3.0 TENNESSEE TIM AND ATIS

This chapter discusses the Traffic Incident Management (TIM) and Advanced Traveler Information System (ATIS) framework for dissemination of information to vehicles for this research study and provides suggestions from the research study that will be made to the Tennessee Department of Transportation regarding further traffic operations analysis.

3.1 Traffic Incident Management

The Traffic Incident Management (TIM) practices of the state of Tennessee range from unique signage alerting motorists of an incident to quickly aiding disabled vehicles through the Highway Emergency Local Patrol or HELP program. For example, in Tennessee, roadway reference markers are placed every 0.2 miles along urban freeways in Chattanooga, Knoxville, Memphis, and Nashville to assist HELP trucks in finding locations of disabled vehicles. Also, the TDOT deploys pre-positioned equipment staging areas; the ready response trailers are stocked with traffic control devices at 15 strategic locations throughout the state. Communication is heightened in Sequatchie County, Tennessee, which has equipped its ambulances with enhanced computer-aided dispatch (E-CAD) systems that combines digital information from 9-1-1 dispatch centers, utility authorities, and the county property assessor's office with real-time incident information. Additionally, TDOT has installed more than 100 signs at key locations along the State's urban freeway system with the message "Move Damaged Vehicles to Shoulder If No Serious Injury" in order to encourage drivers to move their cars quickly in order to keep the roadway clear of congestion. To facilitate this, push bumpers, mounted on response vehicles, are used in Chattanooga, Tennessee to quickly and safely remove disabled vehicles from the shoulder or travel lanes, reducing the likelihood of secondary incidents and improving the safety of both response personnel and motorists. Finally, in many cases, local policy or state law requires that death be certified by a coroner or medical examiner and that the victim not be moved until the coroner has done so. The result causes delays to traffic while the arrival of a coroner is awaited. In Tennessee, fatality certification laws permit law enforcement personnel to facilitate the removal of the victim before the arrival of the coroner when the incident poses a safety hazard.

One of the first freeway service patrol programs used to assist in traffic incident management is TDOT's lime-yellow HELP trucks program established in 1999. The trucks are equipped with a variety of tools, including emergency medical equipment, traffic cones, traffic control signs, absorbent material, emergency and work lights, and other equipment to assist with incident management. The trucks also carry gasoline, diesel fuel, and water. Since then, a number of other states have developed similar service patrol programs, including Arizona's Local Emergency Response Team (ALERT); Maricopa County, Arizona's Regional Emergency Action Coordinating Team (REACT); California and Florida's freeway service patrol (FSP); Atlanta, Georgia's Highway Emergency Response Operators (HERO); Maryland's Coordinated Highways Action Response Team (CHART) and Emergency Traffic Patrol (ETP) program, and Minnesota's Freeway Incident Response Safety Team (FIRST).

In 2000, TDOT's Office of Incident Management was established to provide a statewide comprehensive strategy for "Quick Clearance" and provide a foundation for cost-effective programs. Their activities include the management of various programs including the HELP Program; Merge Left and Protect the Queue initiatives; Reference Marker and the Yellow DOT Program, as well as developing incident management protocols and the Interstate Incident Management Plan. The Office of Incident Management provides training and hosts the Tennessee Highway Safety and Operations Conference, as well as provides guidance to Tennessee 511, a traveler information program, and SmartWay, a web interface that includes live streaming video of traffic from 475 cameras in Nashville, Chattanooga, Knoxville, and Memphis. A summary of key practices in TDOT's incident management is provided in Table 3 (TDOT 2003).

Table 3: Advances in Highway Incident Management in Tennessee, 1996-2016

Action	Year
Regional Incident Management Plan for the Nashville area completed	1996
TDOT Statewide ITS Strategic Plan completed with recommendations for freeway service patrols and incident management	1998
TDOT's internal Freeway Service Patrol Task Force established	1998
Emergency reference markers installed on Interstate highways in Knoxville and Nashville	1999
HELP patrols started in Knoxville and Nashville	1999
"Quick clearance" legislation enacted by the General Assembly	2000
Emergency reference markers and overhead structure reference signs installed on Interstate highways in Chattanooga and Memphis	2000
HELP patrols started in Chattanooga and Memphis	2000
Office of Incident Management established within TDOT	2000
Incident management team established in Chattanooga with leadership from the Chattanooga Metropolitan Planning Agency (MPO)	2000
Incident management team established in Memphis with leadership from the Memphis Police Department	2000
Incident management Memorandum of Understanding signed between the Tennessee Department of Safety and TDOT	2001
HELP patrols expanded to seven days a week in all four cities	2001
Statewide Policy Committee and Steering Committee established for incident management; initial meeting of Policy Committee	2001
Initial meetings of Statewide Steering Committee to establish ongoing planning and coordination and begin work on state incident management plan	2002
Signs installed on controlled-access highways at 117 locations with the message: "Move Damaged Vehicles to Shoulder if No Serious Injury"	2002
Sixteen CCTV cameras installed along Nashville freeways, as the first step toward a total of 58 cameras to help monitor and guide freeway traffic	2002
Initial group of "Ready Response Trailers" deployed by TDOT at 15 strategic locations in suburban and rural areas	2002
TDOT's Traffic Management Center (TMC) for Nashville scheduled to begin operation	2003

Statewide Traffic Incident Management Plan, 2003-2008, scheduled for review and approval	2003
Strategic Highway Safety Plan	2004
Knoxville Transportation Management Center (TMC) Opens	2005
Knoxville SmartWay opens, which includes 70 cameras, 16 electronic message boards, more than 200 speed congestion monitoring stations to spot traffic flow interruptions and highway advisory radio stations that broadcast on AM frequency 1620.	2005
Memphis Transportation Management Center (TMC) and Smartway opens	2008
Chattanooga Transportation Management Center (TMC) and Smartway opens	2011
Open Roads Policy signed by Tennessee Department of Safety and Homeland Security to promote TIMS training and promote Quick Clearance Principles.	2012
Tennessee Department of Safety and Homeland Security (DOHS) and the Tennessee Department of Transportation (TDOT) celebrated the opening of the Tennessee Traffic Incident Management (TIM) Training Facility	2014
Tennessee Highway Patrol CRASH system merged into the operational environment of TDOT's four Regional Traffic Management Centers to optimize its deployment of freeway service patrol units	2016

Over the years, Traffic Incident Management practices have become a science of movements between well-trained professionals. From human to automatic detection, innovations have been used to develop safer and faster TIM procedures. En-route traveler information, such as 5-1-1, message signs, and news media, have proven valuable in reducing the amount of congestion and time it takes for traffic control and clearance. What follows is a literature review of research involved in vehicle incidents, both large-scale accidents, and truck-involved crashes, as well as a review of current en-route diversion decisions and en-route communication efforts.

3.2 Advanced Travelers Information System

Advanced Traveler Information Systems (ATIS) reference any system that acquires, analyzes, and broadcasts information to travelers in order to assist them while moving from origin to destination. Generally, ATIS is part of an intelligent transportation system (ITS), which plays an essential role in the efficiency of traveler's road experience in terms of travel time and cost. ATIS includes all the delivery mechanisms of travel information including radio, telephone, Internet access, variable message signs, travel time displays, dynamic route guidance systems, etc. In incident congestion situations, ATIS may contribute to a driver's decision to make an en-route diversion to an alternative route by providing updated route characteristic information. Such en-route choices can decrease congestion, travel time and cost.

En-route diversion behavior is influenced by real-time traffic information specifically that of incident delay and congestion levels on the primary and alternate routes. Information indicating a long delay and subsequent longer travel time, as well as the availability and decreased congestion level of alternate routes, including past route use, constitute factors that can increase of probability of en-route diversion. Additionally, research has indicated male drivers, who live in the city and are risk seekers, have a higher propensity of diverting to alternative routes

(Khattak et al. 1993). Other factors affecting en-route diversion behavior include access to real-time traffic information relating to traffic demand, incident location and severity, and familiarity with alternative routes – all which impact travel time. The contributing level of each factor directly relates to en-route decision-making.

Al-Deek (1998) developed a framework to evaluate the impacts of ATIS under incident conditions through a composite traffic assignment model. This model classifies the traveler into three groups: 1) drivers who do not have access to Advanced Traveler Information Systems; 2) drivers who receive delay information from radio only, and 3) drivers who access Advanced Traveler Information Systems only. Findings indicate that the decrease in delay due to en-route diversion is not only related to ATIS, but also to radio market penetration and by driver observation of the incident. As a result, when the traffic assignment model includes en-route diversions, the resulting network conditions are closer to an optimum system rather than user equilibrium. When drivers can observe the congestion, and then divert to alternate routes, the benefits of information dissemination decrease (Pan and Khattak 2008). The maximum benefits of typical travel information are on the periphery of congestion, mostly affecting arriving vehicles, at a rate of 95 percent of capacity, while non-recurring congestion benefits are much greater (Levinson, 2003). Interestingly, willingness to pay for travel information services are associated with customized travel information, longer trips, work trips, and radio traffic reports (Khattak et al. 2003).

ATIS contributes to the reliability-based traffic network model design because with the system optimization by ATIS, the travel time reliability of the network is significantly enhanced (H. Sun et al. 2014). A novel ATIS for co-modal passenger transportation with multi-agent system architecture is proposed to answer multi-criteria user requests (Dotoli et al. 2017). ATIS, as an ITS-related system and technology, has been employed in automated driving systems and has been contributing to energy savings. Furthermore, in a truck platooning study equipped with ITS related technologies, the reduction of fuel consumption resulted in reduced carbon dioxide emissions (Tsugawa, 2011).

3.3 ATIS and Intelligent Transportation Systems (ITS)

The literature review clearly states the benefits of deploying the ATIS system into the traffic operations management system. Currently, there are seven ways to deliver traffic information to drivers within Tennessee. This includes 1) 511 phone number; 2) the Tennessee SmartWay System; 3) the Highway Advisory Radio (HAR) System (1640 AM); 4) Cellphone and network to access social media, such as Twitter; 5) Dynamic Message Signs (DMS); 6) Other mapping systems, such as Bing or Google Maps, and 7) Online accident reporting systems, such as WAZE, etc. However, these communication methods are effective only if drivers have access and are familiar with the seven traffic information systems. A report called the Tennessee Statewide ITS Architecture developed by the Tennessee Department of Transportation includes more methods for broadcasting traffic information. TDOT uses a systematic approach to organize and deliver traffic information (Figure 3).

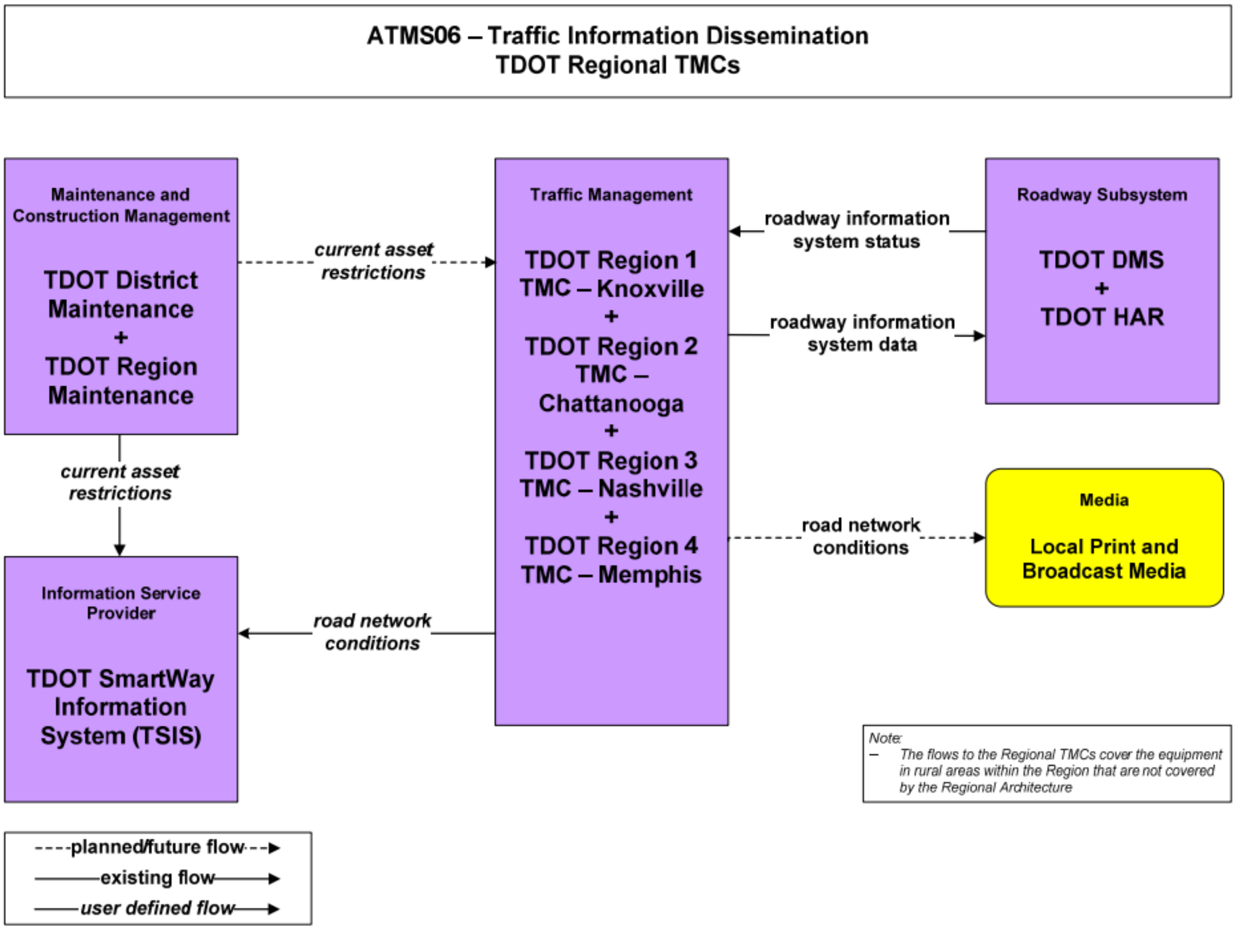


Figure 3: TDOT Statewide Traffic Information Dissemination System

In this ITS process, four systems or subsystems are interconnected. This includes Maintenance and Construction Management System, Information Services Systems (I.e. SmartWay), Traffic Management Centers (TMCs), and Roadway Subsystems, such as Dynamic Message Signs (DMS) and Highway Advisory Radio (HAR). Local Print and Broadcast Media is sometimes, but not always considered a subsystem. In this architecture, Maintenance and Construction communicate with TMCs about planned/future flow restrictions, such as work zones, etc. and with SmartWay about other or user-defined flow restrictions. Then, the TMCs notify SmartWay of any road network conditions and activate roadway information system data (DMS and HAR), which in turn notifies TMCs of roadway status. TMCs may choose to notify local print and broadcast media of road network conditions, as well.

In addition to the ITS process in Figure 3, a more sophisticated communication system is shown in Figure 4. This figure illustrates the detailed interconnect diagram and associated elements within each of the four major subsystems (Travelers, Centers, Vehicle and Field). As seen in Figure 4, travelers utilize remote traveler support and personal information access via wide area wireless (mobile) communications or fixed-point to fixed-point communications. In place are ITS architecture elements to assist Centers that are responsible for traffic management, emergency management, toll administration, commercial vehicle administration, maintenance and construction management, information service providers, transit management and archived data management. Fixed-point to fixed-point communication is used. The vehicles system includes emergency, commercial transit and maintenance and construction which use mobile communications as well as vehicle-to-vehicle communications and dedicated short range. Finally, field communication includes roadway information, security monitoring, toll collection and commercial vehicle check using fixed-point to fixed-point communication as well as short range.

Tennessee-specific elements are identified in the boxes surrounding the main interconnect diagram (Figure 4); they are color-coded to correspond to the subsystem to which they are associated. For example, Centers, color-coded in green, are responsible for Archived Data Management Subsystems (i.e. data warehousing, short-range planning, and data office; SmartWay Information System archives, travel agency archives); Commercial Vehicle Administration (i.e. CVIEW, Tennessee Pre-Pass and THP Truck Weigh and Inspection Stations); Emergency Management (i.e. County level EMA and public safety dispatch, HELP dispatch, municipal level EMA and public safety; Regional AMBER Alert, emergency service coordination, Regions 1 - 4 TMC, TEMA, TBI and THP Dispatch), among others as seen in Figure 5 (TDOT 2006).

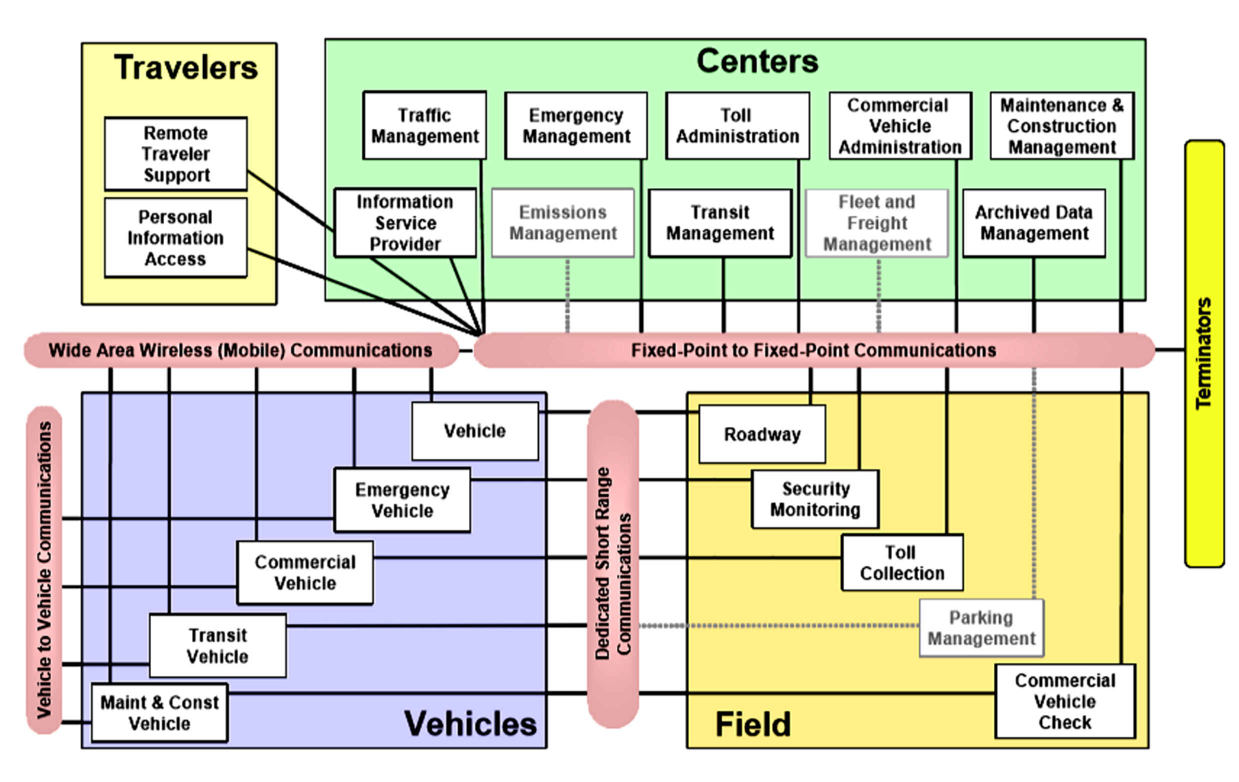


Figure 4: Tennessee Statewide System Interconnect Diagram

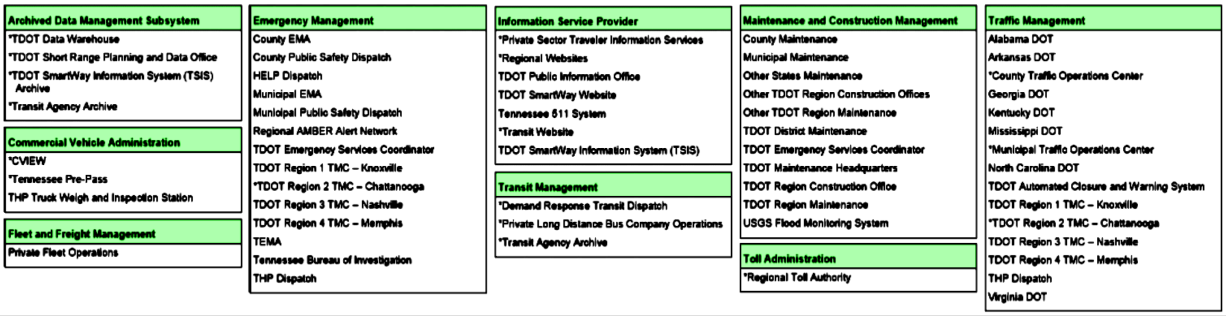


Figure 5: Tennessee Center Responsibilities

The “TDOT Statewide ITS Architecture Executive Summary” provides details on how vehicles, travelers, traffic operational center, and field ITS system applications are connected to create a comfortable driving environment in Tennessee roadways. Recently developed technologies, such as connected, and autonomous vehicles, have changed this architecture by introducing new communication standards, physical infrastructure, and various functions. As such, a review of the current ITS architecture in Tennessee reveals the potential of truck drivers receiving traffic information in new ways, such as connected and autonomous vehicle communication.

This research study will use a simulation method to investigate how travel time savings can be obtained by taking detours under large-scale traffic incident-induced congestion. Additionally, connected and autonomous vehicles technology is investigated to see how this technology impacts the benefits obtained under the simulation scenarios. This research will contribute by discovering the benefits that truck drivers and passenger vehicle drivers can obtain during their trips through en-route diversions if there is congestion and subsequent delay. The information obtained through simulation modeling can be used to enhance the ATIS system to produce a better driving experience.

4.0 DATA SOURCES AND MODELING

This chapter presents the data sources that have been utilized to analyze the various aspects of traffic incident management and en-route traffic diversion operations. In general, most of the data for the research project was provided by the Tennessee Department of Transportation. The data sources are used for TIM performance measurement. The TIM performance measures program in Tennessee was established through a formal agreement between TDOT and the Tennessee Division Office of the Federal Highway Administration (FHWA); this agreement made TIM performance measurement mandatory. The Traffic Management Centers house incident data and include data elements associated with all three of the national TIM performance measures – roadway clearance time, incident clearance time, and secondary crashes. Figure 6 illustrates the location of each TDOT region in Tennessee; each region has its own TMC and regional data collection.

Four datasets were used in this analysis – Locate/IM, E-TRIMS, and FARS. Most incidents are detected by the TMC operators, the HELP trucks, or the Tennessee Highway Patrol; data of these accidents are logged and tracked in each region's incident management system. This system utilizes a web-based traffic incident locator (Locate/IM), which also has activity and reporting capabilities. Locate/IM provides real-time roadway monitoring and location information and reporting of traffic incidents, as well as HELP Truck activity. E-TRIMS (Enhanced Tennessee Roadway Information Management System) is a map-centric, web-based database for state and local roadway structures, pavement, traffic, photo log, and crash data. The application is easy to deploy, has a user-friendly interface, and makes it easy to share data with other agencies and the public. The Fatality Analysis Reporting System or FARS contains national data on fatal traffic crashes. To be included in FARS, a crash must involve a motor vehicle traveling on a public road and result in the death of at least one person (occupant of a vehicle or a non-occupant) within 30 days of the crash. FARS collects information on over 100 different coded data elements that characterizes the crash, the vehicle, and the people involved. Finally, the Freight Analysis Framework (FAF) integrates data from a variety of sources to create a comprehensive picture of freight movement among states and major metropolitan areas by all modes of transportation.

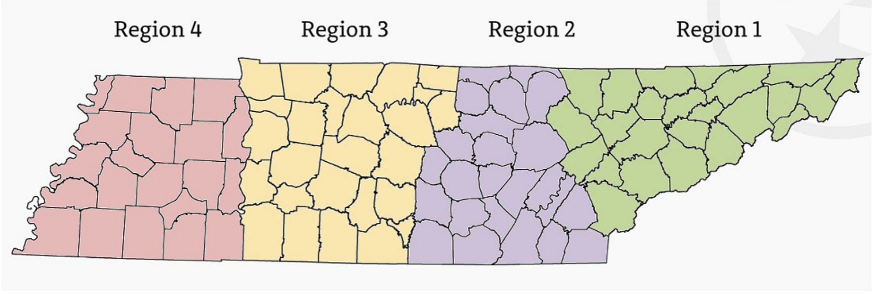


Figure 6: Tennessee's Traffic Management Center Regions

4.1 Locate/IM and E-TRIMS Data

Researchers collected and integrated injury severity and incident data for truck-involved crashes from two different databases provided by the Tennessee Department of Transportation – Locate/IM and E-TRIMS. Both datasets consist of crash data from Region 1. Data was from September 29, 2010 through December 31, 2016. Truck-involved crashes from both databases are collected to analyze the injury severity and incident duration. The two databases are linked by the time (date, time), location (route, direction), and incident type (single- or multi-vehicle involvement) for each incident. All variables used to link the two databases are exactly matched except for the time variable. E-TRIMS and Locate/IM use slightly different operational processes and coded response times, which leads to a slight differential in reported incidence time. After further analysis, the databases with a crash start time differential of less than one hour were able to be matched. Approximately 95% of matched data are within a 30-minute reporting time range. The resulting dataset was error-checked and validated.

Results identified 442 truck-involved incidents that could be matched and analyzed; 68 of the incidents involved single truck crashes and 374 of the incidents involved multi-vehicle truck-involved crashes. Of the 442 incidents in Region 1, 372 occurred in Knox County, most in the City of Knoxville; 24 occurred in Roane County, and less than 50 incidents occurred in other counties. In terms of crash locations, 70.14 percent occurred on I-40; 9.95 percent occurred on I-75, and 19.91 percent occurred at other locations.

To investigate driver and vehicle factors contributing to injury severity, detailed information regarding the total number of vehicles involved in the incident, driver fault – either "yes" or "no", and injury severity. For example, if the total number of vehicles involved in an incident was less than three, the information of all vehicles was kept; however, if the total number of vehicles involved was three or more, only the information of the truck (no matter whether the truck contributed to the incident or not), and the information of the contributing vehicle was kept. Driver fault was assigned based on whether the driver engaged in an unsafe diver action (e.g. distracted behavior, under the influence, etc.). In terms of injury severity, the most severe injury of all parties involved in the incident was used to determine the injury level. There are five levels of injury severity: (1) fatal injury; (2) incapacitating injury; (3) non-incapacitating injury; (4) possible injury or damage; and (5) no injury (property damage only).

Injury severity is a categorical variable in the modeling framework. The modeling method requires both dependent variables - injury severity and incident duration - to be categorical variables. Incident duration is classified into three categories based on the definition of congestion found in the Manual on Uniform Traffic Control Devices (MUTCD). The categories are (1) Low, with congestion duration of 30 minutes or less; (2) Medium, with congestion duration between 30 and 120 minutes, and (3) High, with congestion duration of more than 120 minutes (USDOT 2012). The response time and lane block duration have also been categorized, where response time is: (1) 10 minutes or less; (2) between 10 to 20 minutes; (3) between 20 to 30 minutes; (4) more than 30 minutes. Finally, lane block duration is also classified as (1) 30 minutes or less, (2) between 30 to 120 minutes, and (3) more than 120 minutes.

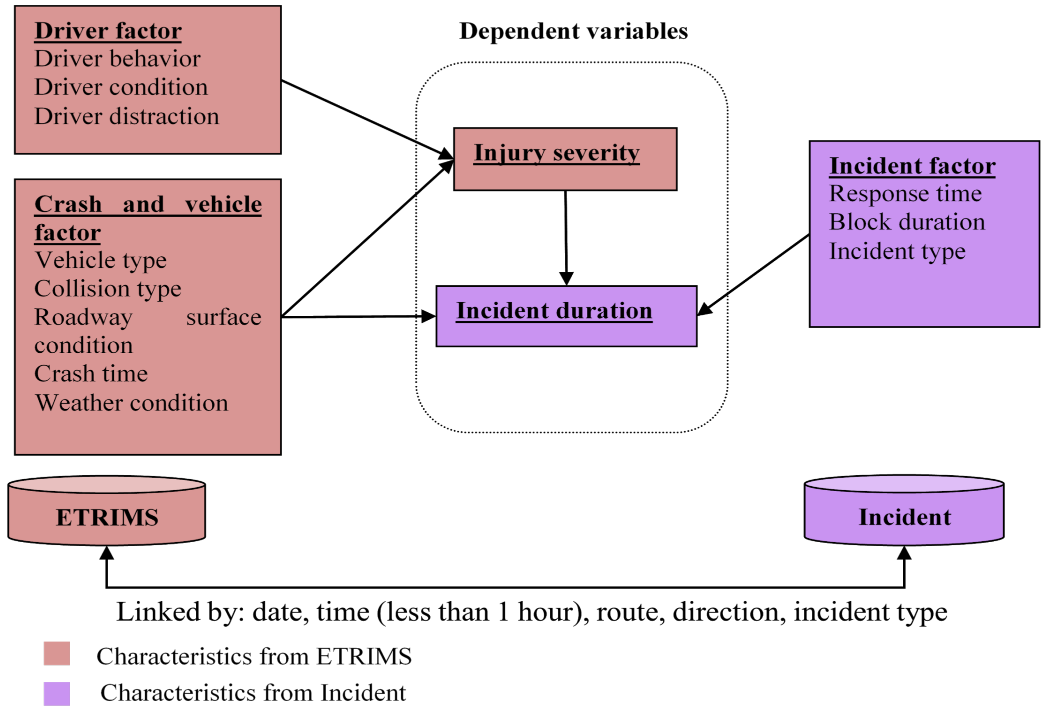


Figure 7: Conceptual Framework for Analyzing Truck-Involved Incidents

A conceptual framework was constructed to analyze injury severity and incident duration simultaneously (See Figure 7). Framework elements include driver factors, crash and vehicle factors, data from E-TRIMS, Incident and Injury information, as well as specific incident factors. Injury severity and incident duration are two dependent variables. As can be deduced from the literature - crash, vehicle, and driver factors can be associated with injury severity. Some incident factors such as response time, lane block duration, and incident type are correlated with incident duration. Additionally, crash factors like collision type may also affect incident duration. Under the assumption that the injury severity has an impact on incident duration, injury severity is considered both a dependent variable for injury prediction equation and an independent variable in the incident duration prediction equation.

A total of 442 truck-involved crashes were analyzed - 68 single truck crashes, and 374 multi-vehicle truck-involved crashes. A total of 957 vehicles were involved in the 442 truck-involved incidents. The descriptive statistics of key variables related to injury severity and incident duration are shown in Table 4. The descriptive statistics display the distributions of injury severity by incident duration. Results indicate that most incidents last between 30 and 120 minutes, accounting for 74.89 percent of the total. The 30 minutes or less incident duration variable accounts for 16.97 percent of the total and crashes with a duration of more than 120 minutes account for 8.14 percent of the total. Results indicate most of the incidents can be cleared within 120 minutes. Incident duration is normally distributed, as is injury severity. A large proportion of injury level is property damage (over the average), accounting for 68.10 percent (301 out of 442). As the injury severity increases, the frequency of crashes decreases. 113 out of 442 accidents involve non-incapacitating injuries, while only 4.30 percent (19/442) and 0.68 percent (3/442) of them are incapacitating or fatal injuries. 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%), 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 severe injury accidents' duration being more than 120 minutes is higher than that of minor injury accidents.

Table 4: Distribution of Injury Severity by Incident Duration

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

4.1.1 Recursive Bivariate Ordered Probit Model

Based on the proposed idea that the categorized dependent variable (injury severity) may be related to another categorized dependent variable (incident duration), the recursive bivariate ordered probit model was adopted. This model has been intensively used in many studies (Caliendo & Guida, 2014; Dong, Clarke, Nambisan, & Huang, 2016; Dong, Nambisan, Richards, & Ma, 2015; Xu, Wong, & Choi, 2014). The methodology is technically sound as the model requires both dependent variables to be categorical. Incident duration is classified into three categories based on the definition from MUTCD (USDOT 2012).

The two dependent variables are determined using equation 1.1 (see Appendix A for all equations). The two dependent variables are categorized using equation 1.2. The unknown cutoffs satisfy that $b_1 < b_2 <\ldots< b_{l-1}$ and $c_2 < c_2 <\ldots< c_{m-1}$, the probability of $y_1^* = i$ and $y_2^* = j$is calculated using equation 1.3. If ε_1 and ε_2 are bivariate standard normally distributed with the correlation, then the likelihood function is calculated using equation 1.4 in Appendix. The logarithmic likelihood for the whole sample size N is calculated using equation 1.5.

4.1.2 Model Results and Discussion

The descriptive statistics of key explanatory variables for the 442 truck accident observations (Obs) are presented in Table 5. The table displays the mean or average, standard deviation (Std. Dev.), minimum and maximum values for each variable. The variables include lane block duration, response time, collision type, driver fault, and roadway surface condition. Descriptive statistics indicate that most lane block duration times are 30 minutes or less (82.8%), and response time is equal to or less than ten minutes (74.2%). Almost half of accidents are rear-end collisions, and 18.3 percent of them are considered no vehicle collisions (single truck collisions or collisions with objects, animals, etc.). Driver fault is nearly split equally between the other vehicle driver and the truck driver. Among all the accidents, most of the roadway surface conditions for the other vehicle are dry (67.4%); accidents involving ice, snow or slush occur less than one percent of the time.

Table 5: 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	0.115	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
	Unknown	1 if unknown, 0 otherwise	442	0	0	0	0
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
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.

The results of recursive bivariate ordered probit model has been presented in Table 6. Preliminary examination indicates that the chi-square value of the model estimated robust standard error is 4.85, which is higher than 3.84 (chi-square test statistic at a 95 percent confidence level). This indicates the bivariate ordered probit model is significant at a 95 percent confidence level and suitable for this analysis. The explanatory variables with a p-value of 0.05 or less will significantly affect the dependent variable at a 95 percent confidence level. Similarly, explanatory variables with a p-value of 0.1 or less, will significantly affect the dependent variable at a 90 percent confidence level. Thus, the recursive bivariate ordered probit model can estimate the effect (distribution) of an endogenous ordered variable on an ordered explanatory variable by allowing variation over the population. This process highlights the casual and consistent effect of an endogenous variable. Table 6 analyzes the variables of incident duration and injury severity where the coefficient (Coef) is used to predict the dependent variable from the independent variable, and the robust standard error (Robust Std. Err.) is the standard error associated with the coefficients. A positive coefficient means that an increase in the predictor leads to an increase in the predicted probability. A negative coefficient means that an increase in the predictor leads to a decrease in the predicted probability. For example, the results indicate that fatalities, lane block durations less than 120 minutes, response times greater than 30 minutes, and angled and head-on collisions (all with positive coefficients) lead to an increase in incident duration. The Z test statistic is the ratio of the coefficient to the standard error of the predictor, and the P>|z| value determines whether the null hypothesis can be rejected, and the parameter estimate is considered statistically significant at that alpha level. The P>|z| value is less than alpha (0.05) in the incident duration variable with regards to injury severity (non-incapacitating injury at 0.022; incapacitating injury at 0.017, and fatality at 0.000), lane block duration (a value of 0.000 for both durations higher than 30 minutes and less than 120 minutes), response time of greater than ten minutes (0.005), and collision type (head on at 0.008, and rear to side at 0.000). Neither of the injury severity variables indicate a P>|z| value of less than alpha (0.05).

Table 6: Recursive Bivariate Ordered Probit Model Results

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

The estimated marginal effects are shown in Tables 7 and 8. The marginal effects present the change of the probability of the dependent variable for a one-unit change in an independent variable. For example, in Table 7, Marginal Effects of Incident Duration, Injury severity resulting in a fatality has a positive effect of 0.893 if the duration is more than 120 minutes. Also, in Table 8 Marginal Effect of Injury Severity are presented. If the roadway surface condition of ice exists, then a fatality has a higher probability of 0.083.

Table 7: Marginal Effects of Incident Duration

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	-0.089	-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	0.0001	-0.00001	-0.0001
	Sideswipe- opposite direction	0.286	-0.186	-0.101
	Sideswipe- same direction	-0.018	0.003	0.0154
	Unknown	-0.071	-0.010	0.081

Table 8: Marginal Effects of Injury Severity

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	-0.009	-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	0.009	0.002
	Unknown	-0.004	-0.047	0.036	0.013	0.003

A detailed discussion of each explanatory variables is provided below. The variables are classified as injury severity, response time, lane block duration, collision type, driver fault, and roadway surface condition.

Injury Severity - Injury severity is the most critical variable in this research study, the important association was found between injury severity and incident duration outcome (see Table 6). Property damage (under the average) is applied as the base level. Most of the injury severity levels, except property damage (over the average), are statistically significant (at a 95 percent confidence level) in the recursive bivariate ordered probit model. A strong correlation between injury severity and incident duration is found to be consistent with the hypothesis proposed at the beginning of this part. It is also in agreement with Zong et al. (Zong et al., 2013). However, the study of Zong (Zong et al., 2013) only investigated the association between the number of fatalities/injuries and the incident duration. This research study further investigates the relationship between injury severity level and incident duration. It is found that the severer the injury severity is, the longer the incident duration will be. The incident duration is often comparatively longer for fatal crashes, and its coefficient in the estimated model is much higher than other injury levels. From an incident management perspective, the finding is essential and meaningful because it highlights that severer injured accidents are often correlated with longer incident duration. Consequently, some actionable countermeasures to reduce the injury severity may be proposed to decrease the incident duration, thus improving the management of transportation safety. The marginal effects reveal that when the injury severity level is a non-incapacitating injury, there is a 77.09 percent increase in the probability of incident duration being more than 120 minutes (Table 7). As for incapacitating injury and fatal injury level, there is an 88.07 percent increase, and an 89.31 percent increase in the chance that the incident duration will be more than 120 minutes, respectively.

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), the response time (between 10 and 20 minutes, between 20 and 30 minutes) is closely associated with incident duration. It is found that if response time is less than 20 minutes, it is more likely to associate with a longer duration than response time is longer than 20 minutes and shorter than 30 minutes. The reason to explain this might be that rescue response would be faster when the injury severity of the incident is higher. Given that higher injury severity often relates to longer incident durations, so even though the response is very fast, it might usually potentially correlate with longer incident duration. This result is consistent with the study of Li et al. (Li, Khattak, & Wali, 2017). In addition, the response time is a critical factor in traffic recovery. To some 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 an 11.37 percent increase in the probability of incident duration being more than 120 minutes. For the response time ranging from 20 to 30 minutes, such chance increases by 9.83 percent, which a little bit lower than response time ranging from 10 to 20 minutes. Thus, the response time ranging from 10 to 20 minutes seems to be more likely to contribute to longer incident duration (more than 120 minutes) than that which is between 20 and 30 minutes.

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. Lane block duration is seen to be significantly associated with incident duration (see Table 6). Compared with 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 lane block duration is between 30 and 120 minutes. It shows that the longer the lane block duration is, the longer the incident duration will be. As can be seen from Table 7, the marginal effects indicate that lane block duration also greatly affects incident duration. It shows when the lane block duration is more than 120 minutes, the chance that incident duration will be more than 120 minutes increases by 89.87 percent.

Collision type - Out of all collision types, angle and head-on collisions are found to be statistically associated with incident duration. Modeling results indicate that the head-on collision is significantly associated with longer incident duration at a 99 percent confidence level, while the angle collision is significantly related with incident duration at the 90 percent confidence level (see Table 6). The rear end collision is not significantly associated with incident duration, even though it represents a large proportion of incidents. The marginal effects show that when a head-on collision occurs, there is a 10.59 percent increase in the probability of resulting in incident duration being more than 120 minutes, while for angle collision, it is a 10.61 percent increase (see Table 7).

Driver Fault - Unsafe driver actions (e.g. distractions, conditions, alcohol or drug use, etc.) are designated as Driver at Fault. A series of studies have successfully examined the associations between driver errors and injury severity (Khorashadi et al., 2005; Kostyniuk et al., 2002; Zhu & Srinivasan, 2011). Given that injury severity strongly contributes to incident duration, risk factors such as driver at fault, roadway surface conditions, etc., which have also been correlated with injury severity, are considered in this research study. Modeling results show that the other vehicle (non-truck) driver at fault is more likely to be associated with severer injury severity than the truck driver at fault (Table 6). Truck driver at fault is significantly correlated with injury severity at a 90 percent confidence level. The marginal effects also show the other vehicle driver at fault increases the likelihood of severely injured crashes than the truck driver (Table 8).

Roadway Surface Condition - Roadway surface condition often affects the injury outcome. The results show that roadway surface conditions of other vehicles (non-truck) are more likely to be associated with injury severity. 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. The roadway surface condition, either ice, snow or slush of the other vehicle is significantly associated with injury severity. Ice surface condition of the other vehicle is correlated with higher injury severity 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 (Table 8). For instance, when the roadway surface condition is ice, the chance of getting incapacitating injury increases by 17.21 percent, while for snow or slush, that chance increases by 7.81 percent.

4.2 Fatality Analysis Reporting System Data

Additional analysis is provided specifically to review injury severity information for truck-involved crashes based on the Fatality Analysis Reporting System (FARS) data. This analysis further provides details of the injury severity information associated with accidents. This analysis is meaningful in that in large-scale traffic incidents, injury severity has a direct relationship. These characteristics will help researchers better understand large-scale traffic accidents. Furthermore, by analyzing the covariates associated with injury severity, other important variables could be identified for future work as an additional indirect relationship with incident duration. The data used for this analysis is collected through the Fatality Analysis Reporting System maintained by the National Highway Traffic Safety Administration (NHTSA). The 2012 crash data was collected and analyzed. The original sample size represented 85,496 records for each person involved in an indecent. After removing records with missing data and no injury severity information, and then focusing on truck-involved crashes, the final sample size is 4,997 records for each person involved in 3,941 incidents; this represents 5.84 percent of the records for each person in the original sample size.

The descriptive statistics for the collected variables are shown in Table 9. The descriptive statistics of key explanatory variables for the 4,997 person records (Obs) are presented. The table displays the mean or average, standard deviation (Std. Dev.), and minimum/maximum value for each variable. In most cases, the minimum value is 0 and the maximum value is 1 representing either a yes or no value. The exceptions are the values contained in the Crash Characteristic variable with the description of VE_FORMS (number of vehicles). The values range from 1 (minimum) to 64 (maximum). Additionally, the values contained in the Personal Characteristic variable with the description of AGE have values ranging from 0 (minimum) to 89 (maximum). There are no values for Vehicle Characteristics under the description of BODY_TYP (Body type of trucks). The results of the descriptive statistics suggest that almost 60 percent of incidents had no injury; most incidents occur between two to three vehicles; about 70 percent of incidents occurred during transport (not parked, etc.), approximately 85 percent of incidents did not have vehicle rollover events, and in about 40 percent of accidents the airbag deployed. The average age is about 45 years, and about 75 percent of the time both lap and shoulder restraints were used.

Some variables are not listed in this table due to their lack of significance in the modeling process. They are gender, manner of collision, roadway functional class, urban, location, etc. Like other data sets with crash injury severity information, the distribution of the injury severity has a long tail, with many crashes at low-level of injury severity such as no injury or property damage, and fewer crashes at high-level injury severity such as fatal injury in the data.

Table 9: Descriptive Statistics for Explanatory Variables

Variable	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	0.5968	0.4906	0	1
	Injury Severity=1 (Possible Injury)	4,997	0.1017	0.3022	0	1
	Injury Severity=2 (Non-Incapacitating injury)	4,997	0.1019	0.3025	0	1
	Injury Severity=3 (Incapacitating Injury)	4,997	0.0452	0.2078	0	1
	Injury Severity=4 (Fatal)	4,997	0.1545	0.3615	0	1
Crash Characteristics	VE_FORMS (number of vehicles)	4,997	2.291	3.239	1	64
	HARM_EV (first injury or damage) base=6 other	4,997	0.012	0.1089	0	1
	HARM_EV =0 (Motor Vehicle in Transport)	4,997	0.717	0.4505	0	1
	HARM_EV =1 (Parked Motor Vehicle)	4,997	0.0212	0.1441	0	1
	HARM_EV =2 (Rollover/Overturn)	4,997	0.0562	0.2304	0	1
	HARM_EV =3 (Non-Motorist)	4,997	0.0904	0.2868	0	1
	HARM_EV =4 (Fixed object)	4,997	0.0968	0.2958	0	1
	HARM_EV =5 (Moving object)	4,997	0.0062	0.0785	0	1
	ROLLOVER (Rollover or overturn in a crash) base=0 no rollover	4,997	0.8533	0.3538	0	1
	ROLLOVER=1 (First event rollover)	4,997	0.1149	0.3189	0	1
	ROLLOVER=2 (Subsequent rollover)	4,997	0.0244	0.1543	0	1
	ROLLOVER=9 (Unknown)	4,997	0.0074	0.0857	0	1
	FIRE_EXP (Fire in a crash) base=0 no fire	4,997	0.9398	0.2379	0	1
	FIRE_EXP=1 (Fire occurred in a crash)	4,997	0.0602	0.2379	0	1
Vehicle Characteristics	BODY_TYP (Body type of trucks)	4,997	---	---	---	---
	AIR_BAG (Air bag deployment in a vehicle) base =2	4,997	0.409	0.4917	0	1
	AIR_BAG=1 (Air bag deployed)	4,997	0.0436	0.2043	0	1
	AIR_BAG=3 (Not a Motor Vehicle Occupant/Not Applicable/unknown)	4,997	0.5473	0.4978	0	1
Personal Characteristics	AGE	4,997	44.93	13.8386	0	89
	PER_TYP =1 (Role of this person in a crash) driver	4,997	0.8281	0.3773	0	1
	PER_TYP=2 (Passenger in transport)	4,997	0.1525	0.3595	0	1
	PER_TYP=3 (Passenger not in transport) base	4,997	0.0176	0.1315	0	1
	PER_TYP=9 (Unknown)	4,997	0.0018	0.0424	0	1
	SEAT_POS (Location of a person in a vehicle) base=1 Front seat	4,997	0.9306	0.2542	0	1
	SEAT_POS=2 (second seat)	4,997	0.0148	0.1208	0	1

	SEAT_POS=5 (Other locations not 3rd or 4th seat)	4,997	0.05	0.218	0	1
	SEAT_POS=6 (Unknown)	4,997	0.0046	0.0677	0	1
	REST_USE (Restraint equipment used by the person) base=0 none restraint used	4,997	0.1549	0.3618	0	1
	REST_USE=1 (Shoulder belt only)	4,997	0.0026	0.0509	0	1
	REST_USE=2 (Lap belt only)	4,997	0.0126	0.1115	0	1
	REST_USE=3 (Lap and shoulder)	4,997	0.7494	0.4434	0	1
	REST_USE=4 (Child safety seat)	4,997	0.0016	0.0399	0	1
	REST_USE=8 (Unknown)	4,997	0.0788	0.2695	0	1
	EJ_PATH (Ejection status and degree of ejection for a person) base=0 not ejected	4,997	0.9534	0.2108	0	1
	EJ_PATH=1 (Side door)	4,997	0.0024	0.0489	0	1
	EJ_PATH=2 (Side window)	4,997	0.0054	0.0733	0	1
	EJ_PATH=3 (Windshield)	4,997	0.0048	0.0691	0	1
	EJ_PATH=4 (Other)	4,997	0.002	0.0447	0	1
	EJ_PATH=9 (Unknown)	4,997	0.032	0.176	0	1
	DRINKING (drunk driving) base=0 no drinking	4,997	0.6498	0.477	0	1
	DRINKING=1 (Drunk)	4,997	0.011	0.1043	0	1
	DRINKING=2 (Unknown)	4,997	0.3392	0.4734	0	1
	DRUGS (drug use) base=0 no drug used	4,997	0.5986	0.4902	0	1
	DRUGS=1 (Drug used)	4,997	0.015	0.1216	0	1
	DRUGS=2 (Unknown)	4,997	0.3864	0.4869	0	1

4.2.1 Multilevel Mixed-Effects Ordered Probit Regression Model

Multilevel mixed-effects models can capture some random effects due to the unobserved heterogeneity. For this reason, this analysis applied a multilevel mixed-effects ordered probit regression model, which contains both fixed effects and random effects. Its formulation is introduced in this section, but all formulas are found in Appendix A. 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 cut points κ, and a set of random effect u_j. The cumulative probability of the response being in a category higher than κ is written as in equation 2.6. Based on equation 2.6, the derived probability for outcome k is formulated using equation 2.7. Based on the above formulation equation 2.7, a model with observed response y_{ij} can be generated from a latent continuous response, it is formulated using equation 2.8. The conditional distribution of y_j given a set of cluster-level random effects u_j is formulated using equation 2.9. 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 2.10. But the integration has no closed form, thus it should be approximated using maximum likelihood procedure.

4.2.2 Model Results and Discussion

Table 10 presents the model estimation results. This table analyzes the crash, vehicle, and person characteristics where the coefficient (Coef) is used to predict the dependent variable from the independent variable, and the standard error (S.E.) is the standard error associated with the coefficients. A positive coefficient means that an increase in the predictor leads to an increase in the predicted probability. A negative coefficient means that an increase in the predictor leads to a decrease in the predicted probability. The Z test statistic is the ratio of the coefficient to the standard error of the predictor used to test the hypothesis that the coefficient is not equal to zero. Finally, the p-value determines whether the null hypothesis can be rejected, and the parameter estimate considered statistically significant at an alpha level.

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 robust 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 using other seemingly independent variables. This is also true for vehicle type level random effects. 19 types of trucks are analyzed in our model, so 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 percent prediction accuracy, which is an acceptable accuracy for these models.

Table 10: Model Estimations of the 3-level Mixed-effects Ordered Probit Regression Model

Description		**Coef.**	**SE.**	**Z**	**Value**
Case level	ST_CASE (crash case number)	0.758	0.109	---*	---*
Crash Characteristics	VE_FORMS (# of vehicles)	-0.016	0.013	-1.24	0.216
	HARM_EV =0 (base=6) (Motor Vehicle in Transport)	-0.719	0.247	-2.92	0.004
	HARM_EV =1 (Parked Motor Vehicle)	0.121	0.319	0.38	0.704
	HARM_EV =2 (Rollover/Overturn)	0.021	0.281	0.07	0.941
	HARM_EV =3 (Non-Motorist)	-2.482	0.299	-8.28	0.000
	HARM_EV =4 (Fixed Object)	0.758	0.258	2.93	0.003
	HARM_EV =5 (Moving Object)	0.635	0.413	1.54	0.125
	ROLLOVER=1 (base=0) (First Rollover)	1.402	0.092	15.30	0.000
	ROLLOVER=2 (Subsequent Rollover)	1.621	0.219	7.38	0.000
	ROLLOVER=9 (Unknown)	1.499	0.298	5.04	0.000
	FIRE_EXP=1 (base=0) (Fire Occurred in a Crash)	1.148	0.111	10.3	0.000
Vehicle Characteristics	BODY_TYP (level 2 random effects) (Body Type of Trucks)	0.054	0.034	---	---

	AIR_BAG=1 (base =2) (Air Bag Deployed)	0.966	0.121	7.99	0.000
	AIR_BAG=3 (Not a Motor Vehicle Occupant/Not Applicable/Unknown)	0.454	0.057	7.98	0.000
Personal Characteristics	AGE	0.012	0.002	6.29	0.000
	PER_TYP=1 (base=3) (Driver)	1.661	0.259	6.42	0.000
	PER_TYP=2 (Passenger in Transport)	1.332	0.259	5.12	0.000
	PER_TYP=9 (Unknown)	1.373	0.678	2.03	0.043
	SEAT_POS=2 (base=1) (Second Seat Beside Driver)	-0.277	0.197	-1.40	0.161
	SEAT_POS=5 (Other Not 3rd of 4th Seat)	-0.592	0.142	-4.18	0.000
	SEAT_POS=6 (Unknown)	-0.443	0.381	-1.16	0.245
	REST_USE=1 (base=0) (Shoulder Belt)	-1.244	0.179	-2.60	0.009
	REST_USE=2 (Lap Belt)	-0.739	0.222	-3.33	0.001
	REST_USE=3 (Lap and Shoulder)	-0.987	0.089	-11.07	0.000
	REST_USE=4 (Child Safety Seat)	-0.515	0.553	-0.93	0.352
	REST_USE=8 (Unknown)	-0.237	0.117	-2.03	0.042
	EJ_PATH=1 (base=0) (Side Door)	8.893	407.81	0.02	0.983
	EJ_PATH=2 (Side Window)	2.048	0.665	3.08	0.002
	EJ_PATH=3 (Windshield)	1.275	0.486	2.63	0.009
	EJ_PATH=4 (Other)	1.608	0.656	2.45	0.014
	EJ_PATH=9 (Unknown)	1.369	0.169	8.10	0.000
	DRINKING=1 (base=0) (Drunk)	0.165	0.259	0.64	0.524
	DRINKING=2 (Unknown)	0.301	0.114	2.63	0.008
	DRUGS=1 (base=0) (Drugs Used)	0.434	0.201	2.16	0.031
	DRUGS=2 (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.

Rollover is a statistically significant variable. If trucks are involved in rollover crashes, then the injury severity level increases – a linear relationship exists. Additionally, if fire is involved in a crash, then statistically the injury severity level increases. When compared to passengers not in transport (e.g. in a parked car), passengers in transport suffer from a higher injury severity level if involved in a truck-related crash. When seating positions are compared, the injury severity level of seating positions other than the driver is lower, indicating that the injury severity level is higher for the driver. In terms of restraint use, the modeling results clearly show that using any type of restraint will significantly reduce the chance of suffering from a high level of injury severity during a truck-involved crash. Similarly, proper vehicle safety equipment such as airbags, if employed, will largely reduce the chance of being injured severely. Alcohol use or drug use have long been acknowledged as having a negative impact on truck driving. The same conclusion can be drawn from the model results. The multilevel mix-effect ordered probit model provides additional prediction power by incorporating the random effects in each level, so it is valuable in modeling ordinal response variables. The marginal effects based on the model with mean values for each variable are presented in Table 11 using the Delta-method for estimation. In this case, dy/dx represents the gradient of a curve, where d represents an infinitesimally small range. SE represents the standard deviation of the sampling distribution.

Table 11: Marginal Effects of Each Variable on Injury Severity Outcomes

Variables	**Injury Severity=0 No Injury**		**Injury Severity=1 Possible Injury**		**Injury Severity=2 Non-incapacitat-ing Injury**		**Injury Severity=3 Incapacita-ting Injury**		**Injury Severity=4 Fatality**	
	dy/dx.	**SE.**	**dy/dx.**	**SE.**	**dy/dx.**	**SE.**	**dy/dx.**	**SE.**	**dy/dx.**	**SE.**
VE_FORMS Number of Vehicles	0.005	0.004	-0.0005	0.002	-0.001	0.001	-0.001	0.001	-0.002	0.003
HARM_EV =0 (base=6) Motor Vehicle in Transport	0.208 ***	0.071	-0.0038	0.061	-0.049	0.051	-0.038 ***	0.013	-0.117	0.105
HARM_EV =1 Parked Motor Vehicle	-0.032	0.085	-0.004	0.014	0.004	0.016	0.006	0.015	0.026	0.071
HARM_EV =2 Rollover/Overturn	-0.006	0.076	-0.001	0.008	0.001	0.011	0.001	0.014	0.004	0.059
HARM_EV =3 Non-Motorist	0.587 ***	0.173	-0.115	0.079	-0.179 ***	0.013	-0.092 **	0.04	-0.2	0.205
HARM_EV =4 Fixed Object	-0.174	0.11	-0.038	0.044	-0.003	0.082	0.024	0.039	0.192	0.094
HARM_EV =5 Moving Object	-0.15	0.117	-0.031	0.045	0.002	0.07	0.022	0.033	0.157	0.125
ROLLOVER=1 (base=0) First Event Rollover	-0.381 ***	0.079	-0.014	0.106	0.067	0.112	0.066 **	0.026	0.262	0.168
ROLLOVER=2 Subsequent Rollover	-0.424 ***	0.112	-0.028	0.115	0.059	0.135	0.07 *	0.039	0.322 *	0.192
ROLLOVER=9 Unknown	-0.401 ***	0.107	-0.019	0.112	0.064	0.123	0.068 **	0.032	0.289	0.193
FIRE_EXP=1 (base=0) Fire occurred in crash	-0.315 ***	0.072	-0.013	0.09	0.055	0.096	0.056 **	0.022	0.217	0.143
AIR_BAG=1 (base =2) Air bag deployed	-0.279 ***	0.036	0.014	0.078	0.07	0.057	0.051 ***	0.007	0.145	0.121
AIR_BAG=3 Not a Motor Vehicle Occupant/Not Applicable/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
PER_TYP=1 (base=3) Driver	-0.391 **	0.16	0.102 **	0.04	0.133 ***	0.037	0.059	0.04	0.098	0.119
PER_TYP=2 Passenger	-0.294 *	0.152	0.089 ***	0.02	0.103 **	0.046	0.042	0.035	0.06	0.081
PER_TYP=9 Unknown	-0.306	0.238	0.091 **	0.037	0.107	0.073	0.044	0.048	0.064	0.106
SEAT_POS=2 (base=1) Second Seat	0.081	0.057	-0.011	0.022	-0.025	0.019	-0.014	0.011	-0.031	0.037
SEAT_POS=5 Other – not 3rd or 4th seat	0.168 ***	0.049	-0.029	0.037	-0.054 ***	0.015	-0.029 **	0.014	-0.057	0.062
SEAT_POS=6 Unknown	0.013	0.107	-0.019	0.037	-0.04	0.036	-0.022	0.019	-0.046	0.057
REST_USE=1 (base=0) Shoulder belt only	0.356 ***	0.131	-0.021	0.099	-0.09	0.079	-0.064 ***	0.021	-0.18	0.153
REST_USE=2 Lap belt only	0.211 ***	0.073	0.003	0.063	-0.044	0.061	-0.039 **	0.015	-0.13	0.099
REST_USE=3 Lap and shoulder belt	0.283 ***	0.037	-0.007	0.081	-0.066	0.066	-0.052 ***	0.007	-0.158	0.124
REST_USE=4 Child safety seat	0.144	0.165	0.007	0.044	-0.026	0.061	-0.026	0.032	-0.098	0.109
REST_USE=8 Unknown	0.064 *	0.037	0.006	0.019	-0.009	0.024	-0.012	0.009	-0.049	0.039
EJ_PATH=1 (base=0) Side door	-0.55 ***	0.026	-0.16 ***	0.007	-0.153	0.009	-0.058 ***	0.006	0.916 ***	0.034
EJ_PATH=2 Side window	-0.469 ***	0.076	-0.073	0.048	0.011	0.058	0.059 ***	0.019	0.472 **	0.195
EJ_PATH=3 Windshield	-0.344 ***	0.103	-0.019	0.031	0.055 ***	0.015	0.059 ***	0.013	0.249 *	0.131
EJ_PATH=4 Other	-0.408 ***	0.11	-0.042	0.047	0.042	0.038	0.064 ***	0.007	0.342 *	0.189
EJ_PATH=9 Unknown	-0.364 ***	0.035	-0.025 *	0.014	0.053 ***	0.012	0.061 ***	0.006	0.027 ***	0.047
DRINKING=1 (base=0) Drunk	-0.049	0.076	0.005	0.015	0.014	0.023	0.009	0.014	0.02	0.039
DRINKING=2 Unknown	-0.089 ***	0.034	0.008	0.024	0.025	0.016	0.016 **	0.007	0.039	0.039
DRUGS=1 (base=0) Drugs Used	-0.128 **	0.058	0.006	0.037	0.033	0.029	0.023 **	0.01	0.065	0.065
DRUGS=2 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.

An interesting outcome found in Table 11 is that if a non-motorist is involved in a crash, the potential for no injury is higher than for motorists involved in a crash. On the other hand, a rollover event has a direct impact on causing a fatality, regardless of the type of rollover. Similarly, if 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 airbag deployment in a truck-involved crash, if the airbag is deployed, it usually indicates a crash with a high probability of injury severity; this relationship is not causal. Compared to an occupant of a motor vehicle not in transport, divers or occupants in transport have higher potential for injury or incapacitating injury. Based on the data, the probability of no injury is related to the use of shoulder belt restraint only. In terms of ejection status and degree level of ejection, the results show that if people are ejected during the crash regardless of path (e.g. side door, side window, windshield, back window, etc.), there is a higher probability of a high level of injury; the fatal category is the most common seen outcome.

4.2.3 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. In this research study, three fatalities are chosen as the criteria to determine a large-scale crash. Once again FARS data is used for the multilevel mixed-effects logistic regression model analysis. Each person file is merged with an associative accident file to obtain relevant variables in the analysis. This task is achieved by matching the crash case identifier (i.e. ST_CASE) in both files. Data records with missing information are removed to obtain a comprehensive merged file. The final sample contains 2,408 records or observations (Obs). In the first analysis, the sample data is modeled using multilevel mixed-effects logistic regression regardless of fatalities. In the second analysis, the data set is segmented to identify fatalities and obtain the time to death information to be used as the dependent variable. In this case, the Heckman selection model is applied, correcting for selection bias.

Geographically, the locations of these crashes occurred throughout the U.S. Mainland (see Figure 8). Crash concentration areas appear to be in Southern Florida and California, as well as near the cities of Atlanta, Georgia; New York, New York, and Houston and Dallas, Texas. Table 12 shows data descriptive statistics; this includes the mean or average, standard deviation, minimum and maximum values. In this table, the crash and person variables indicate that over 57 percent of the individuals involved in these large-scale crashes died; about 63 percent of crash victims were in a passenger vehicle, and the average age is about 33 years. In about 22 percent of cases, equipment or other forces were used to remove a person from the vehicle. Other notable variables include the correct use of a retraining system – about 99 percent used the retraining system correctly, but only about half used restraints at all; about 16 percent of people in the study were ejected from the vehicle, and most accidents occurred on the roadway, but not near an intersection, railway or ramp (Table 12).

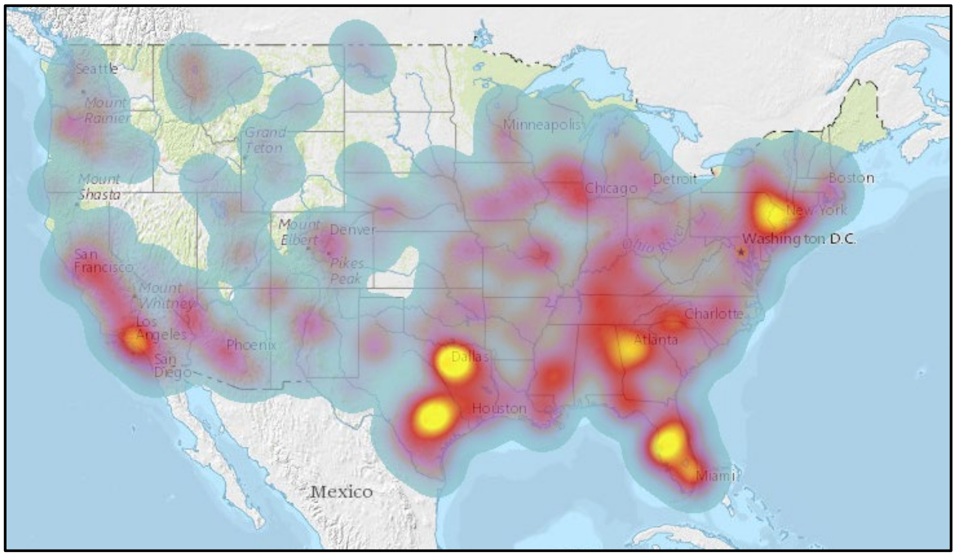


Figure 8: Locations of Large-Scale Fatality Crashes within the U.S. Mainland

Table 12: 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 Character-istics	VE_FORMS (Number of vehicles)-level effect	2,408	0.08	0.054	1	64
	BODY_TYPE (Vehicle body type, base =1 passenger vehicle)	2,408	0.629	0.483	0	1
	BODY_TYPE=2 (Van type)	2,408	0.223	0.416	0	1
	BODY_TYPE=3 (Truck)	2,408	0.135	0.342	0	1
	BODY_TYPE=4 (Other)	2,408	0.013	0.115	0	1
	FIRE_EXP (Fire in a crash) base=0 no fire	2,408	0.872	0.334	0	1
	FIRE_EXP=1 (Fire occurred in a crash)	2,408	0.128	0.334	0	1
	AIR_BAG (Air bag deployment in a vehicle, base =2 not deployed)	2,408	0.173	0.378	0	1
	RELJCT (crash's location with respect to junction or interchange areas, base=1 non-junction)	2,408	0.783	0.412	0	1
	RELJCT=2 (Intersection)	2,408	0.163	0.37	0	1
	RELJCT=3 (Ramp)	2,408	0.008	0.09	0	1
	RELJCT=4 (Railway)	2,408	0.011	0.103	0	1

	RELJCT=9 (Other location)	2,408	0.034	0.182	0	1
	REL_ROAD (location of the crash on traffic way, base=1 on roadway)	2,408	0.729	0.445	0	1
	REL_ROAD=2 (outside roadway)	2,408	0.249	0.433	0	1
	REL_ROAD=9 (other)	2,408	0.022	0.145	0	1
	AIR_BAG (Air bag deployment, base=2, not deployed)	2,408	0.173	0.378	0	1
	AIR_BAG=1 (Air bag deployed)	2,408	0.397	0.489	0	1
	AIR_BAG=0 (Unknown)	2,408	0343	0.495	0	1
Person Characteristics	AGE	2,408	33.11	20.28	0	93
	SEAT_POS (Location of a person in a vehicle, base=1 Front seat)	2,408	0.569	0.495	0	1
	SEAT_POS=2 (second seat)	2,408	0.246	0.431	0	1
	SEAT_POS=3 (Third seat)	2,408	0.026	0.159	0	1
	SEAT_POS=5 (Other locations not 3rd or 4th seat)	2,408	0.098	0.298	0	1
	SEAT_POS=99 (Unknown)	2,408	0.061	0.239	0	1
	REST_USE (Restraint equipment used by the person, base=0 none restraint used)	2,408	0.37	0.483	0	1
	REST_USE=1 (Shoulder belt only)	2,408	0.002	0.049	0	1
	REST_USE=2 (Lap belt only)	2,408	0.005	0.073	0	1
	REST_USE=3 (Lap and shoulder)	2,408	0.444	0.497	0	1
	REST_USE=4 (Child safety seat)	2,408	0.025	0.156	0	1
	REST_USE=5 (Helmet)	2,408	0.004	0.064	0	1
	REST_USE=99 (Unknown)	2,408	0.149	0.356	0	1
	REST_MIS (restraint system misuse, base=0, no)	2,408	0.993	0.086	0	1
	REST_MIS=1 (misuse)	2,408	0.007	0.086	0	1
	EJ_PATH (Ejection status and degree of ejection for a person, base=0 not ejected)	2,408	0.861	0.086	0	1
	EJ_PATH=1 (Side door)	2,408	0.007	0.084	0	1
	EJ_PATH=2 (Side window)	2,408	0.007	0.081	0	1
	EJ_PATH=3 (Windshield)	2,408	0.005	0.07	0	1

	EJ_PATH=4 (Other)	2,408	0.007	0.084	0	1
	EJ_PATH=9 (Unknown)	2,408	0.113	0.317	0	1
	EXTRICAT (equipment or other force to remove person form the vehicle, base =0, no)	2,408	0.749	0.433	0	1
	EXTRICAT=1 (yes)	2,408	0.219	0.414	0	1
	EXTRICAT=99 Unknown	2,408	0.032	0.175	0	1
	PERNOTMVIT (Number of persons not in motor vehicles in transport)	2,408	0.103	0.584	0	11
	PERMVIT (Number of persons in motor vehicles in transport)	2,408	14.61	26.23	1	120

4.2.4 Model Results and Discussion

To investigate more thoroughly the effects of the crashes on the death outcome of each person involved, a 4-level mixed-effects logistic regression model has been constructed. Model results are presented in Table 13. Contained in this table are values for coefficient, standard error or deviation, the Z statistic which measures the standard deviation from the mean, and the P-value, which is the level of significance. Variables are categorized into Crash Characteristics and Person Characteristics. Three additional level random effects are added to the fixed-effects model, including the random effects on case level (variable name: ST_CASE), the number of vehicles level (variable name: VE_TOTAL), and the manner of collision level (variable name: MAN_COLL).

The log likelihood ratio test used for comparing the goodness of fit of two statistical models indicates that the 4-level mixed-effects logistic regression model when compared to the fixed-effect logistic regression model results in a value of 19.41, with a p-value equal to 0.0001. This means that adding the random effect to specific variables will increase the modeling power to capture more heterogeneity in each group, which can be clustered using each level. These variables and their results include:

- Age. This is a statistically significant variable in the model. It shows older people are less likely to die in a fatal crash.
- Fire. If a 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 people are sitting in the vehicle, 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 trucks are involved in a crash, the overall injury severity level of the crash is increased. However, in terms of each person's injury, a person in a truck has a lower potential of dying when compared to a person in a passenger vehicle. The same is true for other big vehicles (e.g. vans, pick-up trucks); the passengers in those vehicles had less potential to die in a crash. However, people on motorcycles and smaller vehicles have a higher potential to die in a fatal crash.

- Restraint System Use. Similarly, if people use a full restraint system with both lap and shoulder belts, the chance of dying in a fatal crash is significantly decreased. However, if the restraint system is being misused, then the potential for death in a fatal crash is significantly increased.

- Airbag. If the airbag is deployed, the chance for a person to die is significantly higher; however, such a relationship is not causal. The installment of airbags is to protect the body from being seriously injured, but the deployment of the airbag indicates the severity of the crash is already very high. Thus, airbag deployment indicates a higher potential of death in the crash due to crash severity.

- Ejection Path. Occupant ejection for a vehicle during a crash can be a very serious event. Compared with no body ejection in a fatal crash, the presence of any type of ejection increases the potential for death. The most significant ejection paths are people ejected from the side door.

- Equipment or Other Force to Remove Person from the Vehicle. Though this is a statistically significant variable, it does not reveal a causal relationship. If such operations are deployed, it usually means people cannot move, and most likely the people are dead or severely incapacitated 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 that the more people involved in a crash, the lower the probability of a person being killed, regardless of whether the individual is in a motor vehicle. This is not a causal relationship as it indicates when the number of people is larger, the survival rate associated with the crash will be higher as not everyone will be killed.

- Geometric Characteristics. If a crash happened near a junction (e.g. intersection, driveway, and interchange area), then the potential for a person to die is much lower. This is probably due to the slowing down of vehicle speeds when approaching a junction. However, if a crash happens at a railway junction, then the potential of a fatality is much higher. Additionally, if a crash happens outside of the roadway, such as on the shoulder or median, then there is a higher potential of fatality than an accident on the roadway.

Table 13: Model Estimations of the 4-level Mixed-effects Logistic Regression Model

Description	Coef.	SE	Z	P-value

Case level	ST_CASE-level effect	0.219	0.115	---	---
	Constant	0.574	0.231	2.48	0.013
Crash Characteristics	VE_TOTAL-level effect (Number of vehicles)	0.078	0.052	---	---
	BODY_TYPE=2 (base =1) (Van)	-0.437	0.136	-3.21	0.001
	BODY_TYPE=3 (Truck)	-1.824	0.295	-6.18	0.000
	BODY_TYPE=4 (Other)	0.676	0.632	1.07	0.285
	FIRE_EXP=1 (base=0) (Fire Occurred in Crash)	1.434	0.218	6.59	0.000
	RELJCT=2 (base=1) (Intersection)	-0.233	0.178	-1.31	0.189
	RELJCT=3 (Ramp)	-0.554	0.654	-0.85	0.397
	RELJCT=4 (Railway)	1.577	0.734	2.15	0.032
	RELJCT=9 (Other Location)	-0.518	0.311	-1.67	0.096
	REL_ROAD=2 (base=1) (Outside Roadway)	0.836	0.217	3.85	0.000
	REL_ROAD=9 (Other)	0.871	0.462	1.88	0.060
	AIR_BAG=1 (base=2) (Air Bag Deployed)	0.466	0.164	2.84	0.004
	AIR_BAG=0 (Unknown)	0.065	0.18	0.36	0.719
	MAN_COLL – level effect	0.078	0.052	---	---
Person Characteristics	AGE	-0.002	0.001	-0.39	0.002
	SEAT_POS=2 (base=1) (Second Seat)	-0.012	0.153	-0.08	0.938
	SEAT_POS=3 (Third Seat)	-1.037	0.295	-6.18	0.001
	SEAT_POS=5 (Other)	-0.515	0.353	-1.46	0.145
	SEAT_POS=99 (Unknown)	-0.708	0.263	-2.70	0.007
	REST_USE=1 (base=0) (Shoulder Belt)	0.147	0.904	0.16	0.870
	REST_USE=2 (Lap Belt)	-0.463	0.703	-0.66	0.51
	REST_USE=3 (Should and Lap Belt)	-0.784	0.158	-4.96	0.000
	REST_USE=4 (Child Safety Seat)	0.0387	0.364	0.11	0.915
	REST_USE=5 (Helmet)	-0.429	1.01	-0.42	0.671
	REST_USE=99 (Unknown)	-0.273	0.193	-1.41	0.159
	REST_MIS=1 (base=0) (No Restraint Misuse)	2.618	1.115	2.35	0.019
	EJ_PATH=1 (base=0) (Side Door)	4.762	1.947	2.45	0.014
	EJ_PATH=2 (Side Window)	1.468	0.888	1.69	0.092
	EJ_PATH=3 (Windshield)	0.679	0.849	0.80	0.424
	EJ_PATH=4 (Other)	2.692	1.127	2.39	0.017
	EJ_PATH=9 (Unknown)	1.264	0.218	5.82	0.000
	EXTRICAT=1 (base =0) (Extracted from vehicle)	1.439	0.159	9.00	0.000
	EXTRICAT=99 (Unknown)	1.394	0.344	4.06	0.000
	PERNOTMVIT (# of persons NOT in transport)	-0.387	0.159	-2.52	0.012
	PERMVIT (# of persons in transport)	-0.039	0.007	-5.10	0.000

4.3 Data for Incident Classification and Duration Prediction

The web-based archiving tool Locate/IM is used to access the TDOT Region 1 Traffic Management Center incident database. TMC derives information for the database through the Tennessee SmartWay, and TDOT HELP programs among others. For this research, the incident data is obtained for the year 2017 involving incidents in TDOT Region 1. There were 24,015 incidents in Region 1 in 2017. Incidents with missing route information were removed from the sample, resulting in the analysis of 24,003 incidents. Due to the sample size, in order to accurately analyze incident duration prediction purposes, additional traffic incident summary and detailed operational reports were included. Summary data were collected between September 29, 2010 through December 31, 2015, covering 26 counties and 17 routes (7 freeways and 10 major highways) in the East Tennessee Region. A total of 129,088 incident records were obtained. The Manual of Uniform Traffic Control Devices has a standard classification system for Large-scale Traffic Incidents found in Section 6I.01 General. The section indicates that 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).

4.3.1 K-Means Cluster Classification Model

Such a general classification criterion does not apply to different regions due to the heterogeneity among various traffic incident cases. Therefore, a new proposed machine learning classification method called K-means Clustering is applied to classify those traffic accidents. K-means clustering is used in cluster analysis to partition observations into clusters based on the closest mean, which serves as a prototype for the cluster. The clustered classification results will be used for further traffic incident duration prediction. The K-Means clustering algorithm begins with a predefined number of clusters, where each observation belongs to a single cluster. A measure of each cluster's variance is defined in such a way as to minimize variation 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 a cluster. The formulation of the problem can be written using equation 2.1. The K-Means clustering algorithm follows an iterative two-step method. In the first step, the researcher randomly selects K clusters and assigns them to each observation. These will be the initial assignments. In the second step, the research calculates the mean value based on the feature's centroid for each of the K clusters and then assigns the observations using the least squared Euclidean distance. This second step is repeated until all the assignments have been made.

The incident data is error checked to validate whether there is any missing information for different variables. In this case, 12 incident records were found to have missing route information, and they were removed from the main body of the data. The resulting data identified 19 different types of incidents. These include 1) Abandoned Vehicle; 2) Amber Alert; 3) Debris; 4) Disabled Vehicle; 5) Jackknifed Tractor-Trailer; 6) Multivehicle Crash; 7) Overturned Vehicle; 8) PD/MED/FIRE Activity; 9) Scheduled Roadwork; 10) Single Vehicle Crash; 11) Special Event/PSA; 12) Test Incident; 13) Travel Time; 14) Unknown; 15) Unscheduled Road Work; 16) Vehicle Fire; 17) Weather; 18) Oversize load, and 19) Grass Fire.

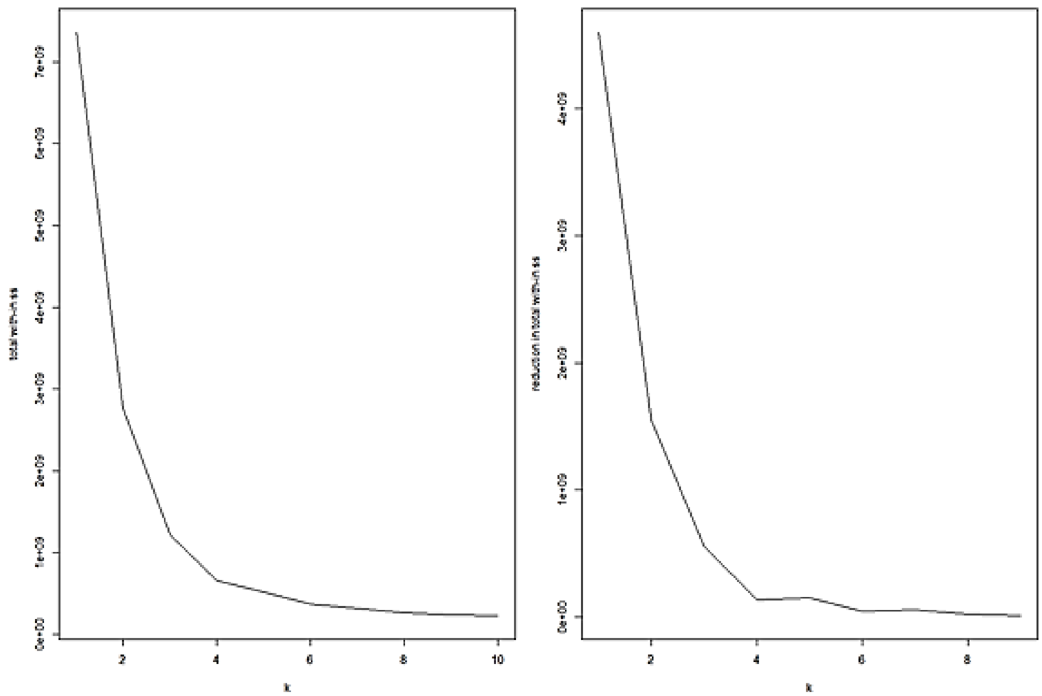


Figure 9: Change in Cluster Sum of Squares for the First Iteration

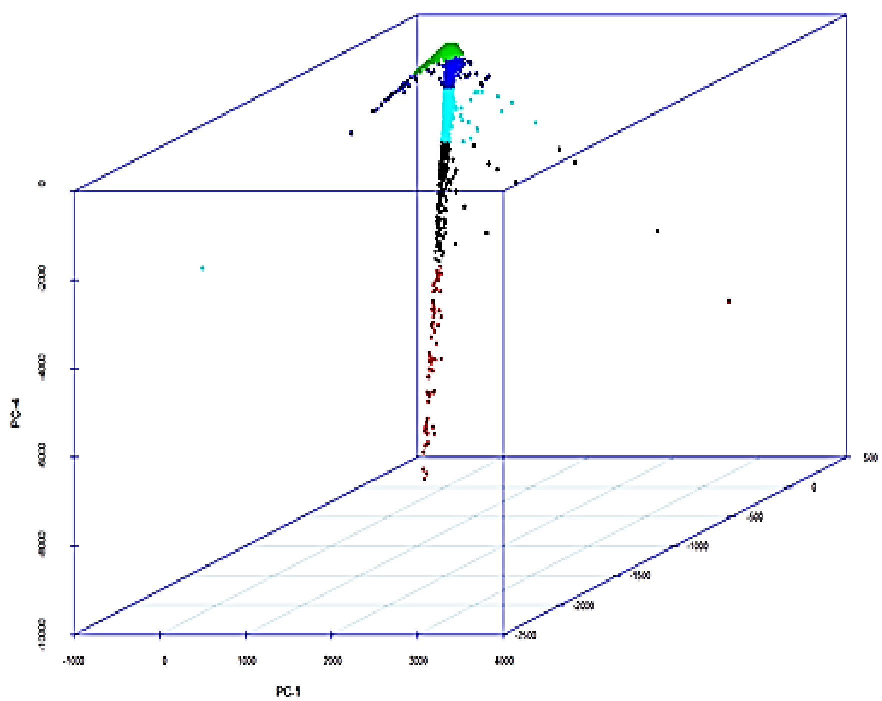


Figure 10: Three-Dimensional Representation for 5 Clusters of Incident Data

.
These incidents either happened on Interstate freeways (e.g. I-40, I-75, I-81, I-640, I-26) or State routes (e.g. SR115, SR158). The incident types, routes, as well as travel direction, morning peak hour, afternoon peak hour, and urban/rural area are all coded as binary variables. A hierarchical clustering method is utilized first to prepare the variables for the K-means clustering process as the K-means clustering method cannot calculate ordinal or categorical variables reliably. Figure 9 presents the change in cluster sum of squares. Notice that a single classification result cannot be represented visually as separated incident data. Therefore, an interactive clustering method was developed to cluster incidents by removing clusters with a small number of candidates. Incidents without response time are removed for better classification. A total number of 4041 incidents were removed from the sample. By inferring from Figure 9, four or five clusters would seem to provide enough categories for the classification of data. After five clusters, the model cannot cluster data in a meaningful way. Finally, the use of five clusters was chosen because it can further reduce the variance within each cluster. A total of 19,962 incidents were analyzed, the clustering results are shown in Figure 7, where blue dots represent cluster 5, green dots represent cluster 4, light blue dots represent cluster 3, black dots represent cluster 2, and red dots represent cluster 1. Figure 10 suggests a pyramid classification where most observations are found on the top of the pyramid, with fewer observations near the bottom of the pyramid.

4.3.2 Model Results and Discussion

As seen in Figure 10, cluster 1 contains incidents involving abandoned vehicles, with an average incident duration time of about 7,009 minutes. In cluster 2, incidents involving either abandoned or disabled vehicles are portrayed, with an average incident duration of about 3,047 minutes. In cluster 3, mixed incident types are found, with an average incident duration of about 1,388 minutes. Most incidents (about 90 percent) are found in cluster 4 with an average incident duration of about 40 minutes. Finally, as in cluster 3 and 4, cluster 5 represents mixed types with an average incident duration of about 594 minutes. Results indicate clusters 1 and 2 both of which contain the most abandoned or disabled vehicles have the longest incident duration times – with duration times between approximately 116 to 50 hours. While clusters 3 and 5 duration times are between approximately 24 to 10 hours long. Cluster 4 contains the majority of incidents and has an incident duration time of 40 minutes.

Data was then divided into three incident groups based on incident duration (1) extreme duration; (2), long duration, and (3) short to moderate duration. Each group was associated with incident type, incident location, vehicle type and peak hour data. For example, in group 1 (extreme duration), most incidents are associated with abandoned vehicles (98.7%), with the remainder being associated with disabled vehicles (1.3%). The same is true for group 2 (long duration) as most incidents are associated with abandoned vehicles (87.4%), followed by disabled vehicles (10.1%). In group 3, (short to moderate duration) most incidents deal with disabled vehicles (72.6%), then abandoned vehicles (8.1%), debris (8.0%), multi-vehicle crashes (7.5%), single-vehicle crashes (2.4%). Route characteristics provide location information. Based on the data, 98.1 percent of group 1 incidents happened on the freeway, and about 68.4 percent of all freeway incidents happened on I-40. Similar statistics can be found for other groups. The annual average daily traffic (AADT) for group 1 incidents include 60,817 freeway incidents, and 35,550 non-freeway incidents. AADT for group 2 include 61,769 freeway incidents, and 38,733 for non-freeway incidents. AADT for group 3 include 66,817 freeway accidents, and 37,327 non-freeway accidents. In group 1, the percentage of truck-involved incidents, both single and multi-unit trucks) is 16.27 percent on the freeway and 4.17 percent for non-freeway routes. The percentages for group 2 include 15.36 percent for freeway incidents and 3.87 percent for non-freeway incidents. In group 2, the percentages are 16.8 percent for freeway incidents, and 4.21 percent for non-freeway incidents. For all groups, about 95 percent of all incidents occurred in urban areas. Regarding the time of the incident, in group 1, 26.2 percent of incidents happened in morning peak hours, and 23.6 percent in the afternoon peak hours. For group 1, about half of all incidents occurred during the peak hours. For group 2, 34 percent of incidents occurred in the morning peak hours, and 27.3 percent in afternoon peak hours, and in group 3, 20.3 percent happened in morning peak hours, and 28.9 percent happened in the afternoon peak hours.

Table 14 presents the descriptive statistics (number, mean in minutes of time, standard deviation, median, minimum and maximum values) associated with lane blockage and incident duration for each group. In group 1, 99.4 percent (311 of 313 accidents) do not involve lane blockage. In group 2, 97.1 percent of all accidents do not involve lane blockages, and in group 3, 93 percent of incidents result in no lane blockage. Table 14 also indicates that when there is no lane blockage, the average incident duration for group 1 (3,954 minutes) and group 2 (925.7 minutes) incidents are usually longer than for group 3 (38.7 minutes). When there is at least one lane blocked during an incident, the average incident duration becomes shorter for group 1 incidents (i.e. from 3,954 minutes to 2639 minutes) and group 2 incidents (i.e. from 925.7 minutes to 715.4 minutes). However, such a trend is not represented with group 3 incidents, as duration increases then decreases depending on the number of lanes blocked. The average incident duration time increases steadily when the number of lanes blocked ranges from zero to three – from 38.7 minutes to 89.57 minutes. Incident duration decreases when four, five or eight lanes are blocked.

Table 14: Descriptive Statistics for Incident Duration Based on Lane Blockage

	N	Mean	Std.	Median	Min	Max
Group 1						
Lanes Blocked = 0	311	3954	1887	3091	2225	9843
Lanes Blocked = 1	2	2639	417.9	2638	2343	2934
Group 2						
Lanes Blocked = 0	1600	925.7	464.4	847	318	2215
Lanes Blocked = 1	29	715.4	424.3	535	315	2207
Lanes Blocked = 2	18	512.4	208.1	422.5	351	1118
Lanes Blocked = 3	3	524.33	248.2	434	334	805
Group 3						
Lanes Blocked = 0	16690	38.7	53.34	17	0	317
Lanes Blocked = 1	872	60.68	51.34	48	1	304
Lanes Blocked = 2	312	69.07	45.98	57	5	295
Lanes Blocked = 3	51	89.57	63.04	71	9	288
Lanes Blocked = 4	8	83.75	32.71	69.5	55	139
Lanes Blocked = 5	3	60.33	21.36	69	36	76
Lanes Blocked = 8	3	7.67	3.51	8	4	11

In terms of lane blockage duration and response time for the incidents, Table 15 presents the descriptive statistics (number, mean in minutes, standard deviation, median, minimum and maximum) for block duration and response time. In terms of response time, on average when no lanes are blocked, it takes agencies a little more than one hour (77 minutes) to respond to group 1 incidents, and about 20 minutes to respond to group 2 incidents, but only about four minutes to respond to group 3 incidents. All cases involving descriptive statistical analysis for lane blockages involve a decreasing number of incidents as the number of lanes blocked increase. This may influence the temporal values derived as there are not enough incidences to accurate extract a meaningful value that can be applied to the population as a whole.

Table 15: Descriptive Statistics for Response Time Based on Lane Blockage

	N	Mean	Std.	Median	Min	Max
Group 1						
Lanes Blocked = 0	311	77.23	461.84	0	0	5723
Lanes Blocked = 1	2	1	1.414	1	0	2
Group 2						
Lanes Blocked = 0	1600	19.66	92.09	0	0	1750
Lanes Blocked = 1	29	16.34	51.44	2	0	274
Lanes Blocked = 2	18	14.28	18.2	5.5	0	53
Lanes Blocked = 3	3	1	1.732	0	0	3
Group 3						
Lanes Blocked = 0	16690	3.72	10.42	0	0	186
Lanes Blocked = 1	872	5.01	9.07	2.5	0	102
Lanes Blocked = 2	312	5.25	9.51	2	0	88
Lanes Blocked = 3	51	5.04	9.49	3	0	68
Lanes Blocked = 4	8	2.25	1.67	2	0	5
Lanes Blocked = 5	3	2.33	2.52	2	0	5
Lanes Blocked = 8	3	0	0	0	0	0

4.3.3 Hazard Based Model

In addition to analyzing incident duration and response time based on lane blockage in an existing dataset, a method for incident duration prediction has also been investigated using the hazard-based model. This type of prediction is very useful for traffic operations, especially under situations involving lane blockage. Past methodologies, MUTCD recommendations, Tennessee traffic incident management goals, such as removing incidents within 90 minutes, as well as mean incident durations contribute to the selection of large-scale traffic incident data to be used in the prediction model. The results include the use of data where large-scale incidents are considered those lasting more than 120 minutes with at least one lane blocked. A total of 890 incidents out of 129,088 incidents were chosen for the sample. All incidents occurred in TDOT Region 1. The incident locations are displayed in Figure 11, indicating that most of them occurred near urban areas. Substantial effort went into creating a comprehensive database for the selected incidents. The data was collected and enhanced by creating new variables from incident operations reports, as well as plotting incidents in google earth to obtain spatial information, e.g., number of lanes. Tennessee crash reports are also used to obtain data, e.g. AADT.

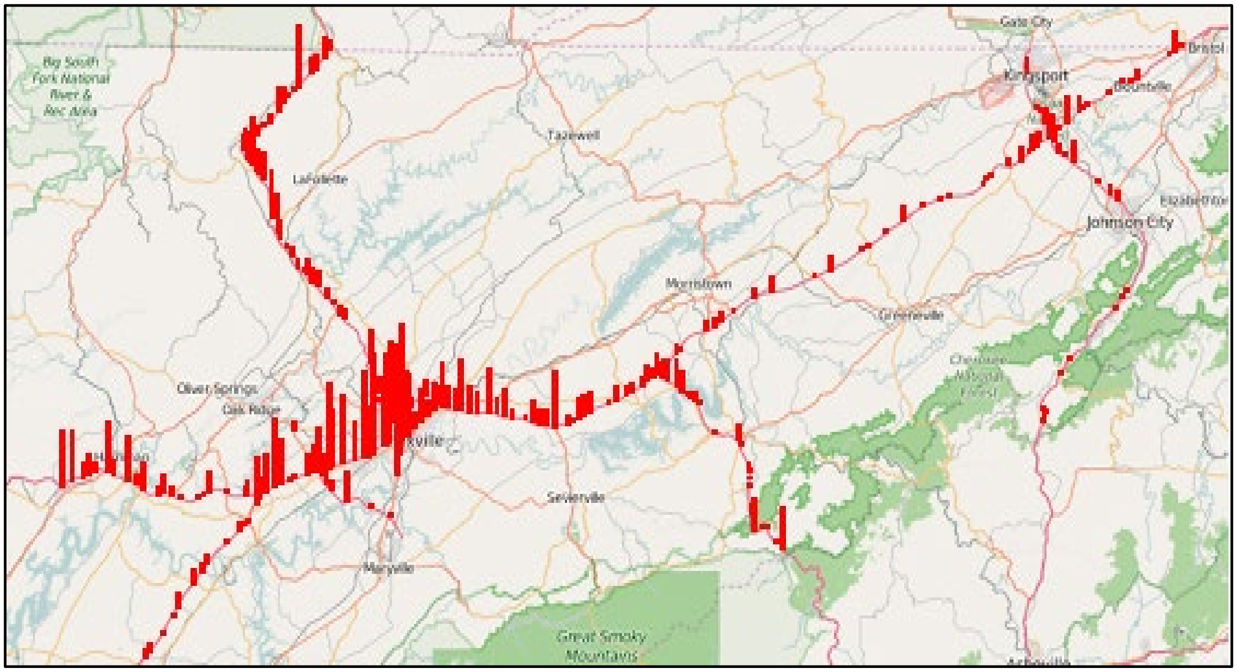


Figure 11: Spatial Distributions of Incidents within Region 1.

Figure 12 illustrates the general structure of the incident management process over time (upper part) and the data obtained (lower part). Focusing on multi-agency operational response during large-scale incidents lasting over 120 minutes, 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 databases and used for coding new variables such as HIRU response, number of vehicles involved, lane blockage, secondary incident occurrence, and HAZMAT incident; attributes 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 ambulance response times 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 this report.

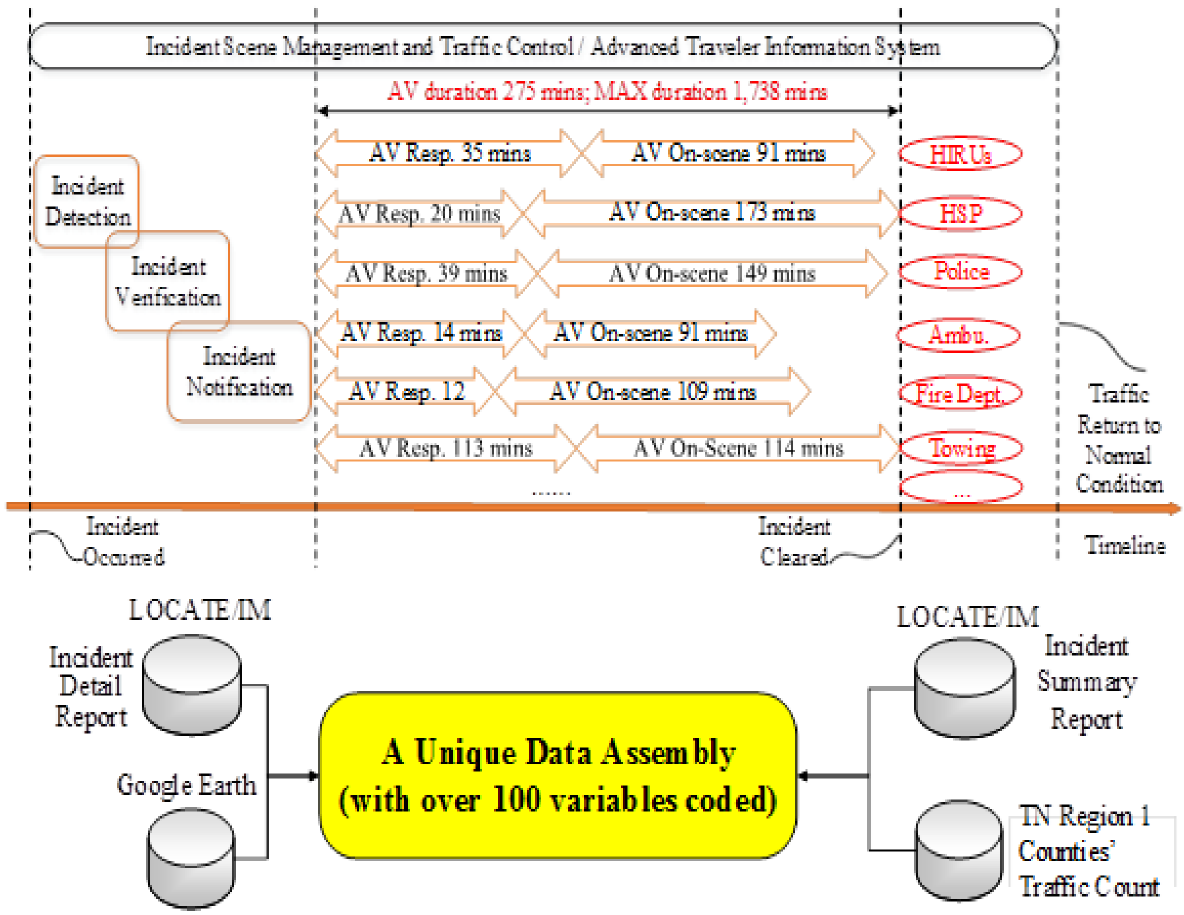


Figure 12: Traffic Incident Management Framework for Data Integration

Note that a bi-directional relationship may exist between incident duration and response times, as opposed to unidirectional relationships, which is assumed in this research. Specifically, researchers have assumed response times of various agencies as correlates of incident duration but understand that incident managers may respond more promptly to larger incidents of longer duration. This fact may reveal itself as a negative correlation between response times and incident durations, indicating that "potentially" longer incident durations can be a predictor of an agency's response time. Simultaneity bias describes this phenomenon where unexpected results happen when the explanatory variable is correlated with another variable that causes a lack of "goodness of fit". As such, capturing simultaneity through modeling was not performed due to many missing values for response times associated with specific agencies.

A hazard-based modeling approach is adopted in this research 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 the data in this study is particularly suitable. Third, the hazard-based approach facilitates interpretation of duration data using a dynamic sequence of conditional probabilities. The formation of a hazard-based modeling approach is described. 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 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 formulated using equation 2.2. 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 using equation 2.3.

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 a 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 match 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 formulated using equation 2.4.

Since the data are truncated, left truncated hazard-based models are estimated, based on equation 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, Khattak, & Wali, 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.

4.3.4 Model Results and Discussion

Table 16 provides descriptive statistics for variables associated with large-scale incidents, such as sample size, mean, standard deviation (SD), minimum, maximum and the variance inflation factor (VIF), which is the ratio of variance in a model with multiple terms, divided by the variance of a model with only one term. 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. Table 16 shows the mean duration of the large-scale incidents is 275 minutes, which is 129 percent larger than the mean duration of all incidents in the database. Almost 10 percent of the large-scale incidents last more than 497 minutes. Key variables (out of all variables in Figure 9) 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 percent, 8 percent, and 13 percent 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 percent of incidents occurred during afternoon peak (4 PM – 8 PM), whereas 80 percent 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 has 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 (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 the Locate//IM dataset, 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 mind the negligible differences between sample sizes of response and the on-scene times of the 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 (First (1^{st}), Second (2^{nd}), Third (3^{rd}) unit, and so on). However, average response times of three or more than three HIRUs units are reported in Table 16. 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 16 shows the average response times for first, second and more than two HIRU units that are 35.4 (1.18*30), 77.5 (2.58*30), and 134.9 (4.49*30) minutes, respectively. The larger response times for a greater number of HIRUs may reflect the severity of large-scale incidents. Intuitively, among other response agencies, ambulances have the shortest average response time (14 minutes) followed by the police (39 minutes). The response time for towing companies is highest with an 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 the longest time (173 and 148 minutes respectively) at large-scale incident scenes. While for a towing company, the time is about 114 minutes and for HIRU units 90 minutes. Notably, only 1.6 percent 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, Highway Advisory Radio (HAR) and Dynamic Message Signs (DMS) are used in 84.6 percent and 92.3 percent 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 16 for key variables. VIF values for key explanatory variables are smaller than 10, which indicates that multicollinearity is not a concern (Khattak, et al., 2016).

Table 16: Descriptive Statistics of Variables Associated with Large-Scale Incidents

Variable	**Sample size**	**Mean**	**SD**	**Min**	**Max**	**VIF**
Incident Durations (in minutes)	890	274.90	199.22	121	1738	---
	10th Percentile: 132 minutes 25th Percentile: 152 minutes 50th Percentile: 203 minutes 75th Percentile: 321 minutes 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 (4 PM – 8 PM)	890	0.228	0.419	0	1	1.08
Weekday	890	0.794	0.404	0	1	1.048
Traffic volume						
Annual Average Daily Traffic (AADT) (log form)	890	11.057	0.553	10.087	12.162	0.112

Operational Responses						
Response time of first Highway Response Unit (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 Highway Safety Patrol (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						
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 Hazardous Materials (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 Highway Advisory Radio (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 Dynamic Message Signs (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

4.4 Model Comparison and Key Findings

Before reviewing incident duration models, potential explanatory variables are identified by developing a series of simple correlation matrices and ordinary least squares regression models (Washington, Karlaftis, & Mannering 2010). This proved valuable in the identification and conceptualization of explanatory variables. Next, a series of fixed-parameter accelerated failure time (AFT) hazard-based duration models were developed. AFT models provide an alternative to the commonly used proportional hazards models. Whereas a proportional hazards model assumes that the effect of a covariate is to multiply the hazard by some constant, an AFT model assumes that the effect of a covariate is to accelerate or decelerate the hazard by some constant. Following the research of 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 16 were included in the models. The fixed-parameter hazard-based duration models are developed using standard maximum likelihood estimation techniques.

For brevity, researchers present the final summary statistics (goodness-of-fit measures) in Table 17. The table compares performance indices of fixed parameters (i.e. log-normal, log-logistic, Weibull, and Weibull with Gamma heterogeneity) and random parameters (i.e. random parameter Weibull). A comparison of a series of values (i.e. Theta, Sigma, P, LL(0), LL(β), number of observations, and likelihood ratio statistics) was performed where Theta is heterogeneity parameter; Sigma is the amount of data variation; P is a hazard distribution parameter; LL(0) is the log-likelihood of constant only model, and LL(β) is the log-likelihood at convergence. To compare the fixed-parameter models with different distributional assumptions, likelihood ratio statistics are calculated in order to select the statistically superior model (Wali, Ahmed, Iqbal, & Hussain 2017). For details regarding likelihood ratio statistics, interested readers are referred to Washington et al. (2010). A higher value of the likelihood ratio statistic parameter for a specific model indicates an improved statistical fit when compared to other fixed-parameter models (Washington 2010). Based on a review of fixed-parameter models found in Table 17, the Weibull model resulted in the best fit 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 were 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.

Table 17: 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

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

Given the fact that several observed and unobserved factors can contribute to large-scale incident durations, random-parameters are incorporated into the fixed-parameter indices, specifically using the random parameter Weibull hazard-based duration model. 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, the 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 likelihood ratio statistic of 831.02.

Whereas, the results of fixed- and random- parameter Weibull models are presented in Table 17, the completed 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. These results are found in Table 18. 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 agrees 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 illustrated in Figure 10.

Table 18 presents the fixed- and random- parameter Weibull model for large-scale traffic incidents, including parameter and t-stat changes for both models. Variables analyzed include incident type, temporal factors, traffic volume, operational response, and dummy variables for missing values of response and on-scene times of different agencies. A positive parameter estimate for an explanatory variable correlates with an increase in incident duration or a 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 18 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 18 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 the indicator variable changing from zero to one. For this analysis, the dependent variable is the log of incident duration in minutes; the response and on-scene times are scaled in 30-minute increments for ease of interpretation, and the percent changes in incident duration are made 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.

Table 18: Model Estimation Results for Fixed- and Random-Parameter Models

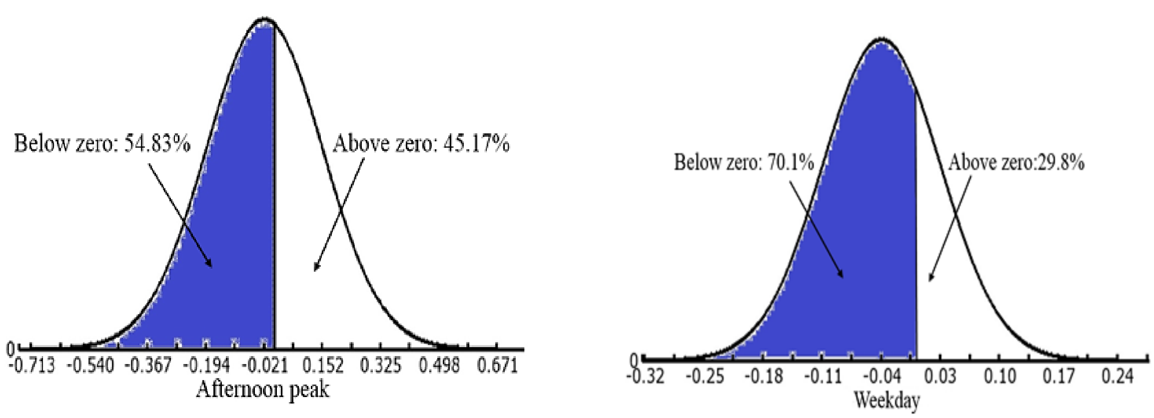
Variables	**Fixed Parameters Weibull***		**Random Parameters Weibull***		
	Parameter	t-stat	Parameter	t-stat	% Changes***
Incident type					
Multivehicle crash	-0.159	-4.52	-0.138	-14.13	-12.90%
Vehicle fire	0.092	1.6	0.16	10.28	17.30%
Unscheduled roadwork	0.4	11.7	0.28	20.59	32.30%
Temporal factors					
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%
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 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.

Regarding the estimation results shown in Table 18, response and on-scene times of different agencies play an important role in determining 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 an 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, the incorporation of random-parameters significantly enhanced the statistical significance of parameter estimates. For instance, a 30-minute increase in response time for HIRUs translates to 2.83 percent, 1.61 percent, and 4.28 percent increases in incident durations for units one, two and three, respectively. Research indicates the mean incident duration is 135 minutes for first and second HIRU units, and 338 minutes for third or more HIRU units. The data suggest that the association of response times for the third or more HIRUs is more pronounced when compared to the response times for first or second units. Likewise, an increase of 30-minute in response times of HSP and towing companies are associated with 3.9 percent and 3.25 percent increases in large-scale incident durations. This is understandable as HSP and towing companies 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 agrees with Hojati et al. (2013), who found a positive correlation between the indicator variable for towing and non-large-scale incident duration. (Hojati et al., 2013).

Contrary to expectations, an increase in response times for the police department and ambulances is associated with 2.5 percent and 2.7 percent shorter incident durations respectively. However, it is possible that response times by police and ambulance to larger incidents in this dataset are shorter. This may result in the unexpected direction of correlation observed. Even if an incident is large-scale, ambulance department response time may differ depending on congestion, etc. 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 13, the response times for ambulance is found to be a normally distributed random parameter implying significant heterogeneity (on average 95.02 percent of the distribution is less than zero and about 4.98 percent greater than zero) in associations between ambulance response time and incident durations.



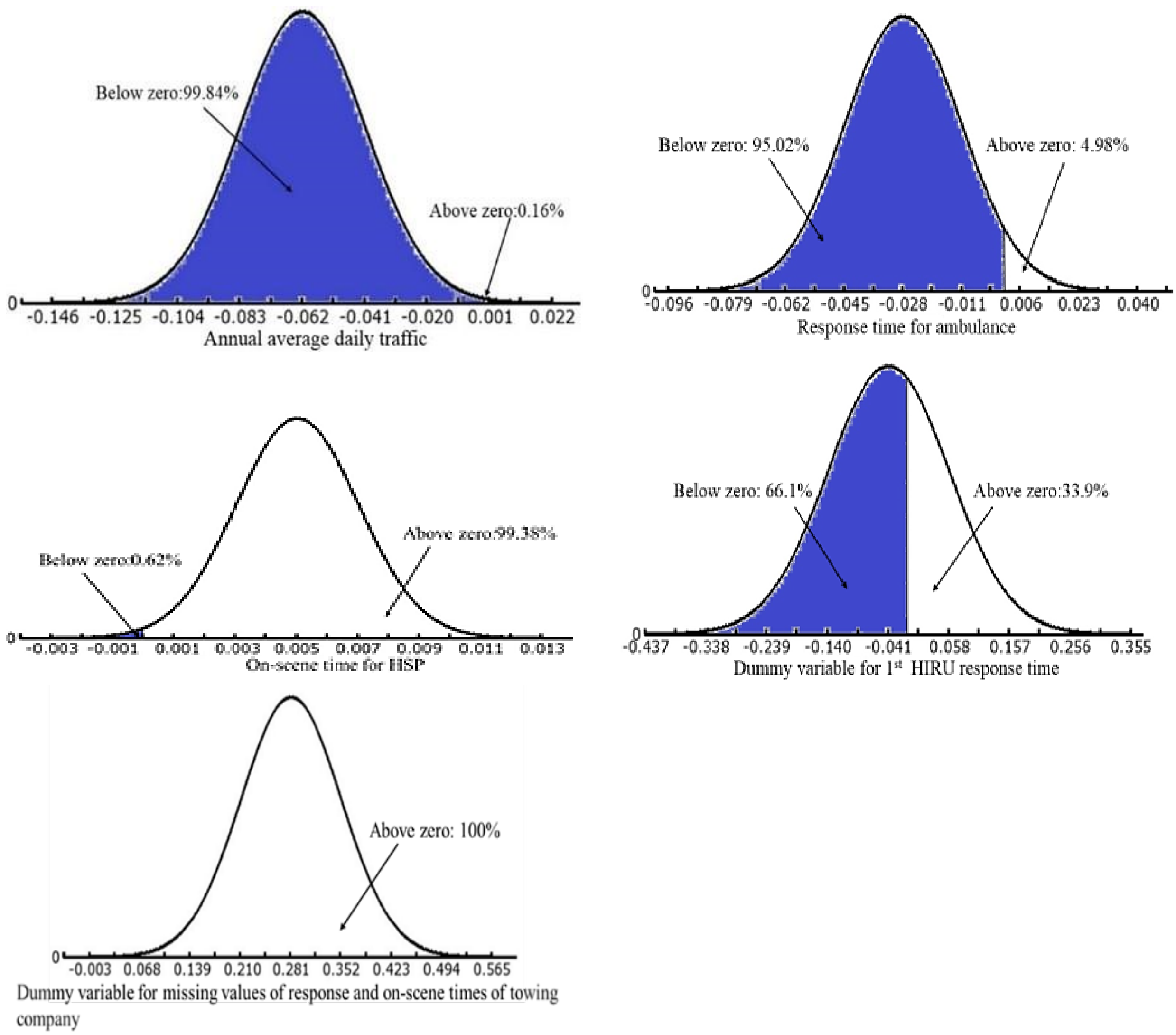


Figure 13: Distributions of Normally Distributed Fandom Parameters

The analysis reveals the 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 a 4.4 percent increase in incident durations. Likewise, a 30-minute increase in on-scene times for HSP, police, ambulance, and towing companies is associated with 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 percent of observations (Figure 10). 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 vehicles, clear debris, manage traffic at the scene, etc.

Finally, incident types, vehicle fire, and unscheduled roadwork are associated with 17.3 percent and 32.3 percent increase in large-scale incident durations, respectively. Incidents in afternoon peak times are associated with relatively shorter durations. However, the associations vary substantially across observations—they are positive for 45.1 percent and negative for 54.9 percent of the data (Figure 13). 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 18, Figure 13). 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 six percent 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. The indicator variables for missing data are statistically insignificant implying missing values are randomly distributed, which is the case for most indicated variables (Figure 13).

4.5 Sequential Prediction for Real-Time Incident Duration

Traffic information is obtained chronologically and transmitted to Traffic Management Centers by various agencies, thus, it is more efficient for incident updates to be processed by traffic operations managers. The literature review indicates that researchers have applied the time sequential prediction approach to different modeling processes (i.e. simple regression models, hazard-based models, combined topic models, hazard-based models, and Artificial Neural Networks) (Khattak et al. 1995; Li et al. 2015; Qi & Teng 2008; Wei & Lee 2007). However, these studies indicate the models are not sophisticated enough to capture heterogeneity and to obtain high accuracy. As a result, hazard-based parametric survival models with frailty distribution, and multilevel mixed-effects hazard-based parametric survival models are adopted to capture heterogeneity and high accuracy.

As discussed before, accelerated failure time (AFT) models provide an alternative to the commonly used proportional hazards models, which assumes the covariate multiplies the hazard by a constant. In AFT modeling, the covariate accelerates or decelerates the understood sequential life course of a variable. Weibull accelerated failure time (WAFT) models are more appropriate for modeling incident data as they can be used to predict time to failure; the equation for the logarithm model is expressed using equation 2.5. In the 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 formulated using equation 2.6.

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 formulated using equation 2.7. Assuming $g(\alpha)$ is the probability density function of the unobservable α, the unconditional survival frailty function is obtained using equation 2.8. And the unconditional density and hazard functions are also obtained using equation 2.9. For mathematical tractability, the choice of g(α) is limited to either the gamma distribution denoted as gamma(1⁄θ,θ) or the inverse-Gaussian distribution with denoted as IG(1,1⁄θ). The probability density function of gamma(a, b) distribution is formulated using equation 2.10, and the probability density function of IG(a, b) distribution is formulated using equation 2.11. Thus, the frailty models for gamma, and inverse-Gaussian, separately will become formulated using equation 2.12.

By adding random effects into the log-logistic AFT models, this generates new models (i.e. the Multilevel Mixed-effects Parametric Survival Model) formulated using equation 2.13. The density and survival function conditional on the linear prediction η is given in equation 2.14. The conditional distribution of t_j for cluster j is written as equation 2.15. The model has no closed form and must be approximated based on the likelihood of all the clusters by integrating $u_j$out of the joint density distribution $f(t_j, u_j)$. The maximum likelihood optimization technique is adopted, and Stata software is used for the modeling tasks. Its formulation is written in equation 2.16.

The data used for this analysis comes from the same Locate/IM incident database as the previous analysis. The data is collected from 2015 to 2016, and the selection criterion for large-scale incidents is if the incident lasts for 90 or more minutes and is blocking at least one lane on the roadway. The selection criterion is reflective of 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. However, the original dataset had 19 incident types; this dataset has 13 incident types. Because this analysis is focused on large-scale incidents, incident types, such as amber alert; scheduled roadwork; test incident, used for training; travel time, oversized load and unknown incidents, were removed. Additionally, the first and second HIRU information are combined in terms of their response and on-scene times. The descriptive statistics are shown in Table 19 and include the mean, standard deviation, minimum and maximum values for each variable.

As seen in Table 19, the average incident time is about 234 minutes (almost four hours) for large-scale accidents. The minimum time is 90 minutes, and the maximum time is 5727 minutes or almost four days. As discussed earlier, in incidents of extreme duration, about 98.7 percent are associated with abandoned vehicles which may require multiple days for clearance. This may explain the maximum time. The incident that results in the longest duration is a multivehicle crash (37%), followed by a single vehicle crash (14%), disabled vehicle (11%) and overturned vehicle (10%). The spatial-temporal and weather factor variables indicate most incidents occur on the weekday, on a freeway in an urban area in bad weather. Other incident characteristics include the number of vehicles involved (1.4); the number of lanes blocked (1.49); the length of time the lane is blocked (about 82 minutes), and the number of HAR deployed (usually 2). Agency response characteristics include the total number of response agencies (slightly more than 2); the first agency response time (about 13 minutes), and response time for ambulances (about 12 minutes).

Table 19: Descriptive Statistics of Variables Associated with Large-Scale Incidents Variables

Variable	**Sample size**	**Mean**	**SD**	**Min**	**Max**
Incident Durations (in minutes)	603	233.97	142	90	5727
Incident type					
Abandoned 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
Jackknifed Tractor Trailer	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 Event/PSA	603	0.01	0.09	0	1
Unscheduled 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 vehicles involved)	603	1.41	0.99	0	9
DetcCCTV	603	0.63	0.48	0	1
Lanecount (number of lanes blocked)	603	1.49	0.76	1	8
BlkDuration (lane blockage duration)	603	81.62	137.53	0	1275
No_HAR (number of HAR deployed)	603	1.84	1.82	0	6

HAR_AveUseTim (average time used)	603	91.63	140.06	0	1077
No_DMS (number of HAR deployed)	603	2.01	1.64	0	11
DMS_AveUseTim (average time used)	603	105.89	138.58	0	1011
No_BEA (number of Beacon used)	603	1.21	2.01	1	20
Agency Responses Characteristics					
1st RespAgen (1st response agency) – HSP (safety patrol)	441	0.09	0.3	0	1
1st RespAgen – HIRU (highway incident response unit)	441	0.53	0.49	0	1
1st RespAgen – PD (police)	441	0.22	0.42	0	1
1st RespAgen – FD (fire department)	441	0.06	0.24	0	1
1st RespAgen – AMB (ambulance)	441	0.05	0.21	0	1
1st RespAgen – CS (county sheriff)	441	0.006	0.08	0	1
1st RespAgen – Tow (towing company)	441	0.02	0.16	0	1
1st RespAgen – ST (service truck)	441	0.007	0.08	0	1
1st RespAgen – TM (TDOT maintenance)	441	0.002	0.05	0	1
RespTime (1st 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 3rd or more HIRUs)	35	109.06	139.1	1	576
HIRU_AveOnsTim36 (Avg. On-scene time if 3rd 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
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

4.6 Summary

The models discussed above illustrate the results of captured unobserved heterogeneity in various models by either adding a multiplicative effect to the hazard or adding cluster-level random effects to the covariates. The model's significance statistics, such as AIC (Akaike information criterion) and BIC (Bayesian information criterion) can be used to compare model performance; however, for practical purpose, RMSE (Root Means Square Error) is selected to compare models where smaller values of RMSE are preferred.

Additionally, the five stages used for sequential prediction based on the availability of incident-related information have been used to predict the elements of a sequence based on the preceding elements. The five stages used include:

1. Location, temporal information, weather;
2. Location, temporal information, weather, incident characteristics (incident type, number of lanes blocked, number of vehicles involved);
3. Location, temporal information, weather, incident characteristics (incident type, number of lanes blocked, number of vehicles involved), incident response (first response agency, the response time of first response agency, number of dynamic message signs (DMS) activated, number of highway advisory radio (HAR) used);
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;
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 robust than that from the previous stage; however, this does not mean all information in each stage is utilized for prediction. By selecting important variables for each stage, the models can predict a reasonable incident duration. The model performance comparison, seen in Figure 14 and Table 20 documents the best modeling results for each stage. Figure 14 shows the root mean square error performance for each prediction stage, and Table 20 shows model comparisons based on AIC and BIC.

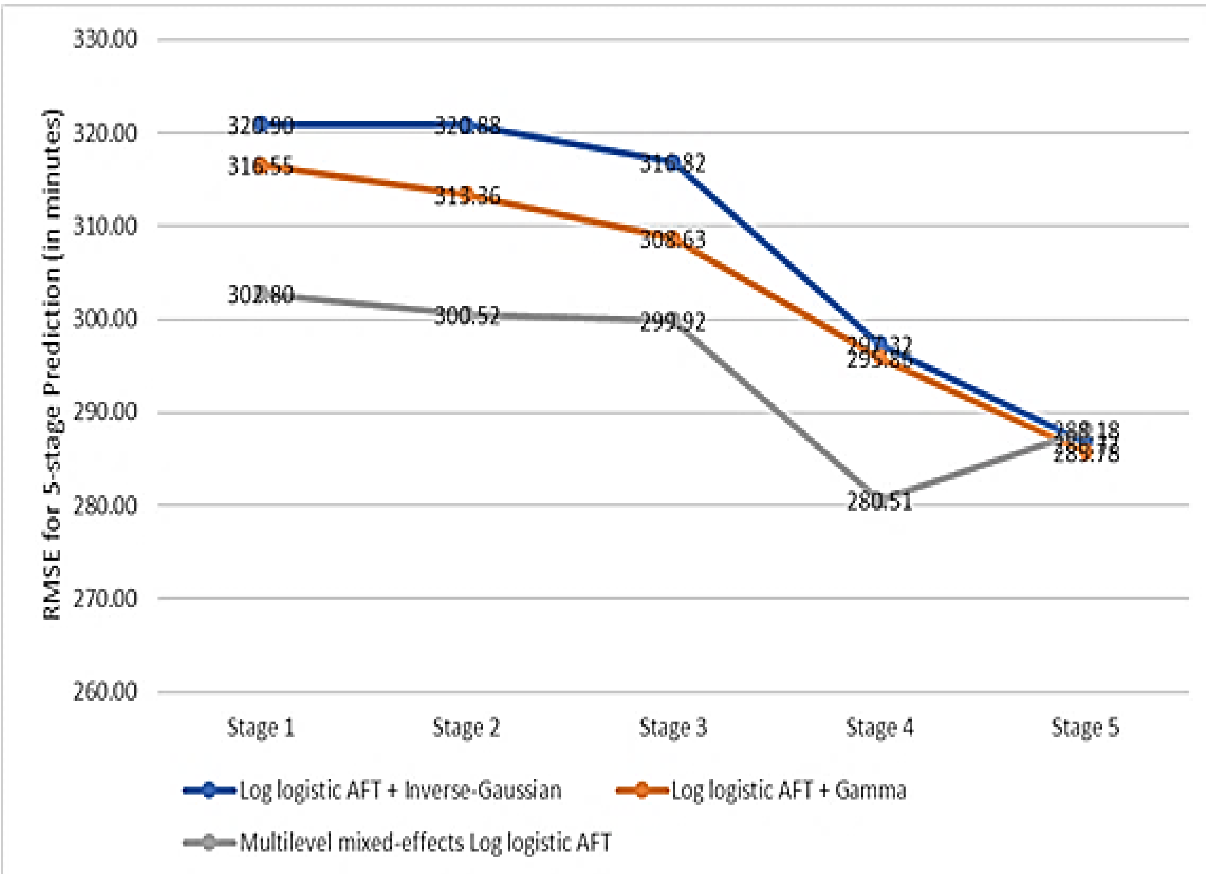


Figure 14: Root Mean Square Error Performance for Each Prediction Stage

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Table 20: Model Comparison Based on AIC and BIC

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

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
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
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
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

Based on the results presented in Table 20, the performance indicators for AIC is constantly decreasing meaning the model is becoming more accurate from Stage 1 through Stage 5. For each stage, the likelihood ratio test statistics (p-value <0.05) for all models show that there is unobserved heterogeneity existing in each model, and 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 (Figure 11). One explanation for this outcome is that multilevel mixed-effects use additional level random effects (i.e. incident types), 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 play a significant role in Stages 1 through 4 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 of improving prediction accuracy is obvious by adding one more level of random effects. However, in Stage 5 when additional information closely related to incident duration is input (i.e. duration of lane blockage, DMS and HAR average time usage, etc.) the results become statistically significant.

Table 21 (Model Estimations for Multilevel Mix-effects (Stages 1-4) and Gamma Frailty Model (Stage 5)) presents a series of variables, their coefficients and standard error at each stage. Based on the results, in Stage 1 morning and afternoon peak hours, as well as route (non-urban) and weather conditions are calculated as having a correlation with incident duration. Though peak hours are at a 95 percent or higher significance level, weather conditions are calculated at a 90 percent significance level. Similarly, the explanation of correlation and statistical significance can be extended to other variables obtained in other stages. For example, in Stage 2, peak hours (both morning and afternoon) have a significance level of 99 percent; whereas lane count has a significance level of 95 percent. Other variables in State 2 that are correlated to incident duration include weather, the number of vehicles, and CCTV detection. Stage 3 shares the significance of lane count with State 2, but at a lower significance level (90 %). Stage 3 also includes the coefficients and significance level of first responding agent (i.e. Highway Safety Patrol (HSP), Highway Incident Response Unit (HIRU), Police, Fire, Ambulance, County Sheriff, Tow Truck, Service Truck or TDOT Maintenance); all first responding agents have a correlation with incident duration, with the exception of TDOT Maintenance. Agents that are statistically significant at the 95 percent or higher level include HIRU, Police, Fire, Ambulance, and Tow Truck. No Highway Advisory Radio (HAR) was found to have a correlation with incident duration as well. Though results in Stages 1 through 3 indicate correlation, they do not indicate causation. Another interesting implication based on the results in these stages is that variables that have values that are considered significant in earlier stages change the values in later stages. For example, weather conditions in Stage 1 change from-0.0975 to -0.0432 in Stage 2. The variables found in Stage 4 and 5 provide valuable information regarding temporal elements, such as agency on-scene and response time information. For example, in Stage 5, fire department response time is correlated to incident duration at a 95 percent significance level.

Table 21: Model Estimations for Multilevel Mix-effects and Gamma Frailty Model

	Variables	Coef.	SE.
	Stage 1		
	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
	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
	AMB_ResTim	0.003*	0.0019
	Tow_ResTim	0.0011***	0.0003
Stage 5			
	Constant	4.628***	0.026

Incident Characteristics	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: *** 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.

5.0 EN-ROUTE DIVERSION SURVEY APPROACH AND ANALYSIS

This report considers two methods to identify en-route diversion responses to traffic congestion: a stated preference survey and a simulation. This chapter presents the methods and results of the stated preference survey. The survey studies the en-route diversion behavior of truck drivers who encounter large-scale freeway congestion.

5.1 Previous Stated Preference Surveys and Other Research

A substantial amount of transportation research relies on the intensive use of questionnaire surveys. Survey data can outline a targeted population's perceptions of almost anything related to transportation. For example, surveys can help us understand how users interact with new technology such as electronic toll collection for freight carriers (Holguín-Veras, José, and Wang 2011), freight mode decision-making before a trip (Shinghal, Nalin, and Fowkes 2002), drivers' stress level during long-distance truck trips (Raggatt 1991), or truck driver health issues such as obesity and other risk factors (Sieber, et al. 2014). Additional research has examined other road user route choices, expanding the scope beyond just truck drivers. Traffic information plays an important role in route making decisions. For example, Emmerink, et al. (1996) investigated the impact of radio information and sign messaging information on route choice behavior. Khattak, et al. (1993) found a positive impact on en-route choices from an advanced traveler information system. With the development of new information communication technologies, drivers use GPS data and web-based data to collect traffic conditions and optimal route choices. Ben-Akiva, et al. (2016) applied these new techniques to investigate the route choice between tolled and free roads.

5.2 En-Route Diversion Stated Preference Survey Methodology and Results

This study conducted a survey that collected information regarding trucker route choices and communication preferences during traffic congestion. More than 30 trucking companies in the state of Tennessee, four trucker-related message boards or blogs with communities of more than 10,000, and two Facebook groups with more than 10,000 members received a web-based survey link. Though more than 30 truckers accessed the survey, one-half (15) provided useable information. The survey did not require respondents to answer all questions. The survey can be found in Appendix B. The survey conducted contains six broad categories of information: 1) the number of times a trucker has been delayed by congestion, the date and location of the most recent event, as well as the delay time, and weather conditions; 2) the trip type (e.g. delivery, pick-up, etc.) and vehicle type; 3) how the driver became aware of congestion (e.g. self-observation, smartphone, etc.); 4) diversion behaviors and the reason for diverting; 5) the preferred types and means of receiving information about congestion; and 6) demographic information. Due to the small sample size, survey data for this study also includes relevant results compiled by other researchers, including:

- TRIP (2016), a national transportation research group that provides numbers related to Tennessee's needs for safe, smooth and efficient mobility.
- ATRI, American Transportation Research Institute, reports (Costello 2017; Hooper 2017) that deal with the shortage of drivers and analysis of operational costs of trucking.

5.2.1 Truck Driver Delay

The survey asks for the number of times the trucker has been delayed by an unexpected traffic incident along the route over the past three months. In this case, an incident is clearly described as a "non-recurring" event such as a crash or emergency roadwork. The possible answers to this question include none-was not delayed, 1 to 4 times, and 5 or more times. Thirty percent of respondents indicated they had not been delayed in the past three months, and 70 percent indicated they had been delayed 1 to 4 times. The times and dates of any delay include January 23, 2019, at 6:30 PM; February 10, 2019, at 5:00; and April 10, 2019, at 4:00 PM. Locations include I-40 near Walbrook Drive in Knoxville, Tennessee and Highway 123 in Seneca, South Carolina. The delay length ranged from 20 to 40 minutes, with an average delay of about 27 minutes. Available answers for weather conditions at the time of latest delay included clear, cloudy and dry, rainy/light snow, blizzard/storm or other. All respondents answered clear or cloudy and dry.

Due to the limited number of survey respondents, this study includes additional delay data by TRIP (2016) and ATRI studies. According to TRIP (2016) the average driver in the Chattanooga area loses 28 hours to congestion annually, while each driver in the Knoxville urban area loses 35 hours each year (TRIP 2016). Drivers in the Memphis area lose 43 hours annually due to congestion and drivers in Nashville/Davidson lose 45 hours annually (TRIP 2016). Nationally, for truck drivers, congestion costs hold steady at an average of $0.26 per vehicle mile traveled or a congestion cost of about $6,478 per truck (Costello 2017).

Between 2015 and 2016, Tennessee was in the top ten for states with a congestion cost decrease, with a decrease of 3.9 percent, even though the Nashville-Davidson-Murfreesboro-Franklin metropolitan area is a top ten area for total congestion cost nationwide and Memphis is in the top ten for metropolitan areas with an increase of 24.9 percent in congestion cost between 2015 to 2016 (Costello 2017). The analysis used four data sources to quantify the impact of traffic congestion on the trucking industry: (1) commercial truck travel times from the Federal Highway Administration (FHWA) National Performance Management Research Data Set, (2) commercial truck volumes from FHWA's Freight Analysis Framework, (3) commercial truck GPS data from ATRI's Freight Performance Measures database, and (4) industry financial data from ATRI's annual "An Analysis of the Operational Costs of Trucking" publication (Costello 2017).

5.2.2 Truck Driver Trip Type and Vehicle Type

Survey results indicate that all respondents were making deliveries when they experienced their latest delay. Other options included pick-up, service call, and other. For vehicle type, respondents answered equally for Small Truck (less than 6000 pounds); Light Truck (6,001 - 14,000 pounds); and Heavy Truck, such as a semi (26,001 - 33,000 pounds). No respondents answered Medium Truck, such as a firetruck (14,001 - 26,000 pounds); Very Heavy Truck (greater than 33,000 pounds); or Other.

As there was a small number of respondents to the survey we distributed, the data from a 2017 American Transportation Research Institute (ATRI) survey was used to create a more complete picture of the types of trucks and trailers used in the US for transportation of goods. The ATRI survey received responses from 89,664 trucks. It was found that 95% of these respondents (85,305) drove truck-tractors which pull semi-trailers, and 5 percent (4,359) drover straight-trucks where all axles are attached to a single frame (Hooper 2017).

The ATRI survey also collected data from 411,956 respondents that drove trailers. Of the 411,956 total trailers used, most were classified as "other" trailer types, including containers, chassis, double-drop, and heated trailers. Trailer type and quantities are presented in Table 22 below.
Of the respondents, 21 percent were conducting local pick-ups and deliveries of less than 100 miles; 40 percent were conducting regional pick-ups and deliveries of 100 to 500 miles; 23 percent were involved in inter-regional pick-ups and deliveries of 500 to 1,000 miles, and 16 percent were conducting national pick-ups and deliveries of over 1,000 miles (Hooper 2017).

Table 22: Trailer Types Used to Transport Freight

Trailer Type	**# of Trailers**	**% of Total**
28' Trailers	97,574	23.69%
45' Trailers	1,509	0.37%
48' Trailers	22157	5.38%
53' Trailers	92052	22.35%
Tank	4582	1.11%
Flatbed	9632	2.34%
Auto Trailers	2234	0.54%
Refrigerated Trailers	17250	4.19%
Other Trailers	164966	40.04%
Total	411,956	100%

5.2.3 Truck Driver Incident Notification

The survey results from this study include how each truck driver was first notified of the incident. Half of the respondents reported self-observation as the method of notification. For the other half of respondents, other information sources included 511, CB Radio, Highway Advisory Radio, Dynamic Message Signs, Google or Bing Maps, and Local Radio. No respondent answered using Cell or Mobile Phone (Internet, Social Media or Emergency Alert Message), GPS (Global Positioning System) or Other, reflective of the small sample size.

More broadly, according to the North Carolina Department of Transportation, "The trucking industry is receptive to our informational efforts—provided they are to the point. They have helped us by providing feedback on our efforts and are genuinely interested in improving highway safety" (NCDOT 2007). Truck drivers may get caught in congested areas because the location, time and duration of congestion is uncertain, and truckers are often just passing through an area without any extensive knowledge of alternative routes.

5.2.4 Truck Driver En-Route Diversion

For the survey conducted in this study, when truck drivers were asked if they diverted to another nearby alternate route to avoid the unexpected delay, 50 percent reported diverting to an alternative route, then returning to the original route; 25 percent reported diverting to an alternative route, without returning to the original route, and 25 percent reported not diverting at all, but staying on the same (original) route. For those who did not divert to another route, the average delay was about 20 minutes. Reasons for choosing not to divert to another route include not enough notice [to make a route change] and no short alternative route. All drivers who reported diverting to an alternative route indicate that they were familiar with the alternative route. Truck drivers who rely on personal Global Positioning Systems (GPS) to utilize unfamiliar alternative routes may face problems as these devices do not identify truck-prohibited roads because GPS devices meant for personal vehicles direct them there. A car GPS device maps out the quickest and shortest route but does not identify truck-restricted routes or roads with weight, height, and hazardous cargo restrictions.

According to Sun, et al. (2013), research suggests that it is not only travel time, cost and delay that impact alternative route choice, but also delivery schedule constraints and the ultimate bearer of costs that affect route choices. The research indicates drivers' level of experience affect their familiarity with the road network and their willingness to use alternative routes – more experienced drivers are willing to change routes. Additionally, drivers who were paid a fixed amount for a specific trip that did not depend on their routing were more likely to made route modifications than those who were paid by book miles or hours. In this research study, 85 percent of truck drivers could change routes while en-route either freely or with permission. Furthermore, when asked about routing decisions, drivers were most concerned with having fuel stations that they could use (88% at least half the time), followed by having predictable travel times (84%) and by being able to find truck parking (81%). In contrast, the effect of the route on fuel consumption did not factor in their responses (Sun 2013).

5.2.5 Truck Driver Preferred Notifications

In the survey conducted for this study, truck drivers were asked, "To avoid future unexpected delays due to incidents, what information would you like to receive?" Drivers responded with the location of the incident, expected duration/delay caused by the incident, the availability of alternative routes, the location and number of lanes blocked as well as the direction of travel, and weather and road conditions, if applicable. When asked how the drivers would like to receive information, all respondents answered smart or cell phone.

Results from a survey conducted by the University of Virginia are relevant. The study indicated that commercial vehicle operators want a 511 Advanced Traveler Information System (ATIS) channel specifically tailored to the trucking community (Swan 2004). This channel would provide weather, construction, traffic, accidents, and road condition information. On average, 511 call times were almost two minutes long, which may prove problematic for truckers navigating through congested or unfamiliar roadways. Specific suggestions for improving the 511 ATIS service include eliminating information not directly related to travel conditions, adding detours/alternate routes to the system, as well as exact location (mile marker designation) and expected duration of road incidents. Finally, more research should be conducted on commercial vehicle operators needs and usage of the 511 phone service (Swan 2004).

5.2.6 Truck Driver Demographics

All respondents to the survey conducted for this study were male between the ages of 31 to 64 years old, with an average age of 48 years. The location of the respondents trucking company included Knoxville, Tennessee, as well as two locations in South Carolina (Anderson and Easley). Finally, respondents were asked if they had any thoughts to share with the Tennessee Department of Transportation regarding traffic congestion or safety issues. One respondent wrote “Memphis is a nightmare. north by-pass like 840 would be great.”

The 2014 ARTI study supports this by reporting 55.5 percent of its workforce to be age 45 or older, with less than five percent of the trucker workforce in the 20 to 24-year-old age bracket. The National Transportation Institute indicates the average trucker to be 54 years old, and about 94 percent of truckers are male. Though there are about one million trucking companies in the United States, the top five states include California, with more than 250,000 trucking companies; Texas, with more than 130,000 companies; Florida, with more than 110,000 companies; New York, with more than 105,000 companies; and Georgia, with more than 82,000 companies (Magoci 2016).

5.3 Summary

This chapter studies en-route diversion strategies through behavioral. The behavioral survey was designed and implemented and provides a framework for a future implementation at a larger scale in terms of sample size. The survey helps understand how truck drivers respond to unexpected congestion. Such knowledge provides a stronger basis for new technologies that may be helpful in avoiding traffic congestion. The number of received responses to the TDOT survey was low, and therefore substantive conclusions cannot be drawn. Nonetheless, the responses indicate that about 70 percent of truck drivers had been delayed due to congestion in the last three months with an average delay time of 27 minutes. When asked how they were notified of the incident, half reported self-observation and the other half reported a variety of other sources including 511, CB Radio, Highway Advisory Radio, Dynamic Message Signs, Google or Bing Maps, and Local Radio. Twenty-five percent of respondents reported that they did not divert. Reasons for not diverting include not enough notice or no short alternative route. All drivers who reported diverting to an alternative route indicate that they were familiar with the alternative route.

6.0 EN-ROUTE DIVERSION SIMULATION AND IMPACTS

This chapter presents the second method used to identify en-route diversion responses to traffic congestion. The discussion will focus on evaluating the impacts of en-route traffic diversion on system travel delay, average system speed, and other measures of the studied network. The report will also use various conversion factors to calculate the monetary value of time delay savings in the system.

6.1 Simulation Design

When large-scale incidents occur on freeways, en-route diversion of traffic is among the effective strategies that reduce the impact of incident-induced congestion. In corridors with substantial commercial traffic, route diversion is especially complex for large trucks. For example, large trucks may not be able to navigate through alternate routes due to narrower streets and small turning radii. To address the issues of en-route diversions to alternate routes in response to large-scale incidents, this research study identifies truck traffic corridors and establishes a simulation methodology for analyzing the impacts of commercial (truck) and non-commercial en-route diversion. The microscopic simulation is helpful in evaluating the impacts that different information dissemination and technology strategies can have on system performance. The simulation analyzes various en-route diversion strategies in corridors for single-unit and multi-unit trucks and passenger vehicles under different incident scenarios, e.g., incidents of different durations. The results show that in addition to the incident duration and lane blockage, important factors such as the availability of incident information, number of intersections, AADT, alternative route availability, and the presence of CAV technologies impact en-route truck diversions and resulting delays. The study considers practices for customizing incident information to truck drivers and passenger vehicles.

6.1.1 TransModeler Network and Experimental Design

This experiment adopted TransModeler for simulation analysis. TransModeler is a powerful and versatile traffic simulation package applicable to a wide array of traffic planning and modeling tasks. 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 detail and high fidelity. It can also model and visualize the behavior of complex traffic systems in a 2 or 3-dimensional Geographic Information System (GIS) environment to illustrate and evaluate traffic flow dynamics, traffic signals, Intelligent Transportation System (ITS) operations, and overall network performance. The traffic simulation package includes public transportation traffic as well as car and truck traffic. It also handles a wide variety of ITS features, such as electronic toll collection, route guidance, traffic detection, and traffic surveillance. Additionally, special consideration is given to Connected and Automated Vehicle (CAV) technology, which has penetrated the vehicle market. Under this environment, driving behaviors will be added that are different from the driving style found in the simulation package. As such, in designing the simulation experiments, different levels of vehicle automation (from

Level 0 to Level 5) were included. The details of these levels of automation are provided by the National Highway Traffic Safety Administration (NHTSA), and are listed as follows:

- **Level 0** - the human driver does everything;
- **Level 1** - an automated system on the vehicle can sometimes assist the human driver conduct some parts of the driving task;
- **Level 2** - an automated system on the vehicle can 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 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.

Regarding dynamic route choices, TransModeler creates behaviors based upon historical or simulated time-dependent travel and then models trips based on Origin-Destination (OD) trip tables and intersection turning movement volumes. To properly run the simulation analysis, the model includes a built-in OD matrix specific to the research. Additionally, in order to achieve a realistic simulation reflecting real-world operational characteristics, researchers integrated Annual Average Daily Traffic (AADT) information obtained from the Enhanced Tennessee Roadway Information Management System (E-TRIMS). Other variables specific to freeways, incidents, and alternative routes have been included and grouped as follows:

- **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 roads connecting freeway and arterial road, and on the arterial road such as Kingston Pike in this study; the number of lanes, number of intersections, and signal timing plans on these roads.

As can be seen from Table 23, the combination of the different variables specific to freeways, incidents, and alternate routes have resulted in thousands of different combinations for experimental designs that can be simulated. This includes variations in the number of lanes, AADT, percentages of passenger vehicles and single or multi-unit trucks, the number of lanes blocked, blockage duration, travel speeds and the AADT, number of lanes and signalized intersections for alternative routes. In order to limit the number of scenarios and keep the experimental designs realistic, eight en-route diversion locations were selected along the I-40 corridor in Knox County, Tennessee. These locations include several exits along the interstate (Exits 369, 373, 374, 376, 378, 379, 380, and 383). Figure 15 shows a conceptual study network for investigating the various outcomes from these simulation runs,

Table 23: Key Variables in the Experimental Design for the En-Route Diversion Strategy

Variables	Description	Values
Fr_Ln	Number of main lanes each direction on 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 incident	3, 4, 5
Inc_BlcDur	Incident blockage duration	2 hours
Inc_Speed	Travel speed on available travel lane on 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 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 alternative route	2, 3, 4, 5

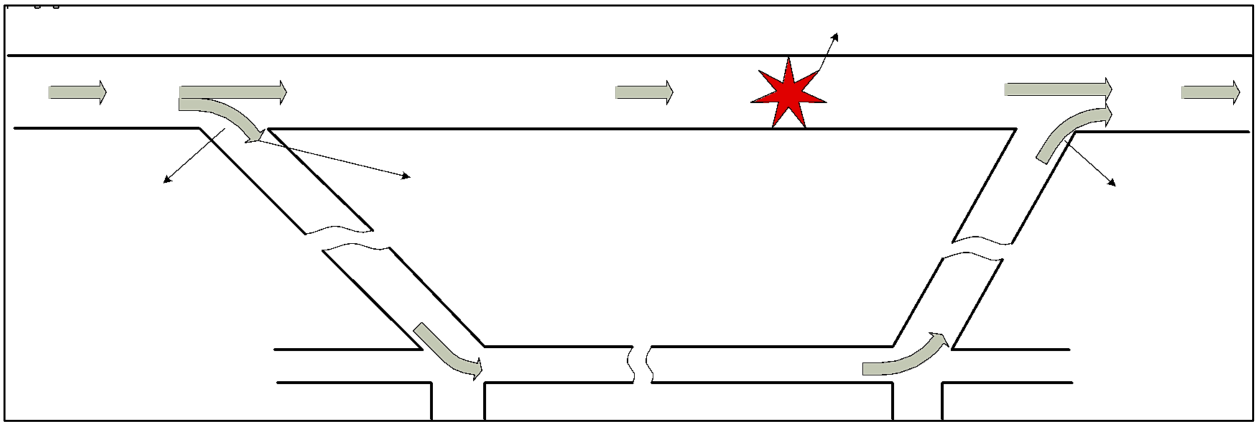

Figure 15: En-Route Diversion Scheme Along the Freeway

The diverted freeway traffic includes both passenger vehicles and single and multi-unit trucks (SU and MU). In TransModeler, if an incident happens and drivers are not informed of the incident and the subsequent updated travel time for the route, then drivers continue their pre-destined route without diversion. Although realistically not all drivers can be informed of an incident, research suggests that traffic information, such as travel times or delays on main or alternative routes can change drivers' en-route choice behaviors (Sundaram, et al 2011; Pan and Khattak 2008). Such variations in travel time related information penetration (from 0% to 100%) are incorporated in the simulation scenarios.

The diversion strategies using the information penetration ratio are unidirectional (eastbound in this study), and all simulation runs are based on the eight I-40 exits mentioned earlier (i.e. exit 369, 373, 374, 376, 378, 379, 380, and 383). Within each simulation scenario, there are also variations in terms of:

- Incident characteristics.
- Percentage of drivers receiving updated travel information.
- Value of travel time for trucks as well as for passenger vehicles.
- Levels of automation, and truck performance.

The initial configurations for these eight exits or diversion locations are listed in Table 24. Freeway variables include the number of freeway lanes (varying between three to five lanes); AADT, with variables ranging between about 100,000 to 200,000; percent of passenger cars, ranging from 78 percent to 88 percent; percentage of single unit trucks, ranging between two and three percent, and the percentage of multi-unit trucks, ranging between 10 and 18 percent. Alternative route characteristics include AADT and the number of lanes and signalized intersections through the entire diversion path (the freeway to the arterial road, the arterial road, from the arterial road to the freeway). Figure 16 illustrates the origins and destinations for the study network. To simplify the traffic network, eight nodes are configured as either an origin or destination in the conceptual network to replicate an OD matrix for the simulation analysis. Additionally, the figure displays the on and off freeway ramps and intersections on the arterial road. Signalized intersections are not illustrated in the simplified network but are utilized in the TransModeler simulations. Trip productions and attractions generate the OD matrix. The simulation model includes data from Table 24, as well as other data from E-TRIMS (i.e.

directional distributions of AADT, peak hour traffic direction, AADT on each node, etc.). The data was error checked.

All these factors are needed to calculate 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 percent (east direction), so the calculated traffic demand or traffic productions for node 1 is 105,970 * 0.6 = 63,582 trips, and attractions are calculated as 105,970 * 0.4 = 42,388. Similar calculations are completed for each location to develop trip productions and attractions for each location, then TransCAD software converts trip productions and attractions into an origin-destination table using a series of proprietary gravity models.

Table 24: Initial Configurations for Eight Diversion Locations

No	1	2	3	4	5	6	7	8
Fr_Ln	3	3	4	5	5	4	5	4
Fr_AADT	105,970	119,300	136,250	179,910	188,060	196,210	196,710	196,410
Fr _PerPC	78%	81%	83%	87%	88%	88%	81%	81%
Fr _PerSU	4%	3%	3%	2%	2%	2%	3%	3%
Fr _PerMU	18%	16%	14%	11%	10%	10%	16%	16%
Alt_Col1AADT	10,740	27,840	41,820	63,990	19,500	11,420	19,450	27,284
Alt_Col2AADT	27,840	41,820	63,990	19,500	11,420	12,550	14,360	77,420
Alt_AADT	22,570	29,340	29,340	28,760	31,090	31,090	31,090	21,960
Alt_Col1Ln	1	2	2	2	3	2	2	2
Alt_Col2Ln	2	2	2	3	2	2	2	3
Alt_Ln	2	2	2	2	2	3	2	2
Alt_Int	11	12	7	11	11	9	10	15

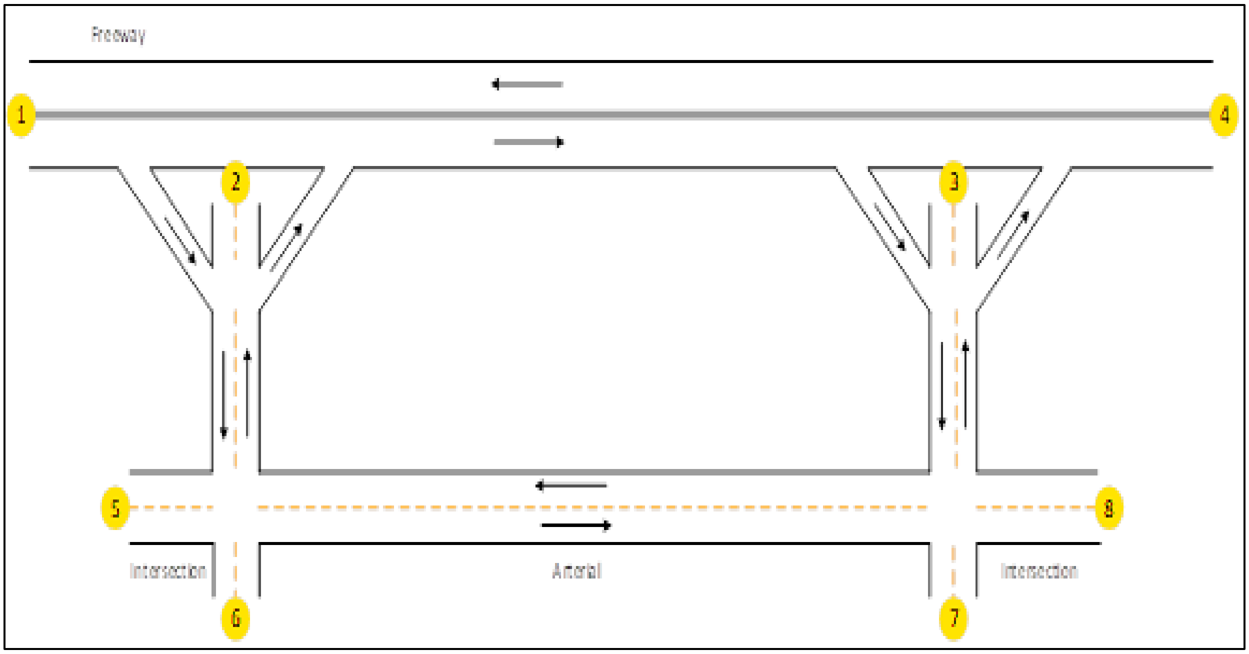

Figure 16: Origins and Destinations for the Study Network

Simulated traffic includes both single-unit and multi-unit trucks, as well as passenger vehicles. E-TRIMS data provides information about real-world percentage values of these three vehicle types (PC – Passenger Cars, SU – Single-Unit trucks, and MU – Multi-Unit trucks). To evaluate the impact of traveler information on implementing the en-route diversion strategy, the information penetration rate to drivers is set up to vary from zero to 100 percent. Each group of drivers (PC, SU, and MU) either receive updated travel time information or not. For groups that do not receive the updated travel time information, they maintain the current traffic flow without changing routes in the TransModeler simulation model. For groups that receive updated travel information, they either stay on the original route or take a designated alternative route based on the threshold value for the difference in travel times. For these simulations, the threshold value is a five percent differential of travel time between the freeway and the alternative route. As for the impact of the value of travel time (VOT) on the diversion strategy, Pan and Khattak (2008) have found that higher VOT is associated with a lower percentage of savings in total travel cost when applying the diversion strategy. This report will explore this relationship in large-scale incident situations.

This research adopts the stochastic shortest path method. This method is based on path costs. Compared to the deterministic shortest path, this method considers the variations in each individual drivers' perception and behavior during pre- and en- route choices. Thus, the path costs are randomized and there are many shortest paths between a given O-D pair. TransModeler is a path-based simulation model. In TransModeler, each vehicle has an assigned path before it departs an origin and enters the network. Drivers only consider en-route alternative paths if they experience a delay on a link that exceeds their expected delay, which is obtained through dynamic traffic assignments using a stochastic user equilibrium method computed through a series of successive averages. The threshold where link delay is considered excessive is determined by each drivers' route choice parameters. These parameters include travel time difference from the current path, choice set threshold, updated delay thresholds, re-route thresholds, etc. These parameters vary among the driving population. Eventually, these parameters determine whether a driver takes an alternative en-route path or not. Key parameters include travel time information, updated delay threshold, and re-route thresholds. Informed drivers in the model have access to updated travel time information. If uninformed, drivers make all route choice decisions based solely on historical travel time information. Depending on the information penetration rate, and the vehicle group, the proportions of the informed and uninformed drivers vary among each scenario. Drivers with access to updated delay thresholds are expressed as the percent difference in experienced travel time on a roadway segment 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, a 20 percent threshold is used to let drivers reconsider current travel path and alternative paths. Finally, the updated re-route threshold is represented as the percentage reduction in travel time relative to the current path (freeway) that is required for a driver to switch to the alternative route. This threshold is five percent. For trucks, the threshold is ten percent since truck drivers' inertial preference is often the freeway.

6.2 Simulation Parameters

Several traffic network performance criteria can be used to evaluate en-route diversion traffic operation strategies. These criteria include (Dunn 2006; Knorring 2005; Liu 2011; Liu 2012; Ng 2006; Pan 2008; Yin 2012):

- Travel time on the freeway and the alternative route
- Level of service on alternative routes and intersections
- Extent of delays on the freeway and alternative routes
- Freeway and intersection queue lengths.

Notably, delay statistics are the most popular performance measure because delay reductions can be treated as travel time savings for both main routes (interstates) and alternative routes (arterials). Additionally, delay reductions of trucks and passenger vehicles can be converted to savings in emissions, fuel and economic costs. Additional criteria used in this analysis include the value of time (VOT), impact of incident durations, benefits of estimation procedures, and the impact of CAVs on network performance.

All simulation runs represent transportation systems performance over one day. Each simulation starts at 00:00:00 and ends at 23:59:59. Each 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. Each incident is set up during morning peak hours from 7:00 AM to 9:00 AM for preliminary analysis. The following sections present results based on these scenarios. These sections discuss the impact on overall delay of travel time information penetration, Value of Time, incident durations, and examines different procedures for benefit estimation of en-route diversion.

6.2.1 Delay Reductions and Travel Time Information

Figures 17 and 18 present the delay changes over increasing information penetration for freeway and alternative routes at eight locations, ranging from highly rural locations (Locations 1 and 2) to highly urban locations (Locations 7 and 8). Figure 17 shows the delay changes over increasing information penetration for the freeway at eight locations in Knox County. A series of incident occurrences and travel time penetration rates are simulated and then compared to the increase in travel times with typical travel times. When drivers do not have updated travel times after an incident occurs along the freeway, the delay on the freeway for the eight diversion locations studied are 6.1 to 12.5 times more than the base travel time, and the delay on the alternative routes are about 4.6 to 8.7 times the base travel time. Statistics indicate simulated drivers spent 20 to 45 minutes getting through a congested freeway segment that normally takes five minutes to get through. When traffic information is available to travelers, based on information penetration, en-route diversion rates increase and travel delay decreases. Additionally, under dynamic traffic simulation environments, results show that en-route diversions from the freeway to alternative routes in rural locations offer more travel time saving benefits.

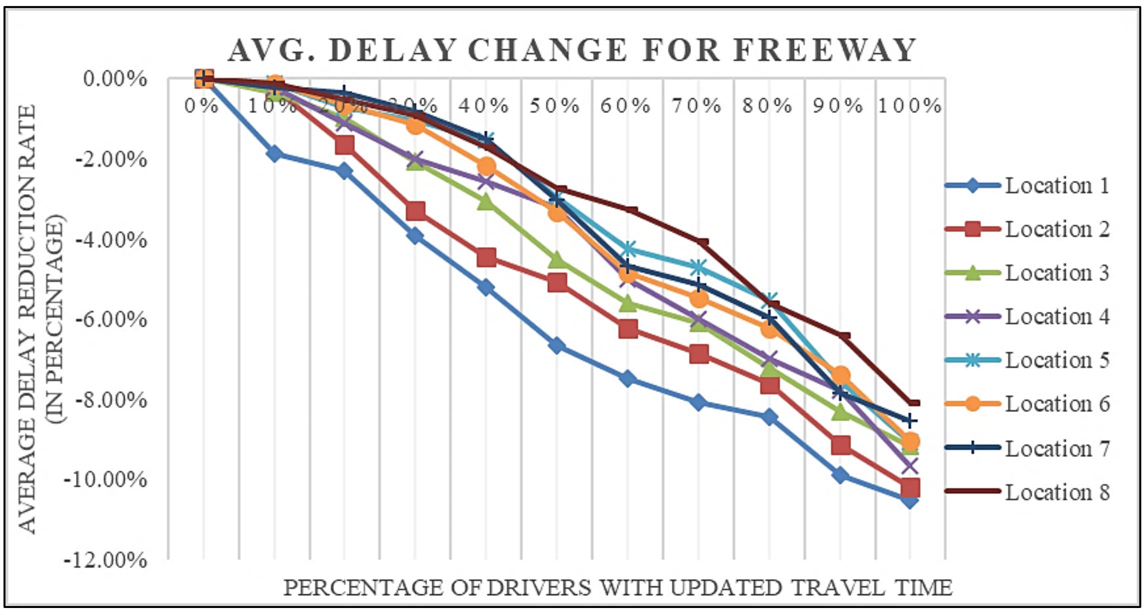

Figure 17: Average Delay Change for Freeway over Increasing Information Penetration

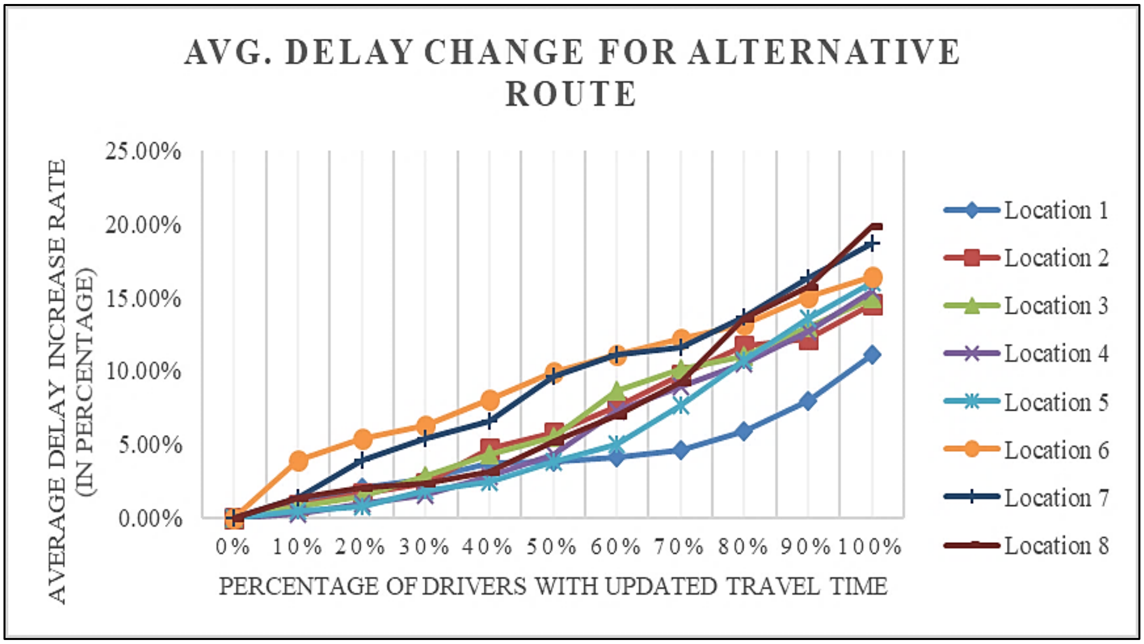

Figure 18: Average Delay Change for Alternative Routes as Information Penetration Increases

Simulation modeling reveals increasing average delay reduction benefits on the freeway (between 8 to 10 percent during 100% information penetration depending on the location), but an average delay increase for alternative routes (between 10 to 20 percent during 100% information penetration depending on location). These results indicate that more traffic-related information penetration is directly related to more en-route diversion activity, which contributes to overall congestion relief on the freeway and overall traffic network performance improvement. Notice that in Figure 17, the average delay reduction rate at urban locations is less than rural locations (such as location 1 and 2). This may be because drivers in urban settings prefer to stay on the freeway since alternative routes at urban locations are also very congested during morning peak hours. Due to the number of intersections and high chances of long intersection delays, the freeway is the primary route choice for drivers, especially truck drivers. In rural areas, fewer intersections possibly lead to more time saving benefits. Results imply that under heavy congestion in urban and downtown areas, freeways are the primary route choice even though traffic information is available to most drivers. Therefore, en-route diversion strategies applied in rural areas might be more effective and beneficial for travel time savings.

6.2.2 Value of Time (VOT) Impact

The value of time (VOT) scenario analyzes the impact of VOT on freeway delay reduction. In this scenario, half of all drivers receive updated traffic information. The base VOT for passenger vehicles is set at $15.00. This cost is for illustration purposes, true values need to be verified for future work. The VOT for trucks (both single-unit and multi-unit) are set at 2, 4, 6, 8, 10, and 12 times more than passenger vehicles. Previous studies have shown that higher VOT is related to savings in travel time and costs for the complete network (freeway and detour routes). However, if VOT was calculated separately for freeway and detour routes, then the simulation analysis results, as seen in Figure 19, show that the delay reductions/increments for freeway and detour routes are unstable. No clear trend in terms of delay change was found with increasing values of time.

Higher VOT indicates poses a higher risk of increasing travel cost. Thus, with no alternative route information, a truck driver is more likely to stay on the freeway even if there is excessive delay due to an incident, because of the uncertainty associated with delays and longer travel times on the alternate routes. However, if real-time information of an incident is available to travelers, especially with detailed instructions to truck drivers about alternate route conditions, then the benefit of implementing the en-route diversions can be calculated. The conversion factors in Table 25 were used to quantify travel time savings into dollars with a fleet composition of 81/3/16 percent for passenger cars, single-unit trucks and multi-unit trucks, respectively. Figure 20 indicates that the VOT for trucks are 2, 4, 6, 8, 10, and 12 times more than that of passenger vehicles ($15.00). The magnitude of overall travel cost savings in percentage terms declines as the value of travel cost savings increases. This result implies that when en-route diversion operations are implemented in incident conditions, diverting trucks (as well as passenger vehicles) should be explicitly considered partly because trucks have higher VOT, which contributes to higher total cost savings.

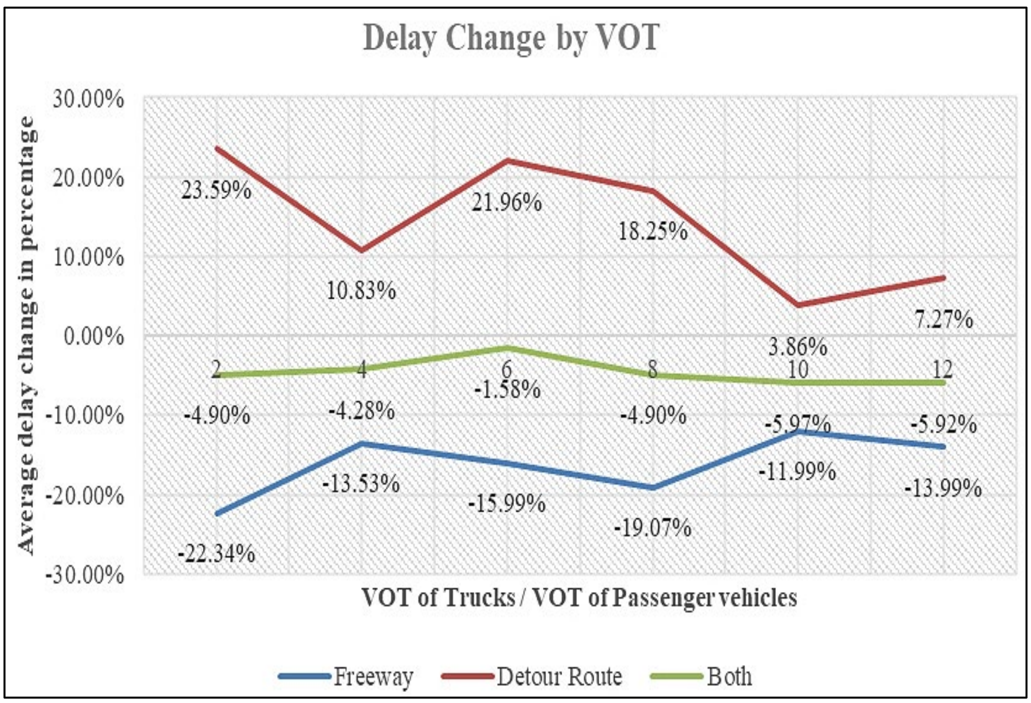

Figure 19: Delay Change on Freeway and Detour Route by VOT ratio (2 to 12)

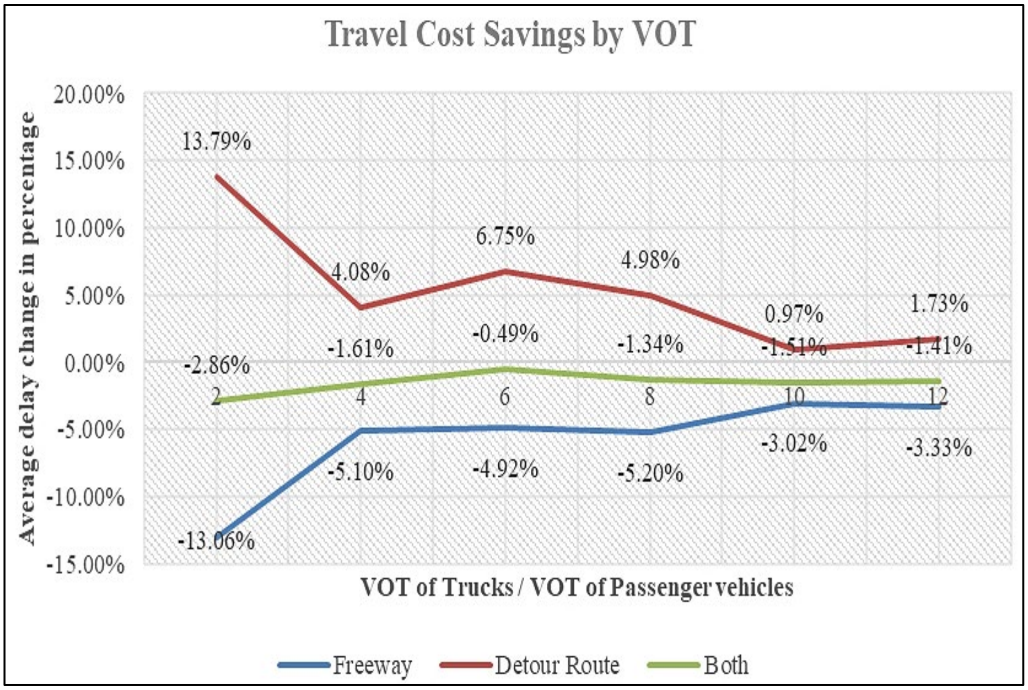

Figure 20: Travel Cost Savings by Value of Time ratio (Truck/Passenger Vehicles).

Table 25: Cost Conversion Factors

Conversion Factor	Value	Source
Delay to HC	13.073 g/h	Chang and Raqib (2013)
Delay to CO	146.831 g/h	Chang and Raqib (2013)
Delay to NO	6.261 g/h	Chang and 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)
CO_2	19.56 lbs/gal of gasoline 22.38 lbs/gal of diesel	Chang and 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)
CO cost	$6,360/ton ($6.36/kg)	Chang and Raqib (2013)
NO cost	$12,875/ton ($12.875/kg)	Chang and Raqib (2013)
CO_2 cost	$23/metric ton ($0.023/kg)	Chang and Raqib (2013)

6.2.3 Impact of Incident Durations

This section examines location eight, a highly urban location along I-40, for a more in-depth analysis of the impacts of incident durations (Figure 21). The eastbound direction is the peak hour direction for I-40 and the en-route diversion alternative route starts from I-40 Exit 383, heads south on Northshore Drive, turns left onto Kingston Pike, heads north on State Route 129 and then back to I-40 eastbound at Exit 386B. Under normal traffic conditions, the travel time on the freeway is four minutes for 4.3 miles of travel. If taking the diversion route via Kingston

Pike, the travel time is 13 minutes for 5.6 miles of travel, since there are 15 signalized intersections. Figure 21 displays the network map for this simulation. The study assumes half of the travelers are updated with traffic information and divert en-route. The incident is set to start at 7:00 AM and last between two to six hours during morning peak hours. Only one lane (the left lane) is available as a travel lane at the incident site for all simulation runs. Figure 22 presents the delay reduction for the study area. The delay reductions for the network increase from about 1,133 hours to about 3,111 hours as the incident duration increases. The total time delay is calculated based on the time delay for each vehicle.

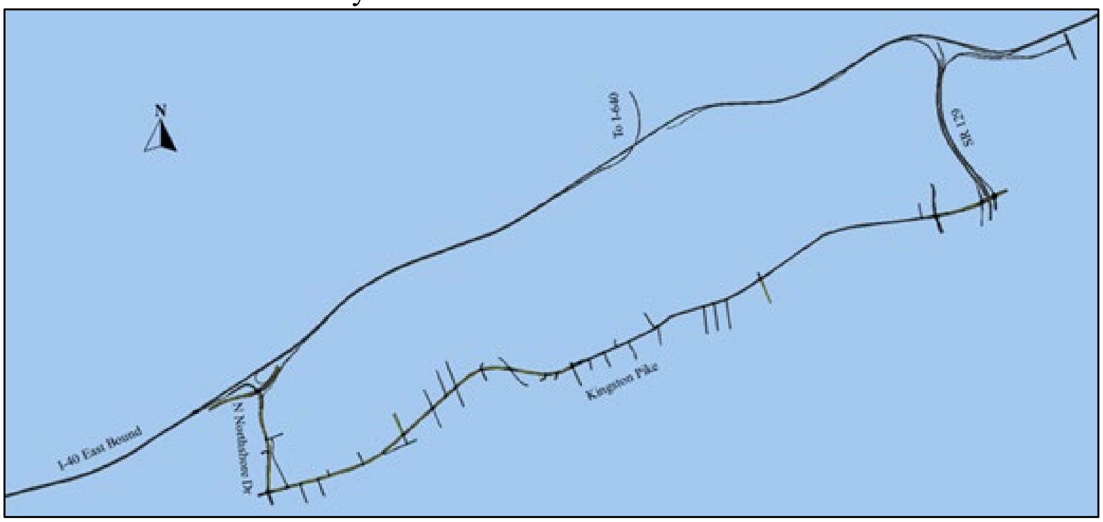

Figure 21: I-40 and Kingston Pike En-route Diversion

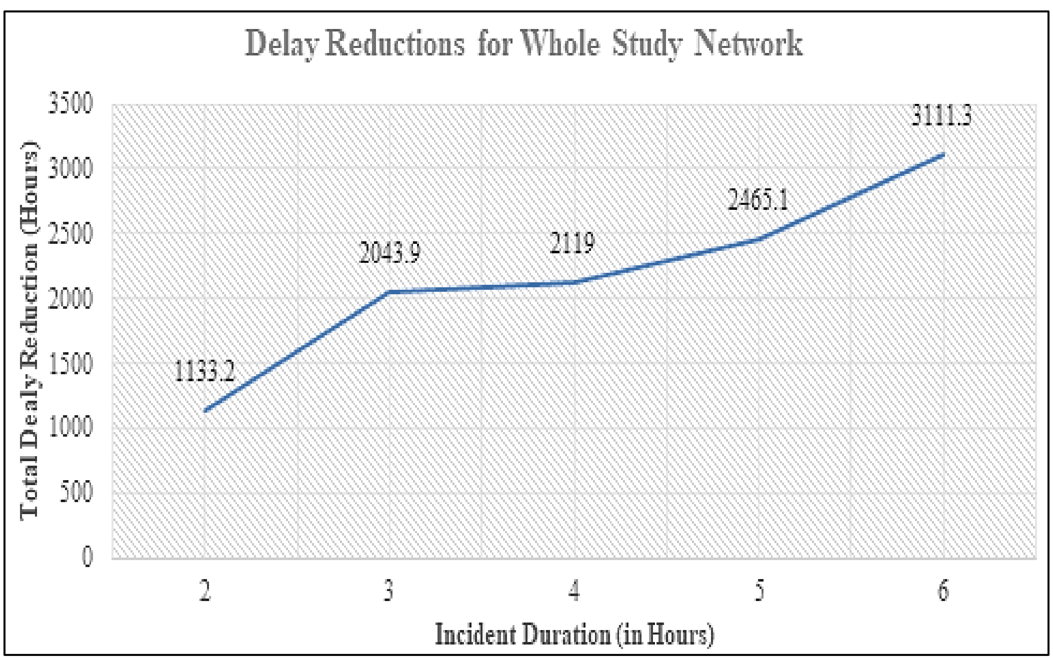

Figure 22: Delay Resulting from Incident Duration (2 - 6 Hours)

6.2.4 Benefit Estimation Procedures

The study can estimate the benefits of en-route diversion in terms of emission and fuel reductions by converting time delay reductions. Table 25 lists the conversion factors for converting travel time savings into dollars for passenger cars, and single- and multi-unit trucks. Table 26 presents the cost savings for the incident scenarios lasting between two to six hours that include vehicles diverting to alternative routes. Columns 2 – 8 list the different cost analysis categories. Results show that the benefit of cost savings (in delay, emissions, and fuel) are greater with longer incident durations. The total cost savings for incidents lasting two hours is about $33,000 but is about $91,000 for incidents lasting six hours. This result is in accordance with other studies (Chang 2013; Liu 2012; Lutsey 2004).

Table 26: Cost Savings for Large-Scale Incident Scenarios

Incident Duration	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

6.3 Impact of Connected and Automated Vehicles

Vehicle connectivity and automation can provide safety and mobility benefits. However, current studies seldom focus their attention on the benefits of CAVs for en-route traffic diversion during large-scale traffic incidents. This research includes an impact analysis of CAVs on network performance indicators including travel delay, the number of stops, stop time, average speed, etc. The research identifies differences in the performance outcomes of CAV enabled vehicles and non-CAV enabled vehicles. Trucks are not treated explicitly in this portion of the analysis.

According to the TransModeler User's Guide version 5.0, TransModeler traditionally uses the General Motors (GM) car-following model. This equation is found in Appendix A (equation 5.1). In this model, the acceleration of the subject vehicles only occurs when its speed is less than the speed of the vehicle in front of it. Therefore, the subject vehicle will either remain at a constant speed or decelerate. Lower and upper bounds of headway are set to prevent vehicles from running faster than the emergency regime and slower than the free flow regime. In the CAV scenario, a Constant Time Gap car-following model (CTG) improves transportation mobility by increasing roadway capacity and travel speed. Additionally, a simplified algorithm approximates the behaviors of the connected vehicles in a cooperative adaptive cruise control environment. This algorithm's formulation, based on TransModeler User's Guide version 5.0, can be found in Appendix A (equation 5.2). Overall, the two methods available for modelling CAVs in TransModeler were changing the headway and using adaptive cruise control.

This study created and executed various scenarios at Location Eight, the I-40 and Kingston Pike en-route diversion location found in Figure 21, that evaluated the impact of CAVs on various network performance measures. In order to verify the accuracy of the simulations, these scenarios compared simulated traffic flows with realistic traffic flows. These comparisons verified the simulation model to represent I-40 and Kingston Pike traffic flow conditions. The segment where traffic enters Kingston Pike from the freeway network is used for this verification. The verified hourly volume for traffic on this segment is 4,918 vehicles per hour. The Mean Absolute Percentage Error (MAPE) for the simulated traffic volume and observed traffic volume is 3.55 percent based on 70 simulations without any incident. This is an acceptable value since the acceptance level is usually 5 percent in TransModeler. No truck traffic was considered in this analysis.

Figures 23 illustrates the total network delay in hours based on connected and autonomous vehicle (CAV) levels and incident durations, and Figure 24 shows the total network delay reduction in percentage. Figure 25 calculates the average speed for incident durations at different CAV levels, and Figure 26 shows the average speed increase in percentage. These scenarios replicated CAV levels at level zero (0), as in Figures 23 and 25, which represent no vehicle automation; CAV level 1, as seen in Figures 24 and 26, which represent some driver assistance system that can assist with either steering or braking/accelerating; through CAV level five (5), which represents total vehicle connectivity and automation. An adjustable headway value was assigned to each level from a headway value of 3 at Level 0 to a headway value of 0.5 at Level 5. The study also examined four different incident delays from no incident delay to one of more than eleven hours (675 minutes). In the figures, a blue line represents no incident delay, an orange line represents an incident duration of 170 minutes, a gray line represents an incident duration of 271 minutes, and a yellow line represents an incident duration of 675 minutes.

As seen in Figure 23, the hours of total network delay without any incident ranges from approximately 52,000 hours with a CAV level of 0 to about 4,000 hours at a CAV level of 5. With an incident duration of 170 minutes, the hours of delay range from about 174,000 hours (CAV Level 0) to about 64,000 hours (CAV Level 5), and with an incident of 271 minutes the delay ranges between approximately 271,000 to 120,000 hours. Finally, with an incident delay of 675 minutes, the delay ranges from about 514,000 for no automation to 349,000 hours for level 5 automation. Under all incident times, there was a decrease in delay as vehicle connectivity and automation level increased. Specifically, the delay could be reduced by 48,000 hours through complete automation of the system if there was no incident. In the case of an extreme incident, the delay could be reduced by 165,000 hours, given the assumptions of the scenario considered.

Figure 24 presents the percentage of delay reduction under similar CAV and incident delay scenarios. The labeled numbers on the graph depict the difference in values between the current line and the line above it. The results presented in Figure 24 demonstrate that as the level of automation increases travel delays seem to decline. With no incident at a CAV level of 1, there is more than 13 percent reduction in total incident delay, and with a CAV level of 5, the reduction in the total incident delay is about 47 percent. When there is an incident duration of 170 minutes, the percentage in the reduction in delay varies from about 10 percent reduction without connectivity or automation to a 58 percent reduction in delay with complete vehicle automation. Similar patterns are found in scenarios with incident durations of 271 and 675 minutes, though the percentage of delay reduction is the same for both incident durations under the condition of no connective or automation. Under CAV Level 3, which is where an automated driving system can perform all aspects of the driving task under some circumstances, but the driver must be ready to take back control at any time the system requests it, the total network delay percentage separates. This means that at level 3 automation, the network delay can decline, especially as incident duration increases.

Figure 25 displays the average speed at various incident durations and CAV levels. In this figure, for all incident durations, the speed increases as the CAV level improves. For example, under no incident duration, the speed increases from an average of ten miles per hour to more than forty miles per hour as CAV technology improves. The same holds true under all incident duration conditions. Figure 26 illustrates the average speed increase in percentage under different incident conditions and different CAV technologies. In this scenario, all values for average speed increase start under 15 percent for CAV level 1 but increase dramatically by CAV level 3 before dropping again. For example, under no incident duration, the percentage increases to about 21 percent at CAV level 3 before dropping to 12 percent and rebounding at about 22 percent at CAV Level 5. Incident durations of 170 or more minutes show a more dramatic increase, decrease, and rebound of average speed. Overall, the scenarios present a monotonically decreasing (total delay) or increasing (average travel speed) trend. Such a phenomenon can be explained by the headway value. With less headway between vehicles, the roadway has more capacity, so vehicles will spend less time in the system. Overall, the introduction of vehicle automation into the transportation network suggests benefits in traffic operations and savings in travel time.

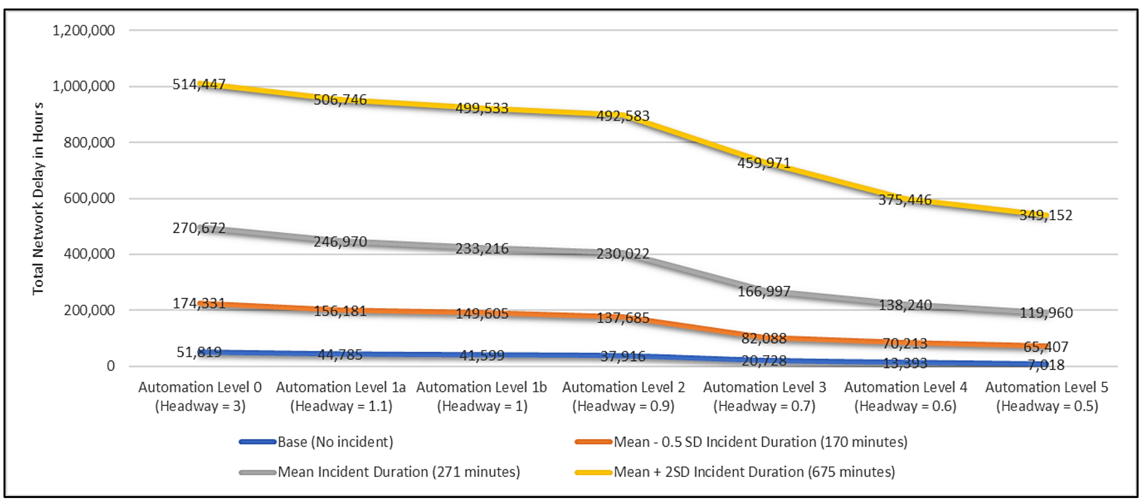

Figure 23: Delay in Hours for Incident Duration at Different CAV Levels

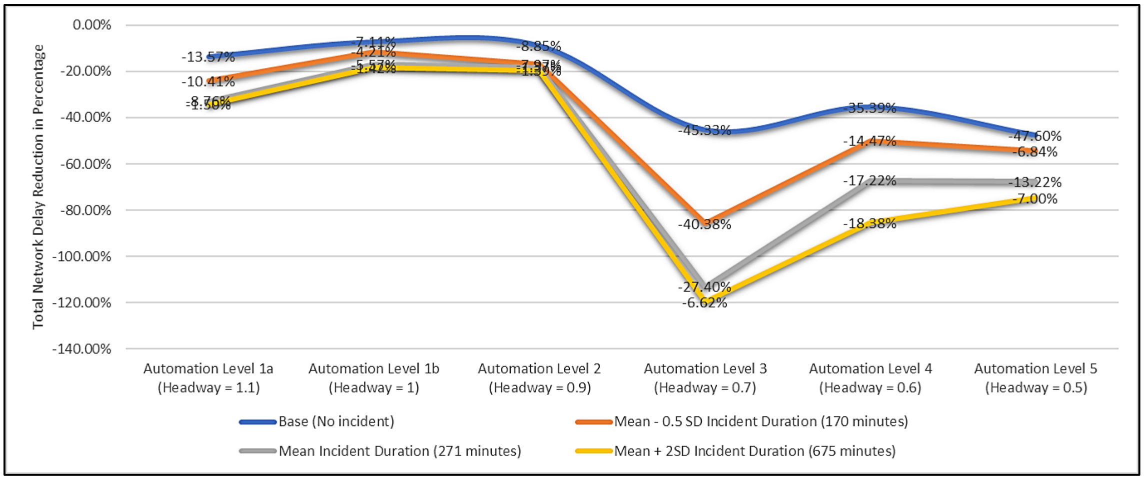

Figure 24: Delay Reduction for Incident Durations at Different CAV Levels-no incident base

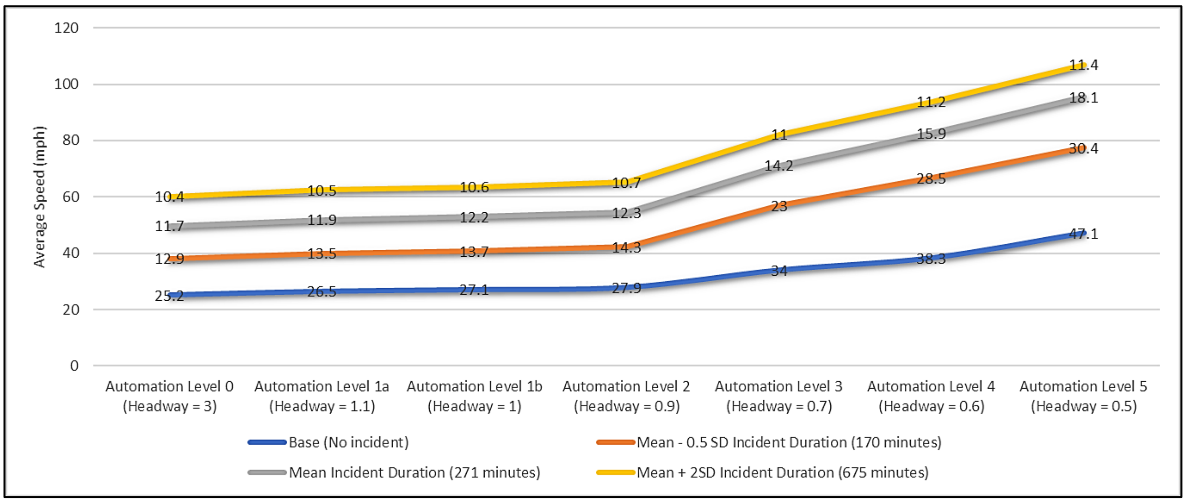

Figure 25: Average Speed for Incident Durations at Different CAV Levels

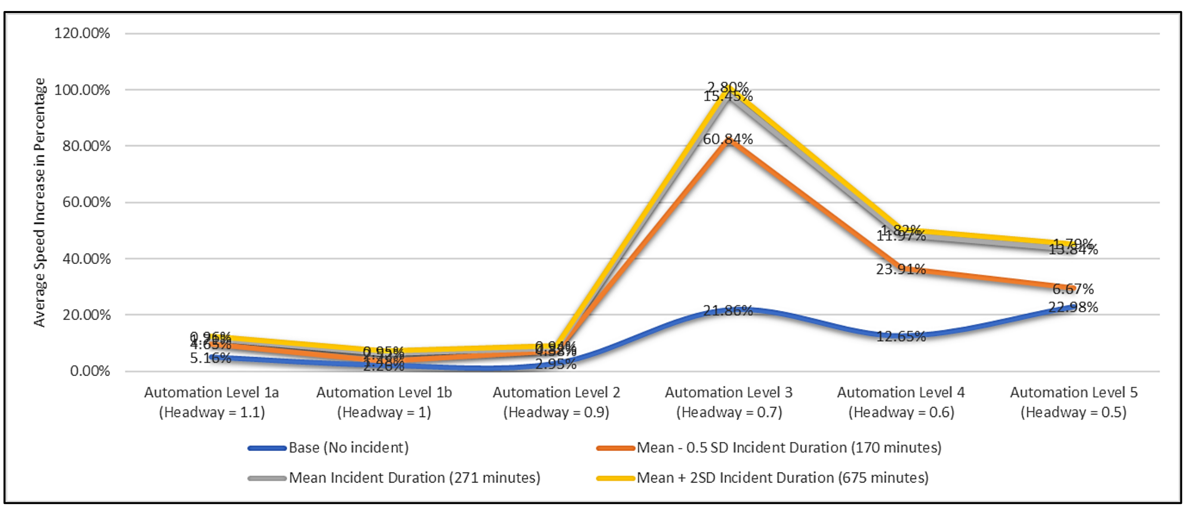

Figure 26: Average Speed Increase for Incident Durations at CAV Levels- no incident base

6.4 Impact of Trucks on Traffic Network

Whereas the previous simulations represented different types of vehicles on the traffic network (i.e. passenger vehicle, and single- and multi-unit trucks), the next series of simulations analyze the performance impact of trucks on the traffic network. These scenarios calculate the traffic network total delay in hours and percentage reductions based on vehicle performance in the five levels of automation (Figures 27 and 28), as well as the traffic network average speed (in miles per hour and percentage increase based on vehicle performance in the five levels of automation (Figure 29 and 30). Vehicle performance is a measure of the reduction of total network delay as vehicles operate more efficiently on the roadway. Vehicle performance increases over each scenario. The blue line represents a base level of performance, an orange line represents a five percent vehicle performance increase, a gray line represents a ten percent vehicle performance increase, and a yellow line represents a fifteen percent increase in vehicle performance.

The following figures present the results of system performance under different levels of automation. As can be seen from these figures, the network performance increases by introducing higher performance trucks combined with other vehicles.

In Figure 27, the base vehicle performance at CAV level 0 starts at about 280,000 hours in total network delay but decreases to about 120,000 hours of total network delay at CAV level 5. This is the same for all increases in vehicle performance values (i.e. increases of 5, 10 and 15 percent). Of note is the significant decline in total network delay at CAV Level 3. At this level, the driver assistance program of the vehicle can control both steering and braking/accelerating under some conditions and monitors the driving environment; however, the driver must continue to pay full attention ("monitor the driving environment") at all times. Figure 28 illustrates the percentage reduction in total network delay associated with CAV levels 1 through 5. The maximum percentage reduction in delays was a 25.97 percent reduction that occurred when the vehicle performance was increased by ten percent at CAV Level 3. However, the percentage reduction rebounds when the automation level increases. This holds true regardless of vehicle performance increases. In fact, when vehicle performance is increased by ten percent (gray line), the percentage of delay reduction at CAV Level 4 nearly matches the delay reduction produced by Level 1a CAVs.

Figure 29 shows similar trends in the average speed of the traffic network. As the CAV level increases so do average vehicle speeds regardless of vehicle performance increases. Between CAV Levels 1a/b and 2, the average speed increases by less than one mile per hour; however, between CAV Level 2 and 3, the average speed increases by more than one mile per hour. Between Levels 3 and 4, the speed increases by more than two miles per hour, and between CAV Levels 4 and 5, the speed increases by nearly four miles per hour. As seen in Figure 30, a large percentage increase of total delay occurs when the vehicle performance is increased by 15 percent between CAV Levels 5 and 4 with the same vehicle performance. However, of note are the trends represented by the base vehicle performance (blue line) and vehicle performance increase of five percent (orange line), which indicate nominal change between CAV Levels of 3 and 4. The trend line representing vehicle performance increases of ten percent (gray line) shows a dramatic decrease in the average speed of about four percent between CAV Levels 3 and 4, before rebounding by six percent between CAV Levels 4 and 5.

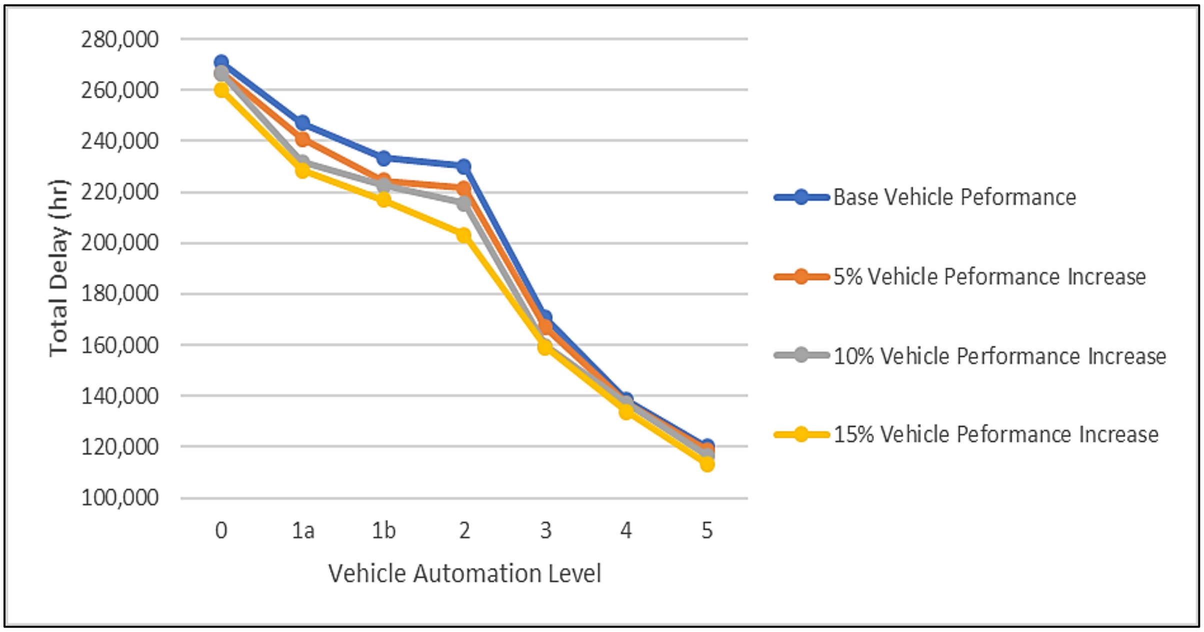

Figure 27: Delay in Hours Based on Vehicle Performance and CAV Level

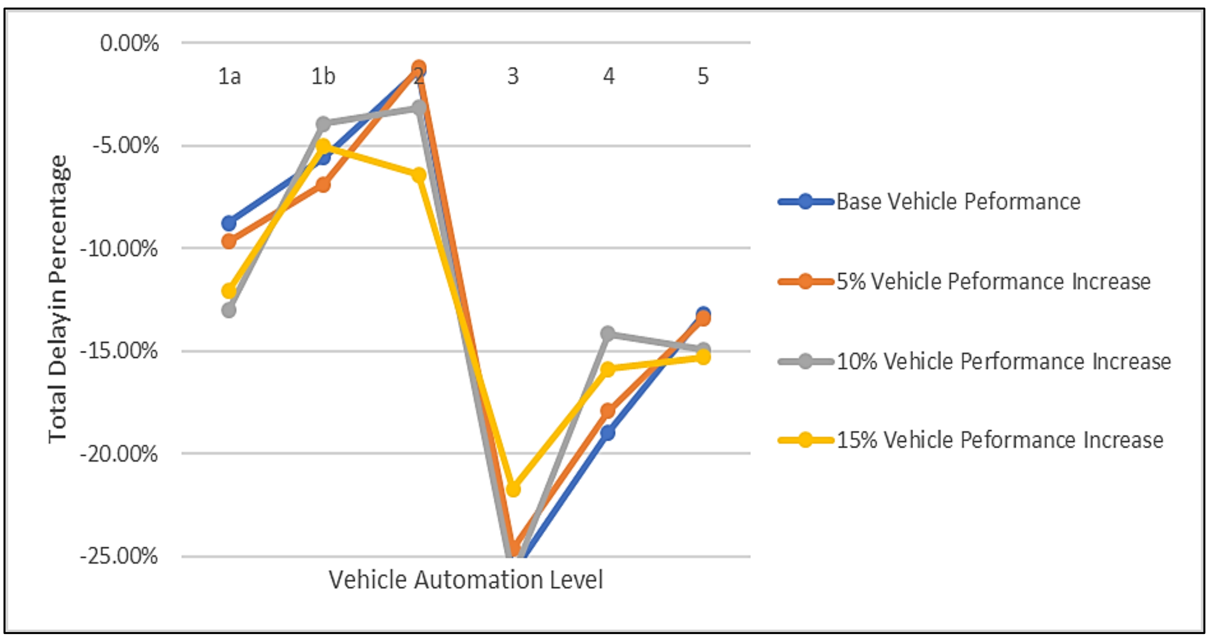

Figure 28: Percentage Reductions Based on Vehicle Performance and CAV Level

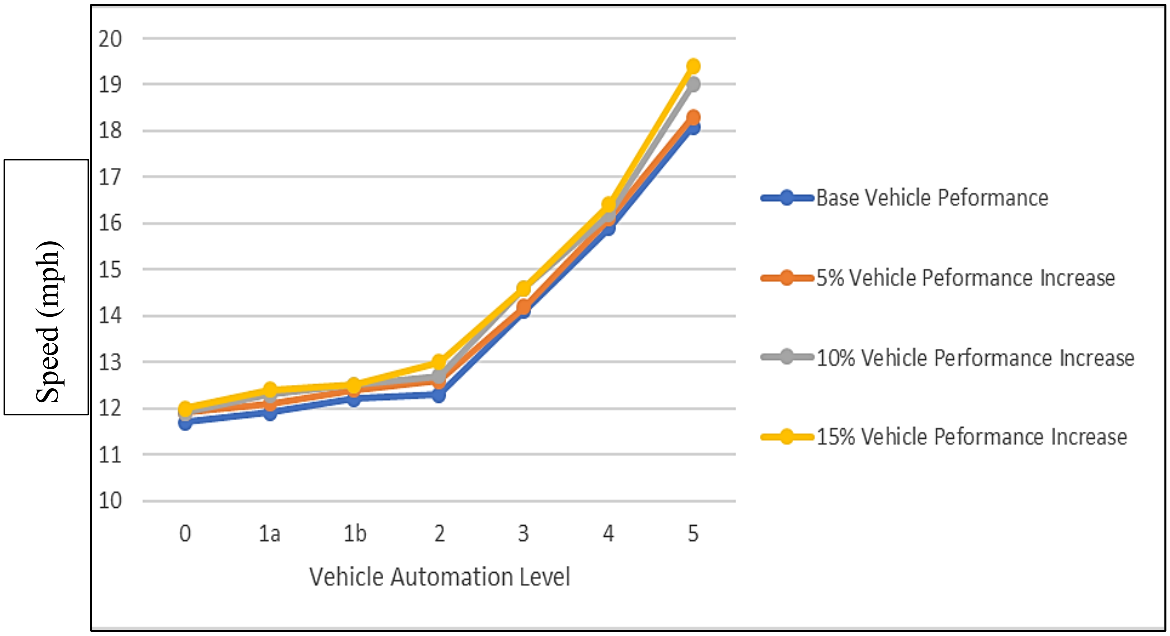

Figure 29: Average Speed (mph) Based on Vehicle Performance and CAV Level

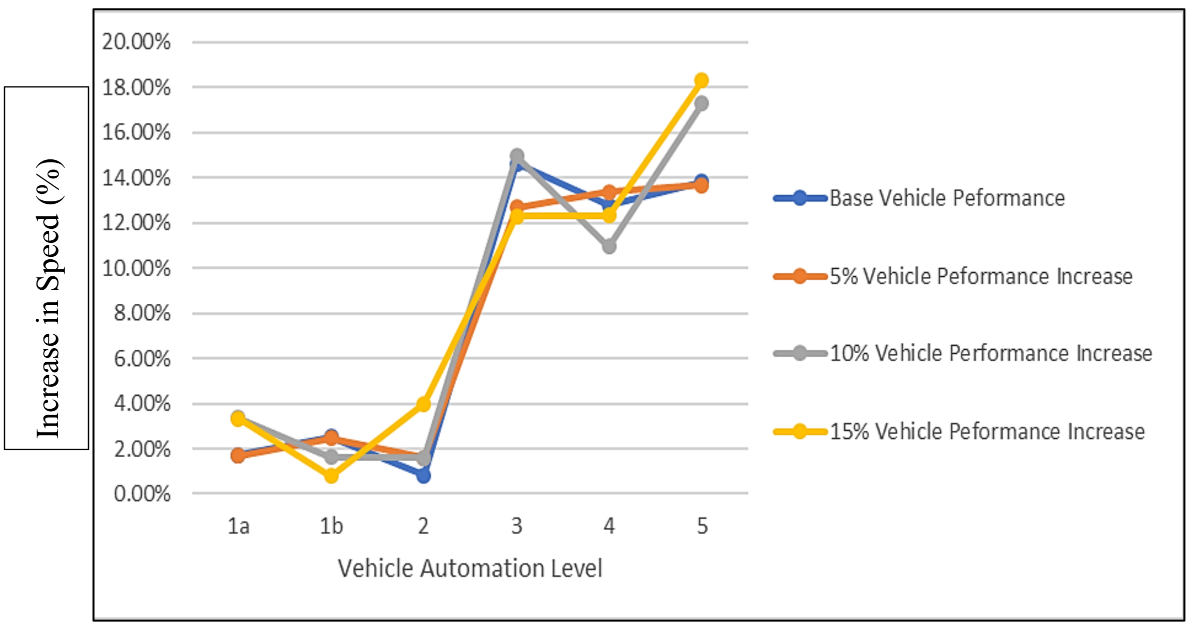

Figure 30: Percentage Increase in Speed Based on Vehicle Performance and CAV Level

6.5 Summary

The objective of the simulation was to demonstrate at the system level how various improvement strategies can work and quantify associated improvements in network performance can be evaluated. The simulation was demonstrated using a case study. The research area for traffic simulation modeling was a corridor along I-40. The modelled freeway had eight diversion choices, two in highly urban areas, two in highly rural areas, and four in dense to light suburban areas. Simulations of diversion routes examined corridors linking Kingston Pike to I-40. These simulations integrated various levels of connectivity and automation from Level 0, no automation, to Level 5, complete automation. Additionally, to create behaviors based upon historical or simulated time-dependent travel, the study developed and utilized a specialized origin-destination matrix table. The model included variations in vehicle types (with associative attributes). The percentage of passenger cars ranged from 78 to 88, the percentage of single unit trucks ranged from 2 to 3, and the percentage of multi-unit trucks ranged from 10 to 18. Finally, the simulation included variations in ATIS information penetration in order to provide a model for en-route diversion behavior. The combination of different variables specific to freeways, incidents, and alternate routes resulted in thousands of combinations of the experimental designs for simulation.

The series of simulation runs assume values are calculated in one day, with each incident blocking all but one lane with travel speeds of ten miles per hour. The simulation platform represented eight diversion locations along I-40 ranging from rural sections (Locations 1 and 2) to highly urban sections of the interstate (Locations 7 and 8). Analysis involving a specific alternative route (Location 8) utilized a segment of the roadway where vehicles were diverted from I-40 onto a segment of Kingston Pike containing 15 signalized intersections before returning to the freeway.

Simulation results indicate that in the event of an incident, without updated traffic information, travel times more than double on both the freeway and alternative routes. However, drivers that use alternative routes in rural settings experience more travel time savings benefits. With updated traffic information, simulations indicate an average delay reduction of about ten percent for freeways and an average delay increase for alternative routes of about 20 percent. When the value of time (VOT) is calculated for both freeway and alternative routes under conditions that assume updated traffic information for half of the vehicles, the VOT changes by about two percent; however, when VOT is calculated separately for freeway and alternative routes, the VOT changes by about 13 percent for both. Finally, delay reductions for the network increase from about 1133 hours to about 3111 hours as the incident duration increases. Thus, if en-route diversion is implemented, the delay reduction increases resulting in total cost savings is about $33,000 for incidents lasting two hours and about $91,000 for incidents lasting six hours.

The integration of connected and autonomous (CAV) vehicles into the simulation scenarios indicates the benefits of CAV technology. For example, the hours of total network delay without any incident ranges from approximately 52,000 hours with a CAV level of 0 to about 4,000 hours at a CAV level of 5. Furthermore, at a CAV level of 1, there is more than a 13 percent reduction in total incident delay, but with a CAV level of 5, the reduction in the total incident delay is about 47 percent. Also, under no incident duration, the speed increases from an average of ten miles per hour to more than forty miles per hour as CAV technology improves. When truck vehicle performance is integrated into the scenarios, there is a significant decline in total network delay at CAV Level 2. The maximum percentage reduction in delays can be as large as 25.97 percent when the vehicle performance increases by ten percent at CAV Level 3. Finally, speeds increase based on the level of automation. The largest percentage increase happens when the vehicle performance increases by 15 percent at CAV Level 5 when compared to level 4 automation with the same vehicle performance.

7.0 CONCLUSIONS & RECOMMENDATIONS

The project benefits Tennessee Department of Transportation in several ways including 1) identifying potential for reductions in truck and non-truck delays through appropriate diversion schemes when large-scale incidents occur; accomplishing TDOT's strategic objectives that include dealing with incident-induced congestion and related improvements in highway level of service, freight distribution, and lower energy use and emissions; and 3) greater customer satisfaction through more customized traveler information on Tennessee roadways, i.e., potential improvements in TDOT's information dissemination system.

Through modeling and simulations, this study transforms traffic incident and crash data into a framework that mimics real conditions in order to analyze en-route diversion behavior during large-scale incidents. The multiple scenarios created include variations in levels of connectivity, traffic incident information penetration, percentage of vehicle types (passenger, single and multiple unit trucks), as well as the value of time and delay. The research integrates data extracted from multiple databases including TDOT's Locate/IM incident data; E-TRIMS crash data; Fatality Analysis Reporting System and other data sources such as weather history and geo-locations. The research creates new linked datasets for each simulation by integrating some of these databases through powerful programming software.

After data collection, the first portion of this project aims at identifying the association between injury severity and incident duration in truck-involved accidents, and how these incidents are correlated with other factors. To achieve this goal, data has been collected and matched through E-TRIMS for crash data with TDOT Region 1 TMC incident data. This resulted in collecting completed data for 442 truck-involved crashes. From this dataset, injury severity and incident duration characteristics are categorized into various levels. A recursive bivariate ordered probit model was applied for the analysis. Descriptive statistics show both incident duration and injury severity are approximately normally distributed. Though most of the incidents can be cleared in 120 minutes or less, some take more than 120 minutes. The probability of a severe injury relating to an incident duration of 120 minutes or longer is higher than that of an accident involving a minor injury. The 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. Research reveals that the incident duration is longest for an incapacitating or fatal crash. Given these results, traffic operations may want to review the countermeasures used to shorten lane block duration and the response time for responders. Given that injury severity significantly affects the incident duration, several proactive actionable countermeasures for decreasing the injury severity can be considered, such as driver safety education. Additionally, traffic operations practitioners like city traffic engineers should be diligent in keeping roads clean of snow and ice as these elements are strongly associated with severe injury accidents.

The research further includes the creation of a specialized 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 primary data sources, including TDOT SmartWay, Locate/IM, and Google Earth. An in-depth investigation of large-scale incident classification and incident duration regarding operational response and on-scene times of different agencies is conducted. The data mining techniques, hierarchical clustering method, and statistical modeling, are applied to identify large-scale traffic incidents and predict incident duration both historically and in real-time. The research contributes to state-of-art incident management strategies by demonstrating how to identify a large-scale incident using advanced data mining techniques. Then, 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 incident duration modeling through estimation of random-parameter hazard-based duration models. The random-parameter Weibull model is observed to be most suitable from a statistical perspective. The key findings from the final model indicate a hazard rate of 0.69 percent for large scale incidents, which require significant response resources. In general, a faster response to an incident site will decrease large-scale incident durations. The results obtained from this study have several implications for large-scale incident management. The findings suggest a reduction in response times for Highway Incident Response Units (HIRU) and Highway Safety Patrol (HSP) can significantly reduce large-scale incident durations. Specifically, the reduction in response times for the third or more HIRU unit, when needed, can potentially reduce large-scale incident durations. However, finding additional units may be difficult. Freeway segments on I-40 and I-75 near urban areas are identified as high-risk segments. Incident managers can potentially reduce incident duration by working with towing companies to respond more quickly in large-scale incident situations. Additionally, close coordination between different response agencies and companies can enhance response resource deployment.

Researchers can extend the methodology proposed in this study to other locations in order to further explore practical solutions for mitigating the negative consequences of large-scale incidents. Future research on incident duration management can use a case-based approach where researchers analyze individual large-scale incidents to obtain insights on how operations could be improved through better coordination. Future research can include HAZMAT incidents, route diversion, and detour management. Also, spatial analysis needs to be investigated further and can be based on additional information obtained from other databases maintained by various response agencies.

Finally, simulation models are applied to analyze the delay reductions and cost savings for both trucks and passenger vehicles under large-scale traffic incidents. The simulation models are based on real-life data. Key findings from the simulation study results are:

- The benefit in delay reduction for trucks as well as passenger vehicles are larger in rural areas than in urban areas when en-route diversions tactics are employed because the Annual Average Daily Traffic (AADT) is less in rural areas, and there are fewer intersections, which may prompt more travelers to take the alternative route upon a large-scale incident on freeway;

- The increase in the average delay for the alternate route is directly related to the amount of traffic diverted to the alternative route, as expected. Additionally, the increase in average delay for alternative routes is directly related to a higher percentage of truck vehicles being diverted as trucks take a longer time in maneuvering. The percentage increase of average delay on alternative routes is higher than that of average delay reduction for freeway traffic;
- The percentage of travelers accessing updated travel time (information penetration) has a significant positive effect on the number of vehicles, both passenger vehicles and trucks, diverting to an alternative route;
- Cost savings in implementing the en-route diversion strategy is significant for large-scale incidents occurring on the freeway when the incident duration is long. This indicates that the longer the incident, the more important implementation of diversion operations;
- Connected and Automated Vehicle (CAV) technology penetration will help improve traffic detour operations in terms of reducing delays and increasing travel speed.

In the long term, this research study will be useful in helping practitioners to evaluate en-route diversion strategies by comparing benefit estimations. This study also highlights the necessity and importance of customizing en-route diversion information for truck drivers as truck drivers' primary choice is the known freeway route if not well informed and guided. Such customized information includes the availability of alternate routes for trucks and travel time for trucks on the current freeway and alternate routes. However, this broad research study is limited due to the limited number of study network scenarios not specific to truck-specific information penetration. Future research could incorporate signal timing plans to accommodate diverted traffic on alternative routes. Other research could include comparing different alternative routes if there are multiple detour routes available to trucks.

This research project of en-route traffic diversion management under large-scale incidents has the potential to be incorporated in an Advanced Traveler Information System (ATIS) application (e.g. displaying travel timing savings by taking alternative routes, especially under the CAV environment). This research study demonstrates a framework to determine a large-scale incident and to activate the en-route diversion strategy. The analysis results indicate that there are substantial benefits to the application of en-route traffic diversion strategies that can result in travel time savings, as well as, energy and emission reduction for both commercial and non-commercial traffic.

RECOMMENDATIONS

1. *TDOT should continue to develop and identify countermeasures for decreasing incident durations, especially for large-scale incidents.* Longer incident duration times, especially when large-scale incidents occur, substantially increase travel time delays and the chances of secondary crashes. This report has identified two ways of decreasing incident durations: 1) review countermeasures to shorten response times and lane blockage duration, and 2) reduce injury severity, given a crash. A strong correlation between injury severity and incident duration was found. The more severe a crash, the longer it will take to clear and restore the freeway to normal traffic conditions. Further research is needed to improve driver safety and

explore ways to decrease injury severity in crashes. Where relevant, TDOT can be diligent in keeping the roads clean of debris, snow, and ice.

2. *Using models provided in this report, TDOT can improve incident identification, predict incident duration, and predict key incident characteristics that will help emergency personnel clear the incident and direct traffic in an efficient manner.* Identifying incident characteristics and expected duration is important for deciding necessary en-route diversions. It can also help improve accurate travel time information for travelers which, as recommendation number 3 explains, is critical for reducing travel time delay.

3. *Simulation scenarios indicate that accurate travel time information for both the freeway and the alternative route decreases average travel time delay during incidents.* In order to provide accurate en-route diversion travel times, TDOT needs to develop strategies for quickly identifying alternative routes and providing drivers with accurate travel times for all available routes. Truck drivers indicated in the surveys that the preferred method of notification is through smart or cell phones. The research suggests that if drivers are provided information about expected travel times, they will generally make more informed decisions and experience less delay.

4. *TDOT can explore ways of creating truck-specific GPS mapping in order to make it easier for truck drivers and emergency personnel to locate available alternative routes that are feasible during incidents.* Commercially available GPS devices for passenger vehicles map out the quickest and shortest route but do not identify truck-restricted routes or roads with weight, height, and hazardous cargo restrictions. In addition, the limited mobility of trucks can create additional delays on arterial roads and limit the usefulness of such roads for passenger vehicles taking these alternative routes. A truck-specific GPS map can increase truck driver confidence in alternative route choices and help TDOT identify feasible alternative routes when incident occur, or in some cases, encourage trucks to stay on the highway in order to increase the capacity and mobility of arterial routes for passenger vehicles.

5. *TDOT could create partnerships with tech companies and developers in order to invest in and promote emerging technology. Specifically, this report explains that "truck platooning" i.e., decreasing the headway and enabling cooperative adaptive cruise control decreased travel time delays and increased speeds.* The simulations in this study used CAV technology through a Constant Time Gap car-following model to model increase in roadway capacity and travel speed, and through a simplified algorithm that approximates cooperative adaptive cruise control. These simulations indicate that CAV technologies have benefits in terms of delay reduction. Truck platooning is a method for decreasing headways, and cooperative adaptive cruise control is in development for private passenger vehicles. Further investigations are needed to understand the role of connectivity with infrastructure during incidents and detours for large trucks.

6. *Truck drivers have heterogeneous personal preferences when it comes to en-route diversion decisions. Future research needs to continue to explore variations in truck driving behavior and their information and notification preferences.* This report outlines the findings of a short truck driver survey with a small sample size. Surveyed drivers indicated that they value familiarity, incident information, and notification through smart or cell phones when making en-route diversion decisions. The survey also revealed that drivers have different values when it comes to navigating traffic incidents. Truck drivers make decisions depending on their contract, value of time, and familiarity with available diversion routes. As stated in recommendation number 3, increasing the amount of available information, especially when large-scale incident happen, allows drivers to make informed decisions that can optimize their time. Future research should explore these variations in preference and other truck driving behaviors in order to help TDOT provide all of the necessary information that allows truck drivers to make informed decisions.

7. *Signalized intersections play a heavy role in alternate route travel time delay and can make accurate travel time predictions difficult. Future research should look at creating signal timing plans for abnormal en-route diversions.* Signal timing plans are programmed for an expected demand. During an en-route diversion, demand due to diversions can exceed expected demand so it might be necessary to create different signal timing plans that appropriately accommodate the diverted traffic. Otherwise, the alternative route/s may experience heavy congestion and disrupt normal traffic flow more than necessary among local connecting streets.

8. *The simulations conducted in this report only analyzed the impact of en-route diversion on one alternative route. Future research can explore en-route diversion behavior when drivers are presented with multiple different alternative detour routes.* In some cases, drivers will have access to more than one viable alternate route during incidents. The number of alternate routes is also heavily dependent on the driver's final destination. The farther the driver's destination is from the incident, the more options the driver will have. Future research should explore how TDOT can identify multiple different alternative routes and how drivers will respond to the information presented to them. This research could also investigate how centralized traffic flow could decrease delays by suggesting specialized alternative routes based on driver preferences (truck restrictions, route preferences and final destination).

APPENDIX A

The following is the model structure for incident duration and injury severity presented in the main body of the report.

Equation 1.1:

$$y_1^* = a_1X_1 + \beta y_2^* + \varepsilon_1$$
$$y_2^* = a_2X_2 + \varepsilon_2$$

Where, y_1^* is incident duration level, y_2^* is injury severity level (the most severe injury level in the crash), X_1 and X_2 are explanatory variables, a_1 and a_2 are the unknown parameters of X_1 and X_2, β is an unknown parameter of y_2^*, ε_1 and ε_2 are the error terms, and they have a joint density distribution with mean (0,0), and covariance matrix as $[0\ \rho\ \rho\ 0\ ]$. The explanatory variables and error terms satisfy the conditions E $(X_1\varepsilon_1)$=0, and E $(X_1\varepsilon_2)$=0.

Equation 1.2:

$$y_1^* = 1\ if\ y_1^* <= b_1$$
$$y_1^* = 2\ if\ b_1 <= \ y_1^* <= b_2$$

…

$$y_1^* = l\ if\ \ y_1^* > b_{l-1}$$

$$y_2^* = 1\ if\ y_2^* <= c_1$$
$$y_2^* = 2\ if\ c_1 <= \ y_2^* <= c_2$$

…

$$y_2^* = m\ if\ \ y_2^* > c_{m-1}$$

Equation 1.3:

$$pr(y_1 = i, y_2 = j) = Pr(b_{i-1} < y_1^* <= b_i, c_{i-1} < y_2^* <= c_i) = Pr(y_1^* <= b_i, y_2^* <= c_i)$$
$$-Pr(y_1^* <= b_{i-1}, y_2^* <= c_i) - Pr(y_1^* <= b_i, y_2^* <= c_{i-1}) + Pr(y_1^* <= b_{i-1}, y_2^* <= c_{i-1})$$

Equation 1.4:

$$pr(y_1 = i, y_2 = j)$$
$$= \phi(b_i - X_1\alpha_1, (c_j - \beta X_1\alpha_1 - X_2\alpha_2)\tau, \rho) - \phi(b_{i-1} - X_1\alpha_1, (c_j - \beta X_1\alpha_1$$
$$- X_2\alpha_2)\tau, \rho)$$
$$-\phi(b_i - X_1\alpha_1, (c_{j-1} - \beta X_1\alpha_1 - X_2\alpha_2)\tau, \rho) + \phi(b_{i-1} - X_1\alpha_1, (c_{j-1} - \beta X_1\alpha_1 - X_2\alpha_2)\tau, \rho)$$

Where ∅ is the bivariate standard normal cumulative distribution function, $\tau = \frac{1}{\sqrt{1+2\beta\rho+\beta^2}}$ and $\rho = \tau(\beta + \rho)$. If $\beta = 0$, it is a seemingly unrelated specification.

Equation 1.5:

$$lnL = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} I(y_1 = i, y_2 = j)\ ln\ ln\ Pr(y_1 = i, y_2 = j\ )$$

Equation 1.6:

$$Pr(y_{ij} > k|x_{ij}, \kappa, u_j) = \Phi(x_{ij}\beta + z_{ij}u_j - \kappa_k)$$

Where j is the index of M clusters, each cluster has observations. And k is the index for the cut points. $\Phi(\cdot)$ represents the standard normal cumulative distribution probability. z_{ij} are the covariates corresponding to the random effects.

Equation 1.7:

$$\begin{aligned} Pr(y_{ij} > k|x_{ij}, \kappa, u_j) &= Pr(\kappa_{k-1} < x_{ij}\beta + z_{ij}u_j + \varepsilon_{ij} < \kappa_k) \\ &= Pr(\kappa_{k-1} - x_{ij}\beta - z_{ij}u_j < \varepsilon_{ij} < \kappa_k - x_{ij}\beta - z_{ij}u_j) \\ &= \Phi(\kappa_k - x_{ij}\beta - z_{ij}u_j) - \Phi(\kappa_{k-1} - x_{ij}\beta - z_{ij}u_j) \end{aligned}$$

Where κ_0 can be taken as $-\infty$, and κ_K is the $+\infty$. K is the number of possible outcomes. $\varepsilon_{ij}$are error terms independent of u_j, and distributed as standard normal with mean 0 and variance 1.

Equation 1.8:

$$\begin{gathered} y_{ij}^* = x_{ij}\beta + z_{ij}u_j + \varepsilon_{ij} \\ y_{ij} = 1 \; if \; y_{ij}^* \le \kappa_1 \\ y_{ij} = 2 \; if \; \kappa_1 < y_{ij}^* \le \kappa_2 \\ \ldots \\ y_{ij} = K \; if \; \kappa_{K-1} < y_{ij}^* \end{gathered}$$

Equation 1.9:

$$f(y_j|u_j) = \prod_{i=1}^{n_j} p_{ij}^{I_k(y_{ij})} = exp \sum_{i=1}^{n_j} \{I_k(y_{ij}) log(p_{ij})\}$$

$I_k(y_{ij}) = 1$ if $y_{ij} = k$

$$I_k(y_{ij}) = 0 \;\; otherwise$$

Equation 1.10:

$$L_i(\beta, \kappa, \Sigma) = (2\pi)^{-q/2}|\Sigma|^{-1/2} \int f(y_j|\kappa, u_j) exp(-u_j'\Sigma^{-1}u_j/2) du_j$$

$$= (2\pi)^{-q/2}|\Sigma|^{-1/2} \int exp\{h(\beta, \kappa, \Sigma, u_j)\} du_j$$

$$h(\beta, \kappa, \Sigma, u_j) = \sum_{i=1}^{n_j} \{I_k(y_{ij}) log(p_{ij})\} - u_j'\Sigma^{-1}u_j/2$$

Equation 1.11:

$$y_i = x_i + u_{1i}$$

Equation 1.12:

$$z_i\gamma + u_{2i} > 0$$

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.

Equation 2.1:

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

Where K is the number of clusters chosen, k is the index, $\frac{1}{|C_k|}\sum_{i,i'\in C_k}\sum_{j=1}^{p}\left(x_{ij}-x_{i'j}\right)^2$ is the within cluster variant for cluster C_k. $|C_k|$ is the number of observations in cluster k. i and j denotes the observation index.

Equation 2.2:

$$h(t) = \lim_{\Delta t\to 0^+} Pr(t \le T < t + \Delta t | T > t)/\Delta t$$

Equation 2.3:

$$h(t) = F(t)/S(t)$$

Equation 2.4:

$$ln(T) = \beta X + \varepsilon$$

Where, β denotes the coefficient vector of covariates. X represents the covariates, ε is an error term.

Equation 2.5:

$$logt_i = x_i\beta + \varepsilon_i$$

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.

Equation 2.6:

$$S(t) = \left\{1 + (\lambda_i t_i)^{1/\gamma}\right\}^{-1}$$

$$f(t) = \lambda_i^{1/\gamma}(t_i)^{1/\gamma-1}/\gamma\left\{1 + (\lambda_i t_i)^{1/\gamma}\right\}^2$$

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

Equation 2.7:

$$S(t) = exp\left\{-\int_0^t h(u|\alpha)du\right\} = exp\left\{-\alpha\int_0^t \frac{f(u)}{S(u)}dy\right\} = \{S(t)\}^{\alpha}$$

Equation 2.8:

$$S(t) = \int_0^{\infty} S(t|\alpha)g(\alpha)d\alpha = \int_0^{\infty} \{S(t)\}^{\alpha}g(\alpha)d\alpha$$

Equation 2.9:

$$f_\theta(t) = -\frac{d}{dt}S_\theta(t)$$

$$h_\theta(t) = \frac{f_\theta(t)}{S_\theta(t)}$$

Equation 2.10:

$$g(x) = \frac{x^{a-1}e^{-x/b}}{\Gamma(a)b^a}$$

Equation 2.11:

$$g(x) = \left(\frac{b}{2\pi x^3}\right)^{1/2} exp\left\{-\frac{b}{2a}\left(\frac{x}{a} - 2 + \frac{a}{x}\right)\right\}$$

Equation 2.12:

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

Equation 2.13:

$$logt_{ji} = x_{ji}\beta + z_{ji}u_j + v_{ji}$$

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

Equation 2.14:

$$g(t|\eta) = g\left(t_{ji}|x_{ji}\beta + z_{ji}u_j\right)$$
$$S(t|\eta) = S\left(t_{ji}|x_{ji}\beta + z_{ji}u_j\right)$$

Equation 2.15:

$$f\left(t_j|n_j\right) = \prod_{i=1}^{n_j} f\left(t_{ji}|\eta_{ji}\right)$$
$$f\left(t_{ji}|\eta_{ji}\right) = \left\{\frac{g\left(t_{ji}|x_{ji}\beta + z_{ji}u_j\right)}{S\left(t_{ji}|x_{ji}\beta + z_{ji}u_j\right)}\right\}^{d_{ji}} \left\{\frac{S\left(t_{ji}|x_{ji}\beta + z_{ji}u_j\right)}{S\left(t_{0ji}|x_{ji}\beta + z_{ji}u_j\right)}\right\}$$

Equation 2.16:

$$L_j(\beta, \Sigma) = (2\pi)^{-q/2}|\Sigma|^{-1/2}\int f\left(t_j|X_i\beta + Z_ju_j\right)exp\left(-u_j'\Sigma^{-1}u_j/2\right)du_j$$

Equation 5.1:

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

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 subject 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.

Equation 5.2:

$$A_i[t] = -\frac{1}{h}(V_i[t] - V_{i-1}[t] + \lambda\delta_i)$$
$$\delta_i[t] = D_{i,i-1}[t] + hV_i[t] + D_{i,i-1}^{desire}$$

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 subject 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.

APPENDIX B

Tennessee Department of Transportation

Questionnaire

Read statement about the survey and confidentiality.

Q1.	**Over the last 3 months, how many times have you been delayed by an unexpected traffic incident along the route you were driving your truck? (An incident is a "non-recurring" event such as a crash or emergency roadwork) # ____________________**
Q2. **Q3.** **Q4.**	**When was the most recent delay?** _________________________________ **How much time did this "unexpected delay" add to your trip?**____Minutes______ Hours **Where did the incident happen?** __________ **Be as specific as possible, such as route I-40 Exit 379.**
Q5. **Q6.**	**What type of trip you were making during this incident?** ☐ Pick-up ☐ Delivery ☐ Service calls ☐ Other (specify) _________________________ **What was the weather like during the event?** ☐ Clear ☐ Cloudy and Dry ☐ Rainy/Light Snow ☐ Blizzard/Storm
Q7.	**On that trip, what type of vehicle were you driving?** ☐ Small Truck (e.g., mini Truck) ☐ Light Truck (e.g., pickup truck, 1 – 14,001 lb.) ☐ Medium Truck (e.g., Van, Firetruck, 14,001 – 26,000 lb.) ☐ Heavy Truck (e.g., Tractor unit, 26,001 – 33,000 lb.) ☐ Very Heavy Truck (e.g., Long-haul truck, > 33,000 lb.) ☐ Other (specify) _________________
Q8. **Q9.**	**Did you observe the incident or did you hear about it from other information sources?** ☐ Self-observation ☐ Other information sources (e.g., smart phone, 511) **If other information source, then what was the first information source used to obtain the incident information?** ☐ 511 ☐CB Radio ☐ Highway Advisory Radio ☐ Dynamic Message Boards ☐ Cell or Mobile phone (Internet, Social Media, or Emergency Alert Message) ☐ GPS (Global Positioning System) ☐ Google/Bing maps, etc. ☐ Local radio channel (FM/AM) ☐ Other _________________________

Q10.	**Did you receive information from any other source after the first information Source?** ☐ 511 ☐CB Radio ☐ Highway Advisory Radio ☐ Dynamic Message Boards ☐ Cellphone (Internet, Social Media, or Emergency Alert Message) ☐ GPS (Global Positioning System) ☐ Google/Bing maps, etc. ☐ Local radio channel (FM/AM) ☐ Other ________________________
Q11.	**Did you divert to a nearby alternate route to avoid the delay?** ☐ Yes – diverted to an alternate route but returned to the original route **[Go to Q14]** ☐ Yes – diverted to an alternate route and did not return to the original route **[Go to Q14]** ☐ No – stayed on the same route ☐ Other (specify) ____________________
Q12. **Q13.**	**If you did not divert to an alternate route, how much time did the unexpected delay add to your trip?** ***(answer this part only if you did not divert)*** ___________________(minutes) **What reasons did you have for not diverting to an alternate route?** __________________ _____________________________________
Q14. **Q15.**	**If you diverted to an alternate route, were you familiar with the alternative route?** ☐ Yes ☐ No **Do you think this alternate route was the best choice for avoiding delays?** ☐ Yes ☐ No
Q16. **Q17.**	**To avoid future unexpected delays due to incidents, what information would you like to receive?** ____ (e.g., additional delays, lanes blocked, expected duration, length of queue, secondary incidents) **How would you like to receive the information?** _________________ (e.g., smart phone, in-vehicle device)
Q18. **Q19.**	**Your Age:** ________________ **Gender:** ☐ Male ☐ Female ***Thanks for your participation!***

REFERENCES

Al-Deek, H. M., Khattak, A. J., & Thananjeyan, P. (1998). “A combined traveler behavior and system performance model with advanced traveler information systems”. *Transportation Research Part A: Policy and Practice*, *32*(7), 479-493.

Belenky, Peter. (2011). "Revised departmental guidance on valuation of travel time in economic analysis." US Department of Transportation, Washington, DC Google Scholar (2011).

Ben-Akiva, Moshe E., Tomer Toledo, Jorge Santos, Nathanael Cox, Fang Zhao, Yin Jin Lee, and Vittorio Marzano. (2016). "Freight data collection using GPS and web-based surveys: Insights from US truck drivers’ survey and perspectives for urban freight." Case studies on transport policy 4, no. 1 (2016): 38-44.

Boyles, Stephen, David Fajardo, and S. Travis Waller. (2007). "A naive Bayesian classifier for incident duration prediction." In 86th Annual Meeting of the Transportation Research Board, Washington, DC. 2007.

Caliendo, Ciro, and Maurizio Guida. (2014). "A new bivariate regression model for the simultaneous analysis of total and severe crashes occurrence." *Journal of Transportation Safety & Security* 6, no. 1 (2014): 78-92.

Chang, Gang-Len, and Steven Rochon. (2009). "Performance evaluation and benefit analysis for CHART." Coordinated Highways Action Response Team, Maryland Department of Transportation (2009).

Chang, Li-Yen, and Fred Mannering. (1999). "Analysis of injury severity and vehicle occupancy in truck-and non-truck-involved accidents." *Accident Analysis & Prevention* 31, no. 5 (1999): 579-592.

Chimba, Deo, Boniphace Kutela, Gary Ogletree, Frank Horne, and Mike Tugwell. (2013). "Impact of abandoned and disabled vehicles on freeway incident duration." *Journal of Transportation Engineering* 140, no. 3 (2013): 04013013.

Costello, Bob. (October 2017). “Truck Driver Shortage Analysis 2017.” American Trucking Associations. American Transportation Research Institute (ATRI). Arlington, VA. https://atri-online.org/wp-content/uploads/2018/10/ATRI-Cost-of-Congestion-to-the-Trucking-Industry-2018-Update-10-2018.pdf

Cragg, Catherine A., and Michael J. Demetsky. (1995). *Simulation Analysis of Route Diversion Strategies for Freeway Incident Management*. No. VTRC-95-R11. 1995.

Crocker, Brittany. (April 13, 2018). "Load of 'baked' sweet potatoes closes northbound Interstate 75 lanes". *Knoxville News Sentinel*. www.knoxnews.com/story/news/2018/04/13/load-baked-sweet-potatoes-closes-northbound-interstate-75-lanes/515487002/

Dong, Chunjiao, David B. Clarke, Shashi S. Nambisan, and Baoshan Huang. (2016). "Analyzing injury crashes using random-parameter bivariate regression models." *Transportmetrica A: Transport Science* 12, no. 9 (2016): 794-810.

Dong, Chunjiao, Shashi S. Nambisan, Stephen H. Richards, and Zhuanglin Ma. (2015). "Assessment of the effects of highway geometric design features on the frequency of truck involved crashes using bivariate regression." *Transportation Research Part A: Policy and Practice* 75 (2015): 30-41.

Dotoli, M., Zgaya, H., Russo, C., & Hammadi, S. (2017). A multi-agent advanced traveler information system for optimal trip planning in a co-modal framework. *IEEE Transactions on Intelligent Transportation Systems*, *18*(9), 2397-2412.

Duncan, Chandler, Asad Khattak, and Forrest Council. (1998)."Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions." *Transportation Research Record*: Journal of the Transportation Research Board 1635 (1998): 63-71.

Dunn Engineering & Associates. (May 2006). *Alternate Route Handbook*. Federal Highway Administration. FHWA-HOP-06-092. https://ops.fhwa.dot.gov/publications/ar_handbook/index.htm

Eluru, N., C. Bhat and D. Hensher. (2008). “A Mixed Generalized Ordered Response Model for Examining Pedestrian and Bicyclist Injury Severity Levels in Traffic Crashes,” *Accident Analysis and Prevention*, 40, 3, pp. 1033-1054.

Emmerink, Richard HM, Peter Nijkamp, Piet Rietveld, and Jos N. van Ommeren. (1996). "Variable message signs and radio traffic information: An integrated empirical analysis of drivers' route choice behaviour." *Transportation Research Part A: Policy and Practice* 30, no. 2 (1996): 135-153.

Garib, A., A. E. Radwan, and H. Al-Deek. (1997). "Estimating magnitude and duration of incident delays." *Journal of Transportation Engineering* 123, no. 6 (1997): 459-466.

Golob, Thomas F., and Amelia C. Regan. (2001). "Impacts of information technology on personal travel and commercial vehicle operations: research challenges and opportunities." *Transportation Research Part C: Emerging Technologies* 9, no. 2 (2001): 87-121.

Golob, Thomas F., Wilfred W. Recker, and John D. Leonard. (1987). "An analysis of the severity and incident duration of truck-involved freeway accidents." *Accident Analysis & Prevention 19,* no. 5 (1987): 375-395.

Hojati, Ahmad Tavassoli, Luis Ferreira, Simon Washington, Phil Charles, and Ameneh Shobeirinejad. (2014). "Modelling total duration of traffic incidents including incident detection and recovery time." *Accident Analysis & Prevention* 71 (2014): 296-305.

Hojati, Ahmad Tavassoli, Luis Ferreira, Simon Washington, and Phil Charles. (2013). "Hazard based models for freeway traffic incident duration." *Accident Analysis & Prevention* 52 (2013): 171-181.

Holguín-Veras, José, and Qian Wang. (2011). "Behavioral investigation on the factors that determine adoption of an electronic toll collection system: Freight carriers." *Transportation Research Part C: Emerging Technologies* 19, no. 4 (2011): 593-605.

Hooper, Alan. October 2017. "An Analysis of the Operational Costs of Trucking: 2017 Update". American Transportation Research Institute (ATRI). http://atri-online.org/wp-content/uploads/2017/10/ATRI-Operational-Costs-of-Trucking-2017-10-2017.pdf

Islam, Mouyid, and Salvador Hernandez. (2013). "Large truck–involved crashes: exploratory injury severity analysis." *Journal of Transportation Engineering* 139, no. 6 (2013): 596-604.

Jones, Bryan, Lester Janssen, and Fred Mannering. (1991). "Analysis of the frequency and duration of freeway accidents in Seattle." *Accident Analysis & Prevention* 23, no. 4 (1991): 239-255.

Kamrani, Mohsen, Behram Wali, and Asad J. Khattak. (2017). "Can data generated by connected vehicles enhance safety? Proactive approach to intersection safety management." *Transportation Research Record: Journal of the Transportation Research Board* 2659 (2017): 80-90.

Khattak, Asad J., Jun Liu, Behram Wali, Xiaobing Li, and ManWo Ng. (2016). "Modeling traffic incident duration using quantile regression." *Transportation Research Record: Journal of the Transportation Research Board* 2554 (2016): 139-148.

Khattak, Asad, Xiaohong Pan, Billy Williams, Nagui Rouphail, and Yingling Fan. (2008). "Traveler information delivery mechanisms: Impact on consumer behavior." *Transportation Research Record: Journal of the Transportation Research Board* 2069 (2008): 77-84.

Khattak, A. J., Yim, Y., & Prokopy, L. S. (2003). Willingness to pay for travel information. *Transportation Research Part C: Emerging Technologies*, *11*(2), 137-159.

Khattak, Asad J., Joseph L. Schofer, and Mu-Han Wang. (1995). "A simple time sequential procedure for predicting freeway incident duration." *Journal of Intelligent Transportation Systems* 2, no. 2 (1995): 113-138.

Khattak, Asad J., Joseph L. Schofer, and Frank S. Koppelman. (1995). "Effect of traffic information on commuters' propensity to change route and departure time." *Journal of Advanced Transportation* 29, no. 2 (1995): 193-212.

Khattak, A. J., Schofer, J. L., & Koppelman, F. S. (1993). “Commuters' enroute diversion and return decisions: analysis and implications for advanced traveler information systems.” *Transportation Research Part A: Policy and Practice*, 27(2), 101-111.

Khattak, Asad J; Schofer, Joseph L and Frank S Koppelman. (1991). “Factors Influencing Commuters' En Route Diversion Behavior in Response to Delay.” *Transportation Research Record*. Issue Number: 1318. Transportation Research Board. ISSN: 0361-1981.

Khattak, Asad J., Joseph L. Schofer, and Frank S. Koppelman. (1993). "Commuters' enroute diversion and return decisions: analysis and implications for advanced traveler information systems." *Transportation Research Part A: Policy and Practice* 27, no. 2 (1993): 101-111.

Knorring, John, Rong He, and Alain Kornhauser. (2005). "Analysis of route choice decisions by long-haul truck drivers." *Transportation Research Record: Journal of the Transportation Research Board* 1923 (2005): 46-60.

Khorashadi, Ahmad, Debbie Niemeier, Venky Shankar, and Fred Mannering. (2005). "Differences in rural and urban driver-injury severities in accidents involving large-trucks: an exploratory analysis." *Accident Analysis & Prevention* 37, no. 5 (2005): 910-921.

Kostyniuk, Lidia P., Frederick Michael Streff, and Jennifer Zakrajsek. (2002). “Identifying unsafe driver actions that lead to fatal car-truck crashes.” *AAA Foundation for Traffic Safety*, 2002. Vol. 9, no. 10.

Lemp, Jason D., Kara M. Kockelman, and Avinash Unnikrishnan. (2011). "Analysis of large truck crash severity using heteroskedastic ordered probit models." *Accident Analysis & Prevention* 43, no. 1 (2011): 370-380.

Levinson, D. (2003). “The value of advanced traveler information systems for route choice” *Transportation Research Part C: Emerging Technologies*, *11*(1), 75-87.

Li, Ruimin, Francisco C. Pereira, and Moshe E. Ben-Akiva. (2015)."Competing risk mixture model and text analysis for sequential incident duration prediction." *Transportation Research Part C: Emerging Technologies* 54 (2015): 74-85.

Li, Xiaobing, Asad J. Khattak, and Behram Wali. (2017). "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.

Liu, Yue, Woon Kim, and Gang-Len Chang. (2012). "Decision model for justifying the benefits of detour operation under non-recurrent congestion." *Journal of Transportation Engineering* 139, no. 1 (2012): 40-49.

Liu, Yue, Gang-Len Chang, and Jie Yu. (2011). "An integrated control model for freeway corridor under nonrecurrent congestion." *IEEE Transactions on Vehicular Technology* 60, no. 4 (2011): 1404-1418.

Lomax, Tim and Lauren Simcic. (2016). “Review of Literature and Practices for Incident Management Programs.” Texas A&M Transportation Institute. PRC 15-56 T.

https://static.tti.tamu.edu/tti.tamu.edu/documents/PRC-15-56-T.pdf

Magoci, Jrica. December 29, 2016. "Top 25 States By Number of Trucking Companies." Fuel Loyal. https://www.fueloyal.com/top-25-states-by-number-of-trucking-companies/

Nam, Doohee, and Fred Mannering. (2000). "An exploratory hazard-based analysis of highway incident duration." *Transportation Research Part A: Policy and Practice* 34, no. 2 (2000): 85-102.

National Transportation Safety Board (NTSB). February 2019. *Highway Accident Reports*. National Transportation Safety Board. www.ntsb.gov/investigations/AccidentReports/Pages/highway.aspx

Ng, Swee Tuan, Ruey Long Cheu, and Der-Horng Lee. (2006). "Simulation evaluation of the benefits of real-time traffic information to trucks during incidents." *Journal of Intelligent Transportation Systems* 10, no. 2 (2006): 89-99.

North Carolina Department of Transportation (NCDOT). Spring 2007. "Communicating Work Zone Information To Truckers in North Carolina." U.S. Department of Transportation Federal Highway Administration. https://ops.fhwa.dot.gov/WZ/practices/factsheets/pdfs/factsheet10.pdf

Ozbay, Kaan, and Nebahat Noyan. (2006). "Estimation of incident clearance times using Bayesian Networks approach." *Accident Analysis & Prevention* 38, no. 3 (2006): 542-555.

Pan, X., & Khattak, A. (2008). Evaluating traveler information effects on commercial and noncommercial users. *Transportation Research Record: Journal of the Transportation Research Board*, (2086), 56-63.

Pereira, Francisco C., Filipe Rodrigues, and Moshe Ben-Akiva. (2013). "Text analysis in incident duration prediction." *Transportation Research Part C: Emerging Technologies* 37 (2013): 177-192.

Qi, Yi, and Hualiang Teng. (2008). "An information-based time sequential approach to online incident duration prediction." *Journal of Intelligent Transportation Systems* 12, no. 1 (2008): 1-12.

Raggatt, Peter TF. (1991). "Work stress among long-distance coach drivers: A survey and correlational study." *Journal of Organizational Behavior* 12, no. 7 (1991): 565-579.

Russell, Kelsey. December 16, 2011. "Potato trailer spill closes I-40 East." WSMV News. www.wsmv.com/news/potato-trailer-spill-closes-i--east/article_de5001f8-ce45-5889-a26e-6283b64b83cb.html+&cd=1&hl=en&ct=clnk&gl=us

Schrank, David, Bill Eisele, Tim Lomax, and Jim Bak. (2015). "2015 urban mobility scorecard." (2015). Trexas Transportation Institute. Texas A&M University. https://static.tti.tamu.edu/tti.tamu.edu/documents/mobility-scorecard-2015-wappx.pdf

Schrank, David, Tim Lomax, and Shawn Turner. (2010). "TTI's 2010 urban mobility report powered by INRIX traffic data." Texas Transportation Institute, The Texas A&M University System 17 (2010).

Shinghal, Nalin, and Tony Fowkes. (2002). "Freight mode choice and adaptive stated preferences." *Transportation Research Part E: Logistics and Transportation* Review 38, no. 5 (2002): 367-378.

Sieber, W. Karl, Cynthia F. Robinson, Jan Birdsey, Guang X. Chen, Edward M. Hitchcock, Jennifer E. Lincoln, Akinori Nakata, and Marie H. Sweeney. (2014). "Obesity and other risk factors: the national survey of US long-haul truck driver health and injury." *American Journal of Industrial Medicine* 57, no. 6 (2014): 615-626.

Sullivan, Edward C. (1997). "New model for predicting freeway incidents and incident delays." *Journal of Transportation Engineering* 123, no. 4 (1997): 267-275.

Sun, H., Wu, J., Wang, W., & Gao, Z. (2014). Reliability-based traffic network design with advanced traveler information systems. *Information Sciences*, *287*, 121-130.

Sun, Yichen, Tomer Toledo, Katherine Rosa, Moshe E. Ben-Akiva, Kate Flanagan, Ricardo Sanchez, and Erika Spissu. (2013)."Route Choice Characteristics for Truckers." Transportation Research Record: Journal of the Transportation Research Board, No. 2354, Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 115–121. DOI: 10.3141/2354-12 https://toledo.net.technion.ac.il/files/2014/05/TRR_TruckRouteChoice_13.pdf

Sundaram, Srinivasan, Haris N. Koutsopoulos, Moshe Ben-Akiva, Constantinos Antoniou, and Ramachandran Balakrishna. (2011). "Simulation-based dynamic traffic assignment for short-term planning applications." *Simulation Modelling Practice and Theory* 19, no. 1 (2011): 450-462.

Swan, Nicole, Stephanie Baker, Dewa Hintz and Tammy Trimble. January 2004. 511 Virginia Evaluation. Virginia Department of Transportation (VDOT). Virginia Tech Transportation Institute. https://rosap.ntl.bts.gov/view/dot/4135/dot_4135_DS1.pdf?

Tennessee Department of Transportation (TDOT). (2019). HELP Program. Tennessee Department of Transportation. https://www.tn.gov/tdot/traffic-operations-division/transportation-management-office/help-program.html

Tennessee Department of Transportation (TDOT). October 10, 2006. "Tennessee Statewide ITS Architecture" Kimberly-Horn and Associates, Inc. Project: 115004066 https://www.tn.gov/content/dam/tn/tdot/traffic-operations/its/TN_Statewide_ITS_Architecture_Executive_Summary.pdf

Tennessee Department of Transportation (TDOT). August 2003. *Strategic Plan for Highway Incident Management in Tennessee.* Tennessee Department of Transportation. Tennessee Department of Commerce & Insurance. Tennessee Emergency Management Agency. https://i95coalition.org/wp-content/uploads/2015/03/Plan_TIM_TN.pdf?x70560

The Road Information Program (TRIP). April 2017. Tennessee Transportation by the Numbers. www.tripnet.org/docs/TN_Transportation_by_the_Numbers_TRIP_Report_April_2017.pdf Report produced by Tripnet.org.

Transportation Research Group (TRIP). January 2016. Tennessee Transportation by the Numbers http://www.tripnet.org/docs/TN_Transportation_by_the_Numbers_TRIP_Report_Jan_2016.pdf

Tsugawa, S., Kato, S., & Aoki, K. (2011). "An automated truck platoon for energy saving". In *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on* (pp. 4109-4114). IEEE.

U.S. Department of Transportation (USDOT). (February 2019). *Guidance for Implementation of Traffic Incident Management Performance Measurement*. NCHRP 07-20. Federal Highway Administration. Traffic Incident management Program. Office of Operations.

U.S. Department of Transportation (USDOT). (May 2018). Large Truck and Bus Crash Facts 2016. U.S. Department of Transportation. Federal Motor Carrier Safety Administration Analysis Division. https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/docs/safety/data-and-statistics/398686/ltbcf-2016-final-508c-may-2018.pdf

U.S. Department of Transportation (USDOT). (February 2018). "Traffic Incident Management." Federal Highway Administration. https://ops.fhwa.dot.gov/eto_tim_pse/about/tim.htm

U.S. Department of Transportation (USDOT). (2015). USDOT Bureau of Transportation Statistics. Website: https://www.bts.gov/sites/bts.dot.gov/files/legacy/tennessee.pdf

U.S. Department of Transportation. (USDOT). (May 2012). *Manual on Uniform Traffic Control Devices*. Federal Highway Administration. https://mutcd.fhwa.dot.gov/

U.S. Department of Transportation (USDOT). (September 2010). *Best Practices in Traffic Incident Management.* U.S. Department of Transportation. Federal Highway Administration, Office of Transportation Operations. 21st Century Operations Using 21st Century Technologies. https://ops.fhwa.dot.gov/publications/fhwahop10050/fhwahop10050.pdf

U.S. Department of Transportation (USDOT). (January 2010). *Traffic Incident Management Handbook*. Federal Highway Administration, Office of Transportation Operations.

https://ops.fhwa.dot.gov/eto_tim_pse/publications/timhandbook/tim_handbook.pdf

Wali, Behram, Anwaar Ahmed, Shahid Iqbal, Arshad Hussaina (June 2017). “Effectiveness of enforcement levels of speed limit and drink driving laws and associated factors – Exploratory empirical analysis using a bivariate ordered probit model.” *Journal of Traffic and Transportation Engineering*. Volume 4, Issue 3, June 2017, Pages 272-279.

Wang, X., and K. Kockelman. (2008). “Application of the Dynamic Spatial Ordered Probit Model: Patterns of Land Development Change in Austin, Texas,” Manuscript, Department of Modeling Ordered Choices. Civil Engineering, University of Texas, Austin.

Washington, Simon P., Matthew G. Karlaftis, and Fred Mannering. (2010) *Statistical and Econometric Methods for Transportation Data Analysis Textbook*. 544 Pages; 90 B/W Illustrations. ISBN 9781420082852 - CAT# C285X. Series: Chapman & Hall/CRC Interdisciplinary Statistics; CRC press, 2010.

Wei, Chien-Hung, and Ying Lee. (2007) "Sequential forecast of incident duration using Artificial Neural Network models." *Accident Analysis & Prevention* 39, no. 5 (2007): 944-954.

Wilmot, Chester & Stephen Glascock. (June 2015). *Improving Freight Crash Incident Management*. National Center for Intermodal Transportation for Economic Competitiveness. Louisiana Transportation Research Center and Department of Civil and Environmental Engineering, Louisiana State University. Project Number: 13-58S. https://www.ltrc.lsu.edu/pdf/2015/FR_542.pdf

Xiaobing Li, (2018). *Analysis of Large-Scale Traffic Incidents and En Route Diversions Due to Congestion on Freeways.* Ph.D. Dissertation, Civil & Environmental Engineering, The University of Tennessee, Knoxville, TN, 2018.

Xu, Xuecai, S. C. Wong, and Keechoo Choi. (2014). "A two-stage bivariate logistic-Tobit model for the safety analysis of signalized intersections." *Analytic Methods in Accident Research* 3 (2014): 1-10.

Yin, Weihao, Pamela Murray-Tuite, and Kris Wernstedt. (2012). "Incident-induced diversion behavior: existence, magnitude, and contributing factors." *Journal of Transportation Engineering* 138, no. 10 (2012): 1239-1249.

Zhang, Hongbing, Yichi Zhang, and Asad Khattak (2012). "Analysis of large-scale incidents on urban freeways." *Transportation Research Record*: Journal of the Transportation Research Board 2278 (2012): 74-84.

Zhang, Hongbing, and Asad Khattak. (2010). "What is the role of multiple secondary incidents in traffic operations?" *Journal of Transportation Engineering* 136, no. 11 (2010): 986-997.

Zhu, Xiaoyu, and Sivaramakrishnan Srinivasan. (2011). "A comprehensive analysis of factors influencing the injury severity of large-truck crashes." *Accident Analysis & Prevention* 43, no. 1 (2011): 49-57.

Zong, Fang, Huiyong Zhang, Hongguo Xu, Xiumei Zhu, and Lu Wang. (2013). "Predicting severity and duration of road traffic accident." *Mathematical Problems in Engineering* 2013 (2013).

Zou, Yajie, Kristian Henrickson, Dominique Lord, Yinhai Wang, and Kun Xu. (2016). "Application of finite mixture models for analyzing freeway incident clearance time." *Transportmetrica A: Transport Science* 12, no. 2 (2016): 99-115.