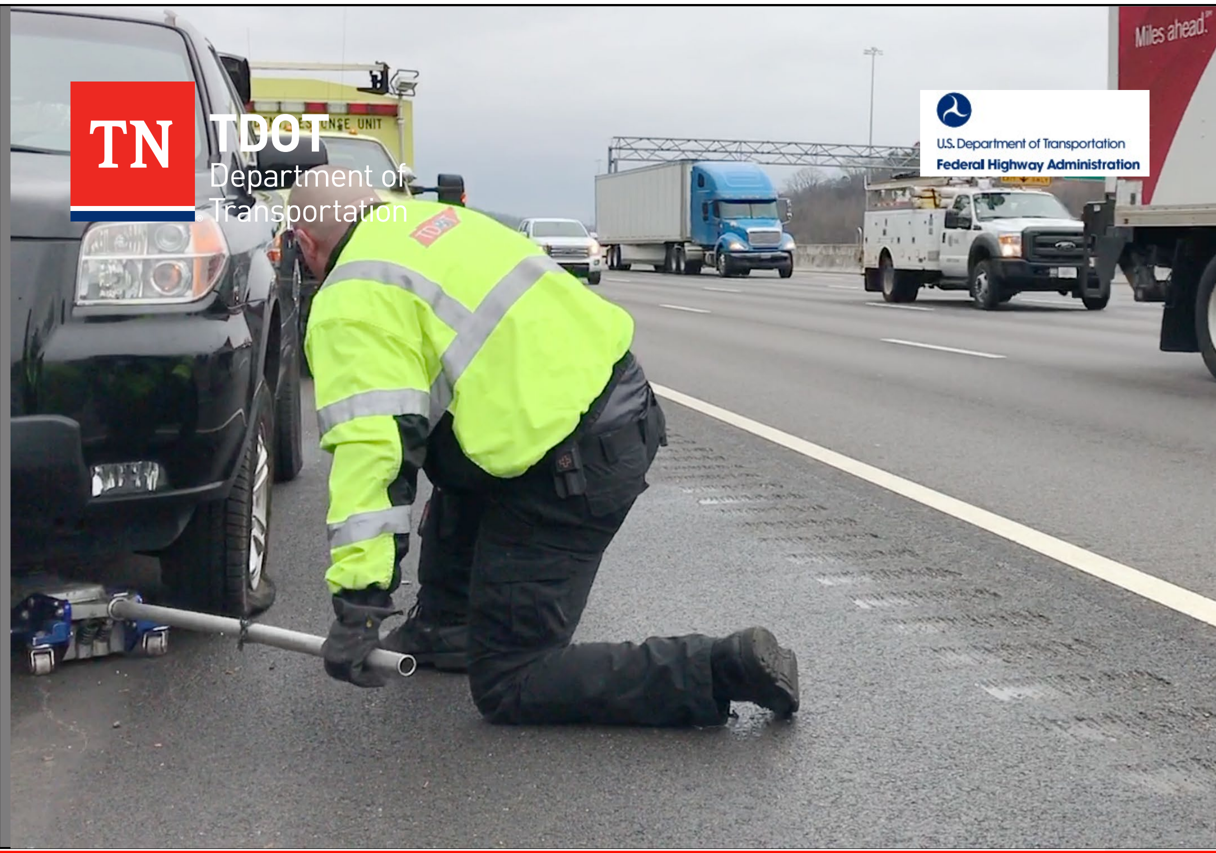

Quantify Freeway Safety Service Patrol and Protect the Queue Impact on Transportation Network Reliability

Research Final Report from the University of Tennessee | (Hairuilong Zhang, Yangsong Gu, Ruqing Huang, and Lee D. Han) | July 15, 2022

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DISCLAIMER

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16. Abstract

The objective of this project is to evaluate and quantify the impacts and benefits of Freeway Safety Service Patrol (FSSP) and Protect the Queue (PTQ) programs using data-driven analysis. TDOT's Locate/IM and PTQ daily working reports data are the primary source of this study, which will help better understand the characteristics of incidents. WAZE's crowd-sourced incident report logs will be also heavily used in this project for the purpose of affording TDOT the flexibility of analyzing incidents outside the coverage areas by Locate/IM. The study reviewed the state-of-the-practice of traffic incident management (TIM) programs' impact evaluation methodologies and end-of-queue crash risk probability estimation methods, evaluated the benefits of HELP program in three different aggregation levels and assessed the benefits of PTQ based on a risk probability model. The study also developed an automated workflow for generating benefit cost analysis for HELP and PTQ programs and provided an Excel-based automation tool for easy implementation. All reports and deliverables are ready to use with TDOT data. The procedures assess benefits resultant from savings in travel delay, emission, fuel consumption, and secondary crash for a wide range of programs. Results from this study will be readily implementable for the entire State, any region, or even individual counties. The deliverables of this project provide factual statistics backed by sound analysis to assist TDOT'S decision making process. The B/C reports for HELP program, for PTQ program, and for a new rural HELP program helps TDOT make important investment decisions to best serve the motoring public. The automated B/C reports for HELP program fulfills the recurring comprehensive performance monitoring objective. Furthermore, the incorporation of crowdsourced WAZE data into TDOT's exiting traffic incident management data framework leads to better understanding of incident characteristics and more efficient incident management.

17. Key Words **TRAFFIC INCIDENT MANAGEMENT, FREEWAY SAFETY SERVICE PATROL, PROTECT THE QUEUE, CROWDSOURCED DATA**	18. Distribution Statement		
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We should also mention that Dr. Yuandong Liu, Dr. Zhihua Zhang, and Dr. Nima Hoseinzadeh contributed significantly to this research endeavor during their doctoral studies at the University of Tennessee.

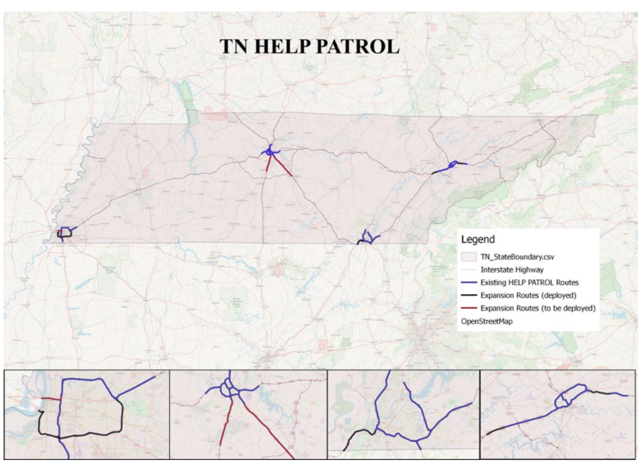
Executive Summary

Problem Statement

Over the past two decades, Tennessee Department of Transportation (TDOT) has dedicated significant amount of resources and efforts towards real-time traffic incident management and substantially improved motorist safety and operational efficiency. Major accomplishments include the establishment of Traffic Management Centers (TMC) with real-time traffic monitoring, the Dynamic Message Signs (DMS) for incident alert and safety warnings, the HELP program providing Freeway Safety Service Patrol (FSSP), the TN511 service, and TDOT's SmartWay web site providing real-time incident/construction information, traffic/roadway conditions, traffic camera views, dynamic messages, and so on. More recently, TDOT deployed the Protect the Queue (PTQ) program for real-time end-of-queue management under significant incident and construction scenarios.

In 2017 alone, TDOT's HELP trucks provided services 145,457 times and the FSSP responded to and managed some 110,175 incidents on Tennessee's highways. Since the establishment of TDOT's Traffic Incident Management program and HELP, millions of motorists in distress have received timely service from TDOT's FSSP. With all these services to the public readily deployed and can potentially be further expanded and enhanced, it is highly desirable to take a close look at the characteristics of these service calls and incidents and quantify the benefit in terms of reduction in travel delay, fuel consumption, emissions, and secondary incidents resultant from the HELP and PTQ programs.

To quantify the benefits of the HELP program, TDOT commissioned Dr. Han at UTK in 2010 to estimate delay reduction, savings in fuel/emission, prevention of secondary crashes, and so on using the agency's incident data and RDS data. A comprehensive methodology was developed and implemented at the time. In 2014, the methodology was further implemented for TDOT to estimate the projected benefits and cost for potential expansion scenarios for the four regions range between 19 and 42 under optimized implementation conditions.



In 2016, TDOT came to agreement with WAZE Connected Citizens Program (CCP) to share data between the two agencies. This opens up the opportunity to enhance the benefit cost (B/C) analysis with WAZE's crowdsourced incident data and travel time database, which is independent to TDOT's Locate/IM and Radar Detection System (RDS) and has a greater coverage. In terms of incidents reported, WAZE covers the entire state; and in terms of travel time based on app users as "probes", selected routes for Tennessee currently covers several times the highway miles patrolled by the HELP trucks. More highways could and have been added to WAZE database to aid TDOT's needs.

Objectives of the Research

To improve the traffic safety on Tennessee Interstate highways, TDOT provides a number of real-time on-site fast-response and proactive safety services, which require considerable initial capital investment and additional expenses to maintain and keep them operational on annual basis. The main purpose of this project is to objectively assess the impacts and benefits of FSSP and PTQ services through the use of sound data-driven analysis. The challenge of such an undertaking is in the accurate and fair estimation of the adverse effects of "bad things" that did not happen or were responded to promptly and removed effectively because of HELP and PTQ. To that end, five phased objectives are identified.

- Attain Better Understanding of Incidents/Service Calls and Level of Service.
- Comprehensive Benefits Estimation for HELP Program.
- Comprehensive Benefits Estimation for PTQ Program.
- Potential Benefit/Cost Estimation for Rural HELP Deployment/Expansion.
- Automation for Annual B/C Analysis.

Key Findings

- Integration of crowdsourced data (WAZE) plays a significant role in estimating the benefits of rural HELP expansion area and leads to a better understanding of the incident characteristics.
- Delay saved and crash prevented are two main contributors of the benefits of HELP program, while PTQ only accounts for the number of crashes prevented.
- Among the four regions, Nashville (region 3) achieves the most benefit and highest B/C ratio at around fifty from 2017 to 2021. In contrast, Knoxville (region 1) has a lowest B/C ratio at around twenty. This is mainly due to the difference of the number of incidents responded by HELP trucks.
- These satisfactory B/C ratios adamantly support the investment decision made by TDOT to best serve the motoring public.
- The automation tool for HELP program enable a fast and quick estimation of the benefits within an average of 10% margin of error.

Key Recommendations

- The deliverables of the proposed research will provide factual statistics backed by sound analysis to assist CMAQ application strategies.
- The B/C reports for HELP program, for PTQ program, and for a new rural HELP program will help TDOT make important investment decisions to best serve the motoring public.

- The automated B/C reports for HELP program will fulfill the recurring comprehensive performance monitoring objective.
- The incorporation of WAZE data into TDOT's exiting traffic incident management data framework will lead to better understanding of incident characteristics and more efficient incident management.
- The analytical procedures can be used for benefits resultant from savings in travel delay, emissions, fuel consumption, and crash prevention for a wide range of programs besides incident management.

Table of Contents

List of Tables

List of Figures

Glossary of Key Terms and Acronyms

AADT	Average Annual Daily Traffic
AM	Ante meridiem, which means “before noon.”
API	Application Programming Interface
ATMS	Advanced Traffic Management System
AVO	Average Vehicle Occupancy
CCP	Connected Citizen Program
CMAQ	Congestion Mitigation and Air Quality
DBSCAN	Density-based spatial clustering of applications with noise
DDOT	District Department of Transportation of Washington DC
DelDOT	Delaware Department of Transportation
DMS	Dynamic Message Sign
DOT	Department of Transportation
EOQ	End of Queue
ETRIMS	Enhanced Tennessee Roadway Information Management System
FHWA	Federal Highway Administration
FSSP	Freeway Service Safety Patrol
GPS	Global Positioning System
HELP	TDOT’s Highway Incident Response Unit
JSON	A data file format system
KYTC	Kentucky Transportation Cabinet
Locate/IM	Locate Incident Management
LOS	Level of Service
MAE	Mean Absolute Error
MOE	Measure of Effectiveness
MPH	Mile per hour
NPMRDS	National performance management research data set
PCMS	Portable changeable message signs

PDI	Pavement distress index
PM	Post meridiem, which means “after noon.”
PTQ	Protect the Queue
RDS	Radar Detection System
RMSE	Root Mean Square Error
RTMS	Remote Traffic Microwave Sensors
ST-DBSCAN	Spatiotemporal Density-based spatial clustering of applications with noise
TDOT	Tennessee Department of Transportation
THP	Tennessee Highway Patrol
TIM	Traffic Incident Management
TMC	Traffic Management Centers
TN	Tennessee
TRB	Transportation Research Board
UTC	Coordinated Universal Time
VOT	Value of Time
W4C	Waze for Cities
WAZE	A subsidiary of Google company that collects real-time traffic information like travel times, and traffic incidents from users.
Wazers	Waze Users
WARP	Waze Analytics Relational-database Platform

Chapter 1 Introduction

1.1 Scope and Objectives

This study will cover HELP and PTQ programs in all four regions of TDOT. The primary study period will focus on 2017 and onward. This is mainly based on the availability of data as the UTK team has archived WAZE incident log since mid-2016 at one-minute intervals. The travel speed/time information on Tennessee's major highways in NPMRDS 2.0 also starts in early 2017, which makes 2017, 2018, and potentially 2019 most desirable study duration. In addition, with Congestion Mitigation and Air Quality (CMAQ) funded HELP program expansion took place in 2015 and 2016, it is logical to focus this study on 2017 and onward. The areas of study will cover the existing routes and the newly expanded areas of HELP program plus the additional routes covered by the WAZE travel time data will be used. Figure 1-1 shows the existing help truck patrolling routes. Additional routes for WAZE travel time logging may be added for this study. TDOT's Radar Detection System (RDS) data will be coordinated with WAZE routes currently designated in the Connected Citizen Program (CCP). Incident scenarios are primarily analyzed to assess the benefits of FSSP and PTQ. As such, TDOT's Locate/IM and WAZE's crowd-sourced incident report logs will be heavily used for the purpose of the project. As an example, the HELP and WAZE routes for region 3 are shown in Figure 1-2.

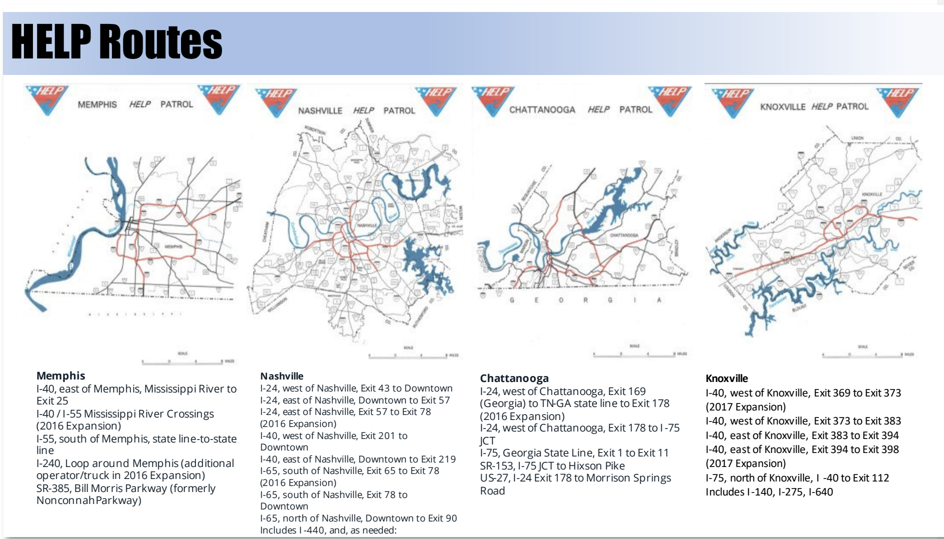


Figure 1-1 Help truck patrolling routes

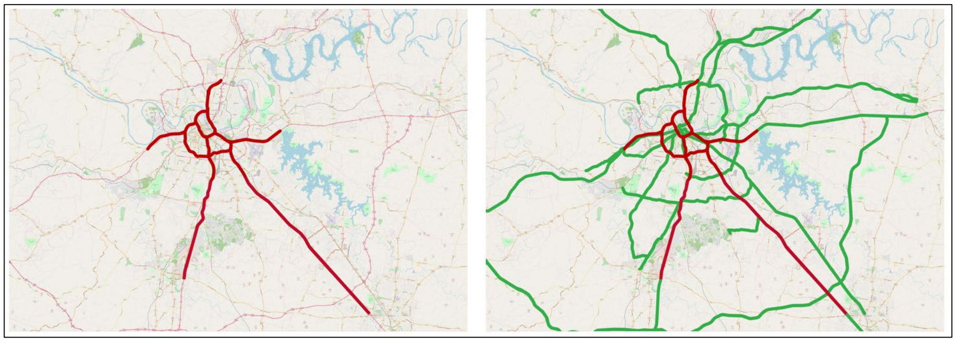


Figure 1-2 Comparison of HELP and WAZE routes for region 3 (Nashville)

Protect the Queue (PTQ) is a TDOT initiative that emphasizes the importance of providing advance warning to upstream traffic of a downstream incident to reduce the likelihood of a secondary accident. TDOT will deploy resources and staff to establish a safe and mobile traffic control plan, including adequate traffic queue protection and motorist information plan especially in a work zone area. Figure 1-3 shows a picture of the PTQ truck equipped with a message sign and an attenuator.

Figure 1-3 TDOT PTQ vehicles

The primary goal of this study is to better understand and quantify the benefits of TDOT's traffic incident management programs, e.g., HELP and PTQ. The challenge of such an undertaking is in the accurate and fair estimation of the adverse effects of "bad things" that did not happen or were responded to promptly and removed effectively because of HELP and PTQ. Examples of such include secondary crashes avoided, fatalities and injuries prevented, major delay significantly reduced, and emission/fuel consumption minimized. To that end, five phased objectives are identified.

- ***Objective 1 – Attain Better Understanding of Incidents/Service Calls and Level of Service***. TDOT has good incident data in its Locate/IM and SWIFT. TDOT currently reports the aggregated incident statistics by region on quarterly basis. With the access to WAZE and its crowdsourced incident information and travel time variations, an in-depth spatiotemporal study with much higher granularity would provide new insights in terms of geographical incident distributions, more accurate incident and response times, temporal and spatial clustering of service calls types and incidents, isochronal service information for each region, level of service and response time at different locations, and so on.
- ***Objective 2 – Comprehensive Benefits Estimation for HELP Program.*** Previous studies performed by UTK focused primarily on delay reduction aspects of the HELP program, based on the findings of dozens of prior studies where near 90% of the benefits derive from delay reduction (see Figure 1-4). With new data from WAZE and new models on fuel/emission and secondary crashes, a more thorough benefits estimation for all TDOT regions will be conducted.

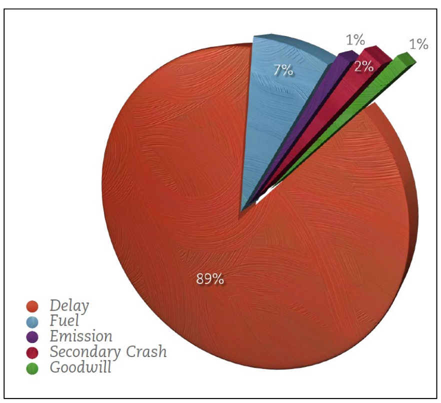


Figure 1-4 Benefits breakdown for past studies

- ***Objective 3 – Comprehensive Benefits Estimation for PTQ Program.*** TDOT's Protect the Queue program is a proactive effort towards better safety and efficiency. Only a handful of DOTs have implemented some flavors of such initiative and reported different levels of reduction in crashes or near-crashes. The reduction in delay is relatively low, if any, in comparison to the benefits of reduction of secondary crashes. A thorough analysis and estimation for Tennessee's unique circumstance would be a major outcome of this project.

- ***Objective 4 – Potential Benefit/Cost Estimation for Rural HELP Deployment/Expansion.*** The efficient response and service of HELP program is primarily deployed in the State's four major metropolitan areas, where in 2017 lane blockage incidents were promptly cleared in less than 30 minutes some 85% of the time and less than 2% of time it took more than 90 minutes to clear. The promptness was less pronounced during the same year for the fringe/rural areas of these metropolitans where less than half of the time incidents were cleared in 30 minutes and more than 20% of the time it took more than 90 minutes (see Figure 1-5). Using the WAZE reports, which covers the entire State of Tennessee, one could identify rural areas where expansions and additional services could result in significant savings in lives and reduction in delay. The benefits and costs for these potential expansions and rural deployment will be helpful for the investment decision-making.

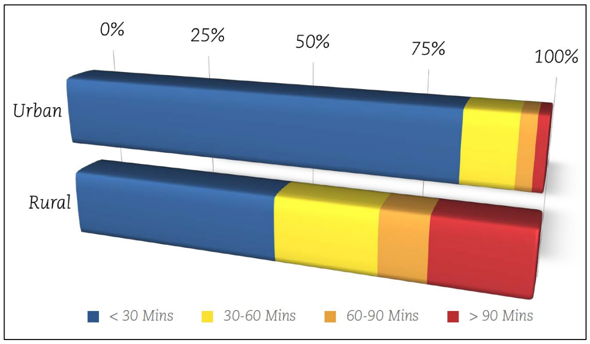


Figure 1-5 Incident clearance time distribution by urban and rural area

- ***Objective 5 – Automation for Annual B/C Analysis.*** It is logical to automate the preceding data-based analysis process and generate benefit/cost reports on yearly basis. This automated tool should be able to interface with the incident database and generate statistics for reporting purposes. Some flexibility for the user to modify and test different scenarios should be considered.

1.2 Methodology

A methodology for estimating delay and delay reduction for a wide range of incident types, severity, location, time of day, duration, and so on was previously developed by UTK under a TDOT contract in 2010. In concept, the baseline incident-free travel condition and delay is established for all roadways. With incident record and traffic data, the travel time and delay under incident conditions can be measured directly. Previously, the methodology required a degree of judgement to estimate the additional time to respond and extra time till clearance of different incident scenarios in order to arrive at the delay savings and, hence, benefits of HELP patrol. With the availability of WAZE data and incident reports and NPMRDS 2.0 travel time data, the existing methodology can be further enhanced and developed.

A new module will be developed to also estimate the delay, secondary crashes, and other effects on routes not patrolled by HELP trucks. This would be crucial for comparing the difference of adverse effects, in terms of delay and secondary crashes, for incidents on routes with and without HELP program. This would also allow better estimation for B/C analysis on future expansion routes and rural deployment of HELP program. The module could even identify routes and time where new HELP services would be most beneficial.

A thorough geostatistical analysis and deep understanding of the spatiotemporal characteristics of various incident data and associated travel information is essential to furthering this study. The actual data from WAZE and Locate/IM incident records will help generate such maps for visually identifying deficient spots in service and redundancies in asset deployment.

Briefly, a queuing-based benefit quantification model is proposed to evaluate the benefits of HELP program and a risk probability model at end of queue is developed to quantify the benefits of PTQ program. Figure 1-6 depicts the overall research framework of this project.

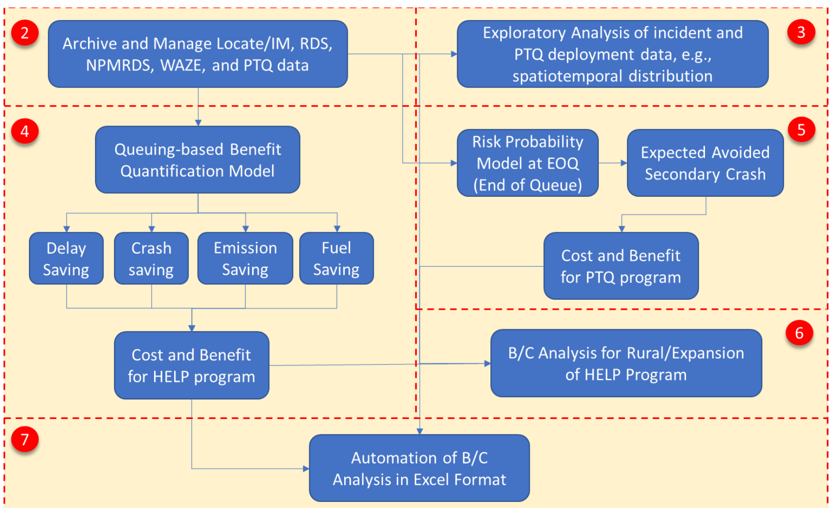


Figure 1-6 Overall research framework

The report is organized as follows. Chapter 1 is the introduction section which briefly discusses the research need, scope and objectives, methodology. Chapter 2 reviews a handful of related work and summarizes the methodology and measures used to quantify the benefits of a Traffic Incident Management (TIM) program. Chapter 3 presents a detailed description of the methodology developed for quantification of the benefits of HELP and PTQ programs. Chapter 4 provides a deep exploratory analysis of Locate/IM and PTQ service data, presents the benefit cost ratio calculation results, and the automation of B/C analysis. Chapter 5 contains the conclusion of the project, providing challenges and recommendations on this area of research.

Chapter 2 Literature Review

Evaluation of the impacts of traffic incidents and the effectiveness of response strategies is useful for the purpose of implementing, prioritizing, and improving traffic incident management programs. The challenge is that existing data usually does not provide direct measures for such evaluation. To address this problem, many efforts have been made to derive measures to estimate the impacts of traffic incidents and effectiveness of response strategies. The purpose of this document is to provide a review of these efforts, which could then be used as a reference for the development of a benefit assessment procedure for TDOT's freeway service patrols or HELP and PTQ, core components of the Traffic Incident Management (TIM) program implemented by TDOT.

This chapter consists of three sections. The first section reviews the assessment measures that are frequently used in cost-benefit analysis for traffic incident management. The section starts with a briefing of the measures identified by USDOT's ITS Program Office, and then some adaptations of these measures in specific applications are illustrated. The second section focuses on the methods used in cost-benefit analysis particularly for TIM. Two general approaches are covered in the review: (1) analytical approaches and simulation-based approaches. The last section provides a summary of several case studies that have been conducted previously in other DOTs.

2.1 Assessment Measures

To evaluate the benefits of TIM, one of the tasks is to select a set of measures to quantify those benefits. USDOT's ITS Program Office identified a set of measures as —a few good measures that are frequently referenced in applications. These measures are classified into several categories, which include safety, mobility, travel time delay, travel time variation, capacity/throughput, customer satisfaction, productivity, and energy and environment, as summarized below.

In terms of ***safety***, three measures of effectiveness are identified:

- Reduction in the rate of crashes
- Reduction in the rate of crashes resulting in fatalities
- Reduction in the rate of crashes resulting in injuries

On the side of ***mobility***, the measures of effectiveness used to quantify improvements include:

- Reductions in travel time delay

Delays may be measured for individual vehicles or at an aggregate level.

For ***energy and environment***, the measures of effectiveness used to quantify improvements are:

- Reduction in emissions
- Reduction in fuel consumption

2.2 Assessment Methods

Different methods have been developed to quantify the benefits of TIM. In general, these methods can be divided into two categories: (1) analytical approaches and (2) simulation-based approaches. Some studies also made use of a combination of these two approaches; yet, usually either an analytical approach or a simulation-based approach is used predominately while the other approach serves as a complimentary solution, e.g., for extension, validation, or comparison purpose.

2.2.1 Analytical Approaches

Analytical approaches focus on the use of empirical formulas and equations which can be either statistical or deterministic. Many analytical approaches are computationally effective. Nevertheless, to set forth these formulas and equations, some of the analytical approaches require the use of theories and assumptions. For this reason, traffic data and simulation models are frequently utilized to valid and verify analytical results.

The study for Michigan DOT conducted by Jun-Seok Oh et al. (Oh, et al., 2015) provides a set of formations that are in the category of analytical approaches and are applicable to the evaluation of various benefits of an incident management program. The use of these formulations facilitates the calculation of benefits derived from reduced impacts that are attributable to traffic management strategies such as highway services patrols. These benefits include the reduction in delay, fuel consumption, reduction in emission, and avoided secondary crashes. Figure 2-1 demonstrated a visual interpretation of the method on how to calculate the incident delay by applying the queue theory.

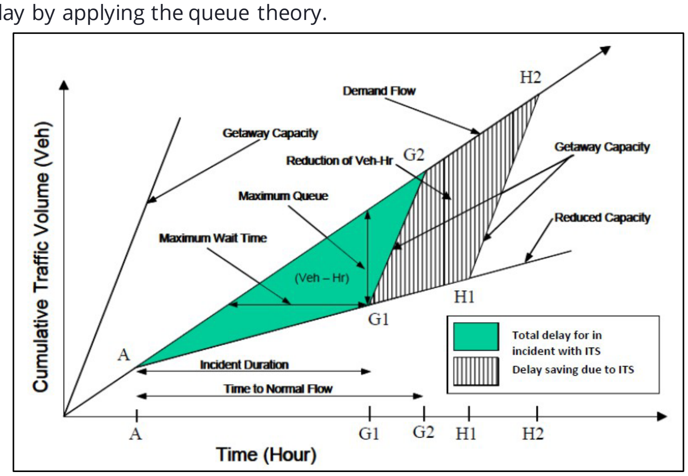


Figure 2-1 Estimation of Incident Delay (Oh, et al., 2015)

The diagram shows that the reduced capacity by an incident was the main cause of the traffic delay. The total delay was reduced when the incident duration was reduced by deploying ITS programs.

The work for Washington State DOT conducted by Wang et al. (Wang, Cheevarunothai, & Hallenbeck, 2008) comes with an algorithm for quantifying travel delays for different incident categories: fatality collision, injury collision, non-injury collision, blocking disabled vehicle, disabled vehicle, abandoned vehicle, and debris blocking traffic. The algorithm makes use of a modified deterministic queuing theory to estimate incident-induced delay using 1-minute aggregated loop detector data. The researchers considered the use of a dynamic traffic-volume-based background profile as a more accurate representation of prevailing traffic conditions. A data-driven approach was also taken in the implementation of the proposed algorithm which allows the automation of all the computational processes.

Simulation and traffic count data were then applied to evaluate the performance of the algorithm. The simulation analysis also provides an example to illustrate the work and depth necessary to derive useful results with simulation-based approach. The study calculated delays in 18 incidents for the evaluation of the performance of the algorithm. In these 18 incidents, nine pairs of simulations were run for each incident. And in each pair of simulations, one simulation was for the normal traffic condition and the other for the actual traffic condition during an incident.

Based on these simulation results, they concluded that their algorithm allows good estimates for incident-induced delay and can capture the evolution of freeway traffic flow during an incident. They also attributed the use of actual traffic data measured by loop detectors as an important factor to derive accurate results in the computation of vehicle arrival and departure rates and incident-induced delays.

The study presented by Menendez and Daganzo (Menendez & Daganzo, 2004) used kinematic wave theory to evaluates how the location and duration of an incident affect delays near a recurrent bottleneck. Formulas are provided to predict extra delay as a function of the characteristics of the highway, the bottleneck and the incident, such as incident magnitude, duration, and location. The authors also suggest that their ideas presented in the paper can be extended to handling more complex networks and more realistic problems, which include:

- a distribution of different sizes of incidents, probably based on historical data,
- incidents upstream of the queue,
- multiple incidents,
- multiple roadside assistance vehicles,
- networks of inhomogeneous links,
- bottlenecks with multiple approaches, and
- multiple bottlenecks.

The study conducted by Karlaftis et al. (Karlaftis, Latoski, Richards, & Sinha, 1999) evaluated the ITS impact on safety and traffic management with an investigation of secondary crash causes. The logistic model in the paper provided a better understanding of what contributes to secondary crash occurrence. The results suggest that each minute increase in clearance time increases the likelihood of secondary crash by 2.8%.

A more recent study (Goodall, 2017) was the first analysis of secondary crash occurrence to integrate incident timelines and traffic volumes with widely available and legally obtained private-sector speed data. The paper also adopted a logistic regression model to evaluate the secondary crash probability and the results indicated that a secondary crash occurrence increases approximately 1 percentage point for every additional 2 to 3 min spent on the scene in high-volume scenarios. The baseline likelihood of a secondary crash once arrival on the scene occurs at all is about 5%.

2.2.2 Simulation-Based Approaches

Traffic conditions, especially during an incident, involve many factors, which make it difficult to derive accurate results for cost-benefit analysis using simple, particularly deterministic approaches. For this reason, simulation-based estimation becomes attractive. Various efforts have been made to utilize simulations as a method to estimate benefits for traffic incident management, e.g., Khattak and Rouphail (Khattak & Nagui Rouphail, 2005), Li and Walton (Li & Walton, 2013), and Sun et al. (Sun, Yuan, Hao, & Haghani, 2017).

Incident Management Assistance Patrols (IMAP) is a program implemented by the North Carolina DOT. The trained personnel in the program help identify incidents, provide temporary traffic management, aid in roadway clearance, and assist with disabled vehicles. To estimate benefits and facilitate implementing and prioritizing the program, a study was conducted to develop a decision support tool (Khattak & Nagui Rouphail, 2005). One element of the decision support tool is the use of the macroscopic simulation model FREEVAL to characterize the queuing and delay effects of incidents on freeway traffic operations. The analysis starts with single incident assessments. For this purpose, FREEVAL facilitates the derivation of delay estimates. To compare delays with and without the presence of IMAP, the delay for no presence of IMAP is estimated first. Results from FREEVAL are connected with various delay models to derive actual delay estimates. The use of the delay models is based on the incident duration, number of lanes involved, and area type. With the incident demand to capacity ratio as the input, the model generates the delay estimate in the form of seconds per vehicle mile traveled (VMT). The same estimation process is then replicated with the presence of IMAP.

In the next step, the annual benefit of implementing an IMAP is to be estimated based on the annual number of crashes. This analysis first calculates the total number of non-crash incidents by combining the user-entered total crashes with the previously reported non-crash to crash ratio. These incidents are divided into categories, and the percentages of the incident categories are then used to calculate the benefits for each incident type based on the results derived from the single incident analysis process. The benefits for each incident are then summarized to provide the estimates of the total annual benefits in terms of vehicle hours of delay for a site with the implementation of IMAP.

Li and Walton's work (Li & Walton, 2013) focused on assessing the performance of Freeway Service Patrol (FSP) in low-traffic areas by applying a discrete-event simulation approach. Most incidents did not cause major traffic delay or secondary crashes in low-traffic area, so it was less likely for low-traffic areas to generate massive traffic delay savings. The function of FSP in low-traffic areas is more focused on providing roadside assistance and helping the stranded drivers. An event-based simulation model performed better than a traditional analytical model under this condition. The ARENA, a fast statistical simulation tool, was selected to evaluate FSP operations because of its ability to handle a long period of operations in a short time and in a very fast speed. In the end, the Safety Assistance for Freeway Emergencies (SAFE) Patrol in Kentucky, which was mostly deployed in low-traffic areas with Kentucky, was utilized as a case study to assess and estimate its benefit-cost ratio under different circumstances.

The research conducted by Sun et al. (Sun, Yuan, Hao, & Haghani, 2017) presented an effective framework for evaluating the effectiveness of FSP in the dense video-based surveillance system (DVBSS) in China. This article utilized VISSIM simulation software to assess the B/C ratio in DVBSS environments and the researchers tried to answer a controversial question that whether the FSP operation is still effective for traffic management in the DVBSS environment. They set up four different operational scenarios and found that FSP programs are still useful and effective to some extent (i.e., B/C ratio was larger than 1.) in the DVBSS environment. Besides, an optimal B/C ratio could be attained by carefully examining the fleet size and the length of patrolling segments. The results of this study were instructional to practitioners and could be directly used for making decisions in real-world traffic operations. In addition, the simulation approach can be used by researchers to evaluate the B/C ratios of FFSP programs.

Chapter 3 Methodology

3.1 Data Collection

This research was highly reliable on the incident data and traffic flow data provided by both TDOT and public crowdsources like WAZE. In this regard, one of the main tasks for the research team was to obtain, archive and manage all the necessary data relevant to this project.

Locate/IM – This is a database provided by TDOT archiving information of traffic incidents and HELP truck activities. This system was integrated with statewide transportation management centers (TMCs) for traffic condition monitoring and incident management control. Every piece of data was entered into the database by an official operator in TMC while communicating with the dispatched HELP operators (Jodoin, King, & Pecheux, 2014). Figure 3-1 displays a piece of sample Locate/IM data in excel format. Important information such as incident type, duration, and response time could be obtained from these data, which were essential to the proposed approach to quantifying the benefits of the HELP program.

TDOT Region 3
Incidents Report
1/1/2018 to 12/31/2018 11:59:00 PM

Incident ID	Incident Type	Location	Start Time	Duration	Lanes Blocked	Block Duration	Resp Time	Rural/Urban
227584	Disabled Vehicle	I-24 Eastbound Milepost 53 I-440	1/1/2018 12:31:02 AM	33	0	0	0	Urban
227585	Disabled Vehicle	I-24 Eastbound Milepost 61	1/1/2018 12:40:39 AM	539	0	0	0	Urban
227587	Disabled Vehicle	SR155 Southbound Milepost 6	1/1/2018 1:04:37 AM	17	0	0	0	Urban
227588	Unknown	I-40 Westbound Milepost 206 I-440	1/1/2018 1:05:59 AM	6	0	0	0	Urban
227589	Alien Vehicle	I-24 Eastbound Milepost 52 M-Boro Rd	1/1/2018 1:20:55 AM	739	0	0	0	Urban
227590	Disabled Vehicle	I-24 Eastbound Milepost 53 I-440	1/1/2018 1:23:09 AM	3	0	0	N/A	Urban
227591	Disabled Vehicle	I-40 Eastbound Milepost 210 I-65S Jct	1/1/2018 1:35:34 AM	403	1	32	352	Urban
227592	Disabled Vehicle	I-40 Westbound Milepost 213 I-24 Jct	1/1/2018 2:01:26 AM	460	0	0	N/A	Urban
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 3-1 Sample Locate/IM data in excel format

TDOT RDS Data – TDOT has also provided the team with the access to its own Radar Detector Stations (RDS) traffic data. This database archived hundreds of detector stations in the state's four major urban areas. Figure 3-2 showed the geographical location of these detector stations. Each station reported the lane-by-lane traffic flow, average speed, and occupancy every 30 seconds.

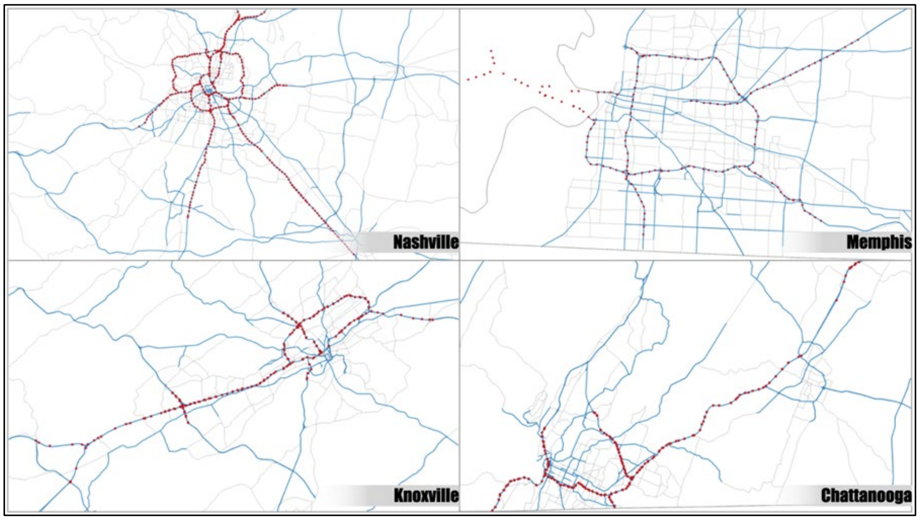


Figure 3-2 TDOT RDS stations in four major urban areas

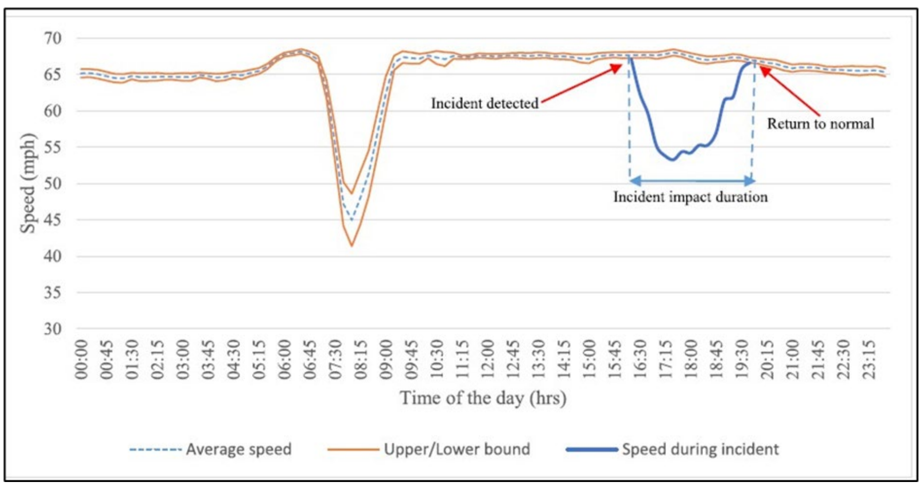


Figure 3-3 NPMRDS speed profile for an entire day

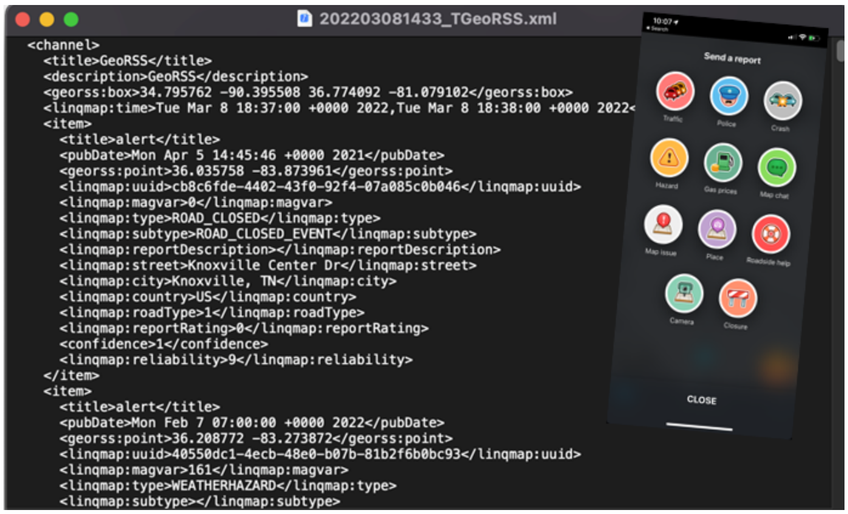
NPMRDS – The National Performance Management Research Data Set (NPMRDS) contains field-observed travel time and speed data collected anonymously from a fleet of probe vehicles (cars and trucks) equipped with mobile devices (The NPMRDS and Application for Work Zone Performance Measurement, 2020). The NPMRDS calculates average speed and travel time data aggregated in 5-minute, 15-minute, or 1-hour increments utilizing the temporal and spatial information provided by the probe vehicles. The data are available across the National Highway System (NHS), with a spatial resolution defined by Traffic Message Channel (TMC) codes. A TMC represents a unique, directional roadway segment. The NPMRDS data played a significant role in estimating the roadway clearance time or incident impact duration in the proposed framework. Figure 3-3 displayed an entire day's average speed data for a TMC link. The blue solid part denoted the incident impact duration.

TDOT PTQ Data – PTQ was launched in June of 2013. This program emphasizes on the importance of protecting the drivers in a traffic queue caused by either an accident or a scheduled work zone. Figure 3-4 displayed several PTQ records, providing the location, time, whether an accident occurred, labor and material cost information, and labor work time, which are essential to calculating the B/C ratio of PTQ program.

WR_Date_Format	Activity	Work Desc	Route	egin l	End l	Len	Direction	Position	locic	Lat	quipme	Mater
[illegible]	Traffic Control	Protect The Q	SR444	1.93	2.35	0.42	BOTH	SHOULDR	N	3,202	1,644	
[illegible]	Traffic Control	Protect The Q	SR360	1.55	1.55	0	BOTH	ROADWAY	N	793	134	
[illegible]	Traffic Control	Protect The Q	SR107	12.65	12.65	0	BOTH	ROADWAY	N	1,393	111	
[illegible]	Traffic Control	Protect The Q	I0081	32	32	0	N	RIGHTWY	Y	66	8	
[illegible]	Traffic Control	Protect The Q	SR034	26.8	26.8	0	N	ROADWAY	Y	383	241	
[illegible]	Traffic Control	Protect The Q	I0081	23	27	4	BOTH	ROADWAY	N	755	229	
[illegible]	Traffic Control	Protect The Q	I0081	23	27	4	N	ROADWAY	Y	389	95	
[illegible]	Traffic Control	Protect The Q	I0081	24	25	1	N	ROADWAY	Y	402	117	
[illegible]	Traffic Control	Protect The Q	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	ROADWAY	[illegible]	[illegible]	[illegible]	

Figure 3-4 Sample PTQ daily working report data

WAZE Event Log – Figure 3-5 shows sample WAZE event data in XML format and the user interface for reporting event via mobile Application. WAZE disseminates event logs based on the crowdsourced user reports from all WAZE app users. The XML file was updated every 1 minute on a dedicated web-based server. Each data file contained all user reports that were active during the past 1 minute. After parsing the XML files and aggregating the records over time, one could compile a more comprehensive log file as shown in Figure 3-6, where one could sort, query, and examine events reported by WAZE users on different roadways in different cities at different time and day.




```xml
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  <description>GeoRSS</description>
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  <linqmap:time>Tue Mar 8 18:37:00 +0000 2022,Tue Mar 8 18:38:00 +0000 2022<
  <item>
    <title>alert</title>
    <pubDate>Mon Apr 5 14:45:46 +0000 2021</pubDate>
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    <linqmap:subtype>ROAD_CLOSED_EVENT</linqmap:subtype>
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  <item>
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    <linqmap:magvar>161</linqmap:magvar>
    <linqmap:type>WEATHERHAZARD</linqmap:type>
    <linqmap:subtype></linqmap:subtype>
```
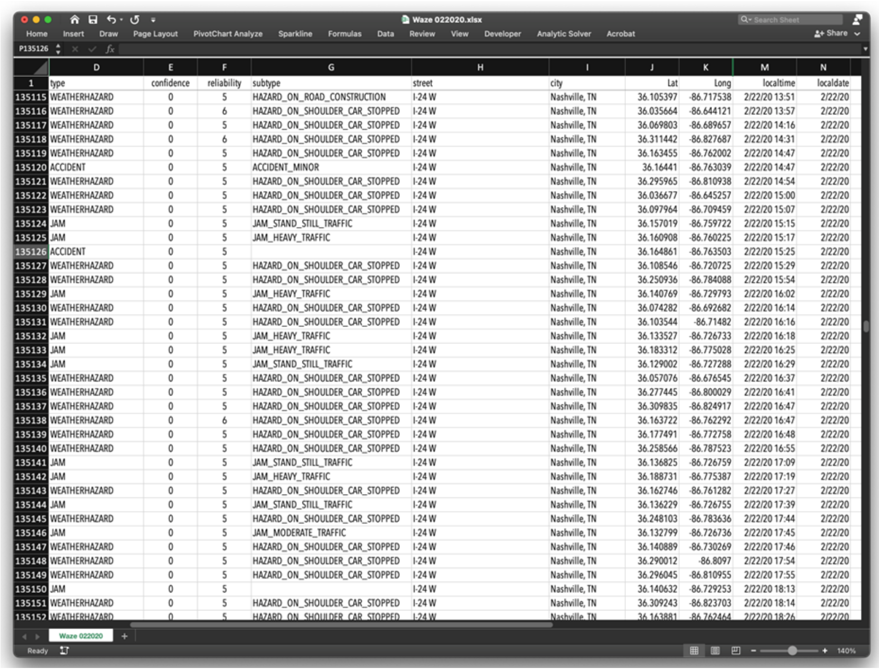


Figure 3-5 Sample event log file in XML format and WAZE reporting interface



	D	E	F	G	H	I	J	K	M	N
1	type	confidence	reliability	subtype	street	city	Lat	Long	localtime	localdate
135115	WEATHERHAZARD	0	5	HAZARD_ON_ROAD_CONSTRUCTION	I-24 W	Nashville, TN	36.105397	-86.717538	2/22/20 13:51	2/22/20
135116	WEATHERHAZARD	0	6	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.035664	-86.644121	2/22/20 13:57	2/22/20
135117	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.069803	-86.689657	2/22/20 14:16	2/22/20
135118	WEATHERHAZARD	0	6	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.311442	-86.827687	2/22/20 14:31	2/22/20
135119	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.163455	-86.762002	2/22/20 14:47	2/22/20
135120	ACCIDENT	0	5	ACCIDENT_MINOR	I-24 W	Nashville, TN	36.16441	-86.763039	2/22/20 14:47	2/22/20
135121	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.295965	-86.810938	2/22/20 14:54	2/22/20
135122	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.036677	-86.645257	2/22/20 15:00	2/22/20
135123	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.097964	-86.709459	2/22/20 15:07	2/22/20
135124	JAM	0	5	JAM_STAND_STILL_TRAFFIC	I-24 W	Nashville, TN	36.157019	-86.759722	2/22/20 15:15	2/22/20
135125	JAM	0	5	JAM_HEAVY_TRAFFIC	I-24 W	Nashville, TN	36.160908	-86.760225	2/22/20 15:17	2/22/20
135126	ACCIDENT	0	5		I-24 W	Nashville, TN	36.164861	-86.763503	2/22/20 15:25	2/22/20
135127	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.108546	-86.720725	2/22/20 15:29	2/22/20
135128	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.250936	-86.784088	2/22/20 15:54	2/22/20
135129	JAM	0	5	JAM_HEAVY_TRAFFIC	I-24 W	Nashville, TN	36.140769	-86.729793	2/22/20 16:02	2/22/20
135130	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.074282	-86.692682	2/22/20 16:14	2/22/20
135131	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.103544	-86.71482	2/22/20 16:16	2/22/20
135132	JAM	0	5	JAM_HEAVY_TRAFFIC	I-24 W	Nashville, TN	36.133527	-86.726733	2/22/20 16:18	2/22/20
135133	JAM	0	5	JAM_HEAVY_TRAFFIC	I-24 W	Nashville, TN	36.183312	-86.775028	2/22/20 16:25	2/22/20
135134	JAM	0	5	JAM_STAND_STILL_TRAFFIC	I-24 W	Nashville, TN	36.129002	-86.727288	2/22/20 16:29	2/22/20
135135	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.057076	-86.676545	2/22/20 16:37	2/22/20
135136	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.277445	-86.800029	2/22/20 16:41	2/22/20
135137	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.309835	-86.824917	2/22/20 16:47	2/22/20
135138	WEATHERHAZARD	0	6	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.163722	-86.762292	2/22/20 16:47	2/22/20
135139	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.177491	-86.772758	2/22/20 16:48	2/22/20
135140	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.258566	-86.787523	2/22/20 16:55	2/22/20
135141	JAM	0	5	JAM_STAND_STILL_TRAFFIC	I-24 W	Nashville, TN	36.136825	-86.726759	2/22/20 17:09	2/22/20
135142	JAM	0	5	JAM_HEAVY_TRAFFIC	I-24 W	Nashville, TN	36.188731	-86.775387	2/22/20 17:19	2/22/20
135143	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.162746	-86.761282	2/22/20 17:27	2/22/20
135144	JAM	0	5	JAM_STAND_STILL_TRAFFIC	I-24 W	Nashville, TN	36.136229	-86.726755	2/22/20 17:39	2/22/20
135145	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.248103	-86.783636	2/22/20 17:44	2/22/20
135146	JAM	0	5	JAM_MODERATE_TRAFFIC	I-24 W	Nashville, TN	36.132799	-86.726736	2/22/20 17:45	2/22/20
135147	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.140889	-86.730269	2/22/20 17:46	2/22/20
135148	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.290012	-86.8097	2/22/20 17:54	2/22/20
135149	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.296045	-86.810955	2/22/20 17:55	2/22/20
135150	JAM	0	5		I-24 W	Nashville, TN	36.140632	-86.729253	2/22/20 18:13	2/22/20
135151	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.309243	-86.823703	2/22/20 18:14	2/22/20
135152	WEATHERHAZARD	0	5	HAZARD_ON_SHOULDER_CAR_STOPPED	I-24 W	Nashville, TN	36.163881	-86.762464	2/22/20 18:26	2/22/20

Figure 3-6 Parsed & aggregated WAZE event data

3.2 Methodology

This section introduces a queueing-based methodology for evaluating the impacts of HELP and a risk probability model for assessing the PTQ program.

For the HELP program, the benefits consist of the total delay reduction due to the deployment of HELP trucks, secondary crashes prevented, fuel saved, and emissions prevented. Among these benefits, fuel and emissions are entirely associated with the total delay saved. A queuing-based method was adopted to quantify the traffic delay caused by an incident.

The PTQ program focused more on the number of incidents prevented during the deployment of PTQ trucks. A risk probability model was proposed to assess the likelihood of the occurrence of a secondary crash using logistic regression.

3.2.1 Incident Log

An incident is defined as any non-recurring event that causes a reduction in the capacity of a roadway or an abnormal increase in demand (Nicholas, et al., 2010). Each incident in Tennessee that is reported by the Traffic Management Center (TMC), roadway service patrols (HELP trucks), or by the local authorities, was recorded in an incident log that was kept for records with TDOT and stored in Locate/IM database. The incident log contained information about the time the incident was identified, the type of incident that occurred, how long a HELP truck response time was, the location of the incident, and how long the lane was blocked. From the year 2017 to 2019, around 120,000 incidents were recorded in the database per year for the interstates within the boundaries of the Tennessee incident system alone.

There were too many incidents per year to calculate the delay associated with each one, therefore, every incident in the incident log was classified based on four parameters:

- Incident type, the incident types as identified by TDOT are: Abandoned Vehicle, Debris, Disabled Vehicle, Grass Fire, Multivehicle Crash, PD/MED/FIRE Activity, Single Vehicle Crash, and Vehicle Fire. These are 8 main incident types that were used in the analysis.
- The time of day, which was meant to be representative of the demands experienced at different times of the day, was divided into four time periods: Morning Peak from 6 AM until 10AM, Mid-Day from 10 AM until 3 PM, Afternoon Peak from 3 PM until 7 PM, and Off Peak from 7 PM until 12 AM and from 12 AM until 6 AM.
- The queue clearance time, which was divided into four lengths: Less Than One Hour, One to Two Hours, Two to Three Hours, and Greater than Three Hours. This is the only derived variable.
- The number of lanes blocked, which accounts for the different effects an incident's lane location would have on the delay, was divided into five types: 0 Lane, One Lane, Two Lanes, Three Lanes, Four or More Lanes.

Each incident was categorized into one group for each of the four parameters allowing the delay of similar incidents to be estimated based on common criteria; therefore, a representative sample of the data can be used to estimate the delay for similar incidents. Once the incidents were classified, they were organized into different matrices that represent groups of incidents with similar delays. Each matrix consists of a count of all the incidents for each cause and each location and there is one matrix for each combination of time of day and duration categories. Overall, there were two types of matrices. One was incident input matrix, and the other was delay saving matrix. For incident input matrix, there are 640 individual cells, each containing the number of incidents that occurred for each category, comprising sixteen similar matrices corresponding to each time and duration category. The delay saving matrix has the same shape of incident input matrix and the difference was that each cell contained the delay saving values in vehicle-hour for each classification and the values came from the analysis of all data from 2017 to 2019. We believed that average values for three years could yield a good evaluation of the incidents of the similar features. It should be noted that 2017-2019 data was used as training data to build the saving matrix and 2020-2021 data was used as test data to apply to the model as a demonstration of the application scenario. A sample of one of the organizational incident input matrices for Nashville in 2017 is presented Table 1, while all the matrices can be found in an attached Excel file (Moss, 2012).

Table 1: The number of incidents for each type and lanes blocked (Nashville 2017)

Incident Type	*Number of Lanes Blocked*				
	0	1	2	3	>= 4
Abandoned Vehicle	1232	16	1	0	0
Debris	87	87	31	0	0
Disabled Vehicle	2085	139	15	0	0
GRASS FIRE	0	2	0	0	0
Multivehicle Crash	316	159	70	15	2
PD/MED/FIRE Activity	86	11	5	0	0
Single Vehicle Crash	41	33	19	1	0
Vehicle Fire	3	5	3	2	0

Note: occurring during the “Morning Peak” and lasting for less than one hour.

3.2.2 Queuing-based Delay Calculation for HELP

The total delay caused by an incident can be directly calculated by applying the equations derived from the fundamental traffic stream relationship. However, this will not give the delay that was saved by HELP program. To find the delay benefits of HELP program, the delay caused by an incident without the HELP deployment must be known. The Locate/IM database provided incident records with and without HELP deployed. Because of this, the queuing diagram was used to estimate what the delay would have been in the absence of the HELP program. The basic queuing diagram, shown in Figure 3-7, was modified to represent the total delay if an incident’s duration were extended due to the absence of HELP trucks. The modified queuing diagram illustrates a comparison between the actual delay and the delay that would occur without an incident management system. To calculate the delay benefits, equations were derived from the modified queuing diagram. As depicted in Figure 3-7, based on the triangular relationship, it can be observed that the sum of CT_2 and C_1T_1 is equal to D times the sum of T_1 and T_2. With this relationship, the incident clearance time T_1 can be represented by the queue clearance time T and other known parameters. Then, an equation of the traffic delay can be derived from the diagram:

$$Delay = \frac{1}{2} \cdot (D - C_1) \cdot T_1 \cdot T = \frac{1}{2} \cdot T^2 \cdot \frac{(D - C_1) \cdot (C - D)}{C - C_1} \quad (1)$$

Commented [ZH1]: Delay equals one over two times D minus C one times T one times T, then equals one over two times T square times D minus C one times C minus D divided by C minus C one.

Where:

- T: queue clearance time, how long the incident impacted the area
- T_1: incident clearance time, how long it took to clear the incident
- T_2: time duration between the moment incident cleared and traffic flow was back to normal
- C: getaway capacity, namely the standard capacity
- C_1: reduced capacity
- D: traffic demand

It can be concluded that the total delay (the area of the shaded area) is proportional to the square of queue clearance time T. With other parameters held fixed, when T is reduced to 50%, the total delay caused by the incident will be decreased to 25%.

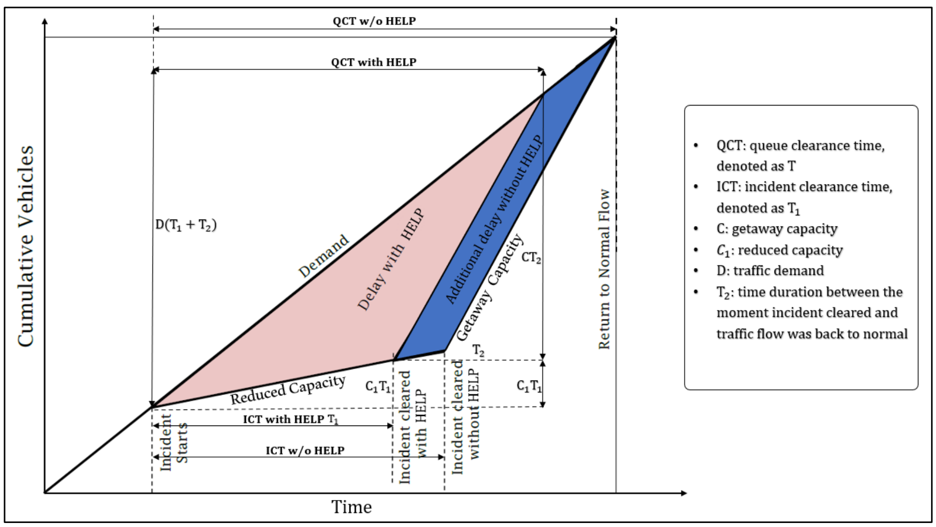


Figure 3-7 Queuing diagram showing the effect of extended duration on total delay

Based on the analysis from RDS traffic volume data, the standard capacity used in the calculation is estimated to be around 1500 vehicles per hour per lane. It should be noted that most of the interstate in TN remained 4 or more lanes. Therefore, the delay analysis assumed that most of the incidents occurred on a section of the interstate that contained four or more lanes in each direction. This resulted in the determination that most of the interstate roadway in TN had a standard capacity of around 6000 vehicles per hour per direction.

Capacity is constant for most of the roadway in Tennessee. The occurrence of an incident will result in a decrease in the capacity of the roadway. Some studies have shown that the location of the incident along with the type of incident and how many lanes are affected all have an effect on the actual capacity of the roadway (Chou & Miller-Hooks, 2010). The actual capacity after an incident is difficult to quantify but a range of values, presented in Table 2, were utilized in the model to obtain the theoretical reduced capacity which was needed in the queuing diagram.

Table 2: Capacity reduction rate for each number of lanes blocked

Lane Count	*Capacity Reduction Rate*
0	0.8
1	0.6
2	0.3
3	0.15
4 and more	0

Note: Rates were used for all four regions in TN.

Demand is the actual number of vehicles that passed the roadway segment. Based on the analysis of RDS traffic volume data, some average traffic volumes for different time of day used in this project were presented in Table 3.

Table 3: Traffic demand for each time of day

Time of Day	*Demand (vehicles per hour)*
AM Peak (06:00-09:59)	5000
Mid-Day (10:00-14:59)	4000
PM Peak (15:00-18:59)	5000
Off Peak (19:00-05:59)	2750

In order to obtain the total delay, we need to find out how long the incident impact duration was and assume the arrival rate and the capacity reduction rate. In this project, the incident impact duration, namely, the queue/roadway clearance time could be acquired from the analysis of NPMRDS travel time data associated with the corresponding incident.

Each incident in the Locate/IM database may result in a major bottleneck on the roadway. As shown in Figure 3-8, the bottleneck conditions are determined by comparing the current reported speed with the historical reference speed of the segment. If the current speed falls below 60% of the reference speed for 5 minutes, this segment is identified as a bottleneck. Adjacent road segments meeting this criterion will be joined together to calculate the queue length. When reported speed returns to values over 60% of the associated reference speed and stays for more than 10 minutes, the bottleneck is identified as cleared.

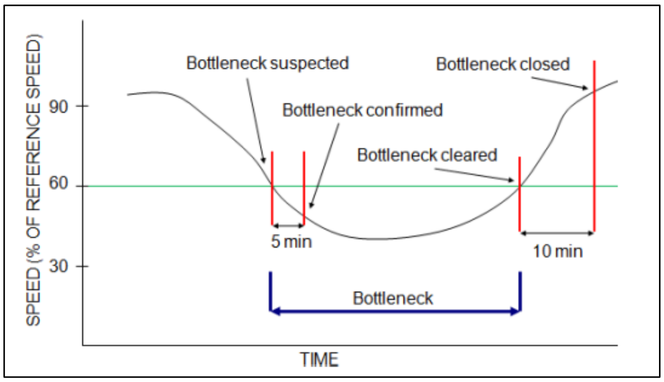


Figure 3-8 The life of a bottleneck by speed and time (Pu, 2016)

Despite that there is one column called “blocked duration” in Locate/IM data, the quality is not reliable enough for accurate computation and analysis. Thus, using NPMRDS data to analyze the traffic congestion time around the incident area is a good and feasible method. The steps of calculating the duration associated with the incident are demonstrated in Figure 3-9.

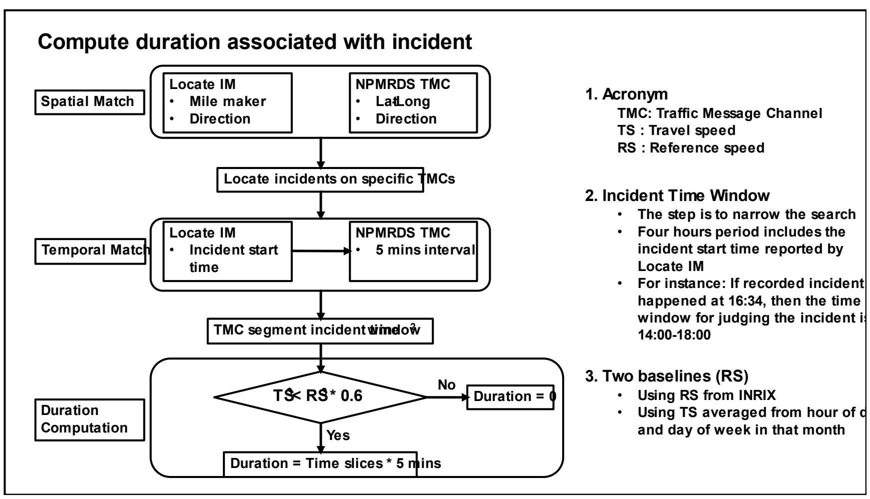


Figure 3-9 Steps of computing incident impact duration

After obtaining the queue clearance time T, the traffic delay could be derived from equation (1) for both with and without-HELP scenarios. The difference of the two delays were the delay saving values for each classification case. Following this procedure, all 640 cells could be filled and a sample of one of the organizational delay-saving matrices is presented in Table 4.

In some cases, either the demand was less than the reduced capacity or there were no records for that type and lane count, the analytical queuing model would not accurately reflect the traffic delay. In these cases, a linear interpolation method with respect to time and lanes blocked was found to be a more accurate representation of the delay for that incident classification.

Table 4: The average delay savings for each type and lanes blocked (vehicle-hour)

Incident Type	*Number of Lanes Blocked*				
	0	1	2	3	>= 4
Aban Vehicle	1.7	59.8	212.5	617.3	715.0
Debris	5.4	54.1	230.1	617.3	715.0
Disabled Vehicle	6.4	64.1	227.8	617.3	709.5
GRASS FIRE	4.6	45.6	161.8	617.3	797.5
Multivehicle Crash	5.9	59.3	235.8	617.3	715.0
PD/MED/FIRE Activity	5.4	54.1	275.7	617.3	715.0
Single Vehicle Crash	5.4	54.1	241.5	617.3	797.5
Vehicle Fire	5.9	59.0	241.5	617.3	715.0

Note: occurring during the "Morning Peak"
and lasting for less than one hour.

In order to get the B/C ratio of an ITS program, we need to monetize the saved traffic delay using the value of time presented by the following equation:

$$Value\ of\ Time\ (VOT) = \\ (Average\ Vehicle\ Occupancy \times (1 - Truck\ Percentage) \times Passenger\ Car\ VOT) + \\ (Truck\ Percentage \times Truck\ VOT) \qquad (2)$$

Commented [ZH2]: Value of time equals average vehicle occupancy times one minus truck percentage times passenger car value-of-time plus truck percentage times truck value-of-time.

Parameters including the truck and passenger car hourly value of time, the average vehicle occupancy (AVO) and the truck percentage were presented in Table 5. It should be noted that these parameters are always subject to change, so they are designed to be adjustable parameters in the calculation spreadsheet named "Parameter Configuration" (see attached Excel document).

Table 5: Value of time calculations and values for parameters

Time of Day	*Truck Value*	*Percent Trucks*	*Passenger Value*	*AVO*	*Value of Time*
AM Peak (06:00-09:59)	$100.00	20%	$20.00	1.70	$47.20
Mid-Day (10:00-14:59)	$100.00	20%	$20.00	1.70	$47.20
PM Peak (15:00-18:59)	$100.00	15%	$20.00	1.70	$43.90
Off Peak (19:00-05:59)	$100.00	50%	$20.00	1.70	$67.00

The value of saved delay, representing the money that would have been lost due to the total delay of the incident, can be calculated by the following equation:

$$Value\ of\ Delay\ Saved = Amount\ of\ Delay\ Saved \times Value\ of\ Time \quad (3)$$

Commented [ZH3]: Value of delay saved equals amount of delay saved times value of time.

Value of delay saved is obviously the most important part of the total benefits. Besides, the benefits of HELP program were composed of the value of prevented crashes, the value of saved fuel and emission, and people's willingness to pay for reducing the risk of an incident. The crash cost by severity was shown in Table 6. Knowing the portion of different crash severity types for each year, a unit crash cost could be calculated as presented in Table 7. The calculation details were included in the attached Excel document.

Table 6: Crash unit cost by severity (Harmon, Bahar, & Gross, 2018)

Crash Severity	*National Comprehensive Crash Cost*	*PCI Adjustment for TN (*0.87511)*
Fatality	$4,008,900	$3,508,228
Injury	$82,000	$72,284
PDO	$7,400	$6,476

Table 7: Unit crash cost by year for Tennessee

Year	*Crash Cost*
2017	$38,581.5
2018	$38,408.6
2019	$40,347.5
2020	$45,373.4
2021	$45,459.4

By assuming the number of crashes prevented, we can obtain the total dollar value of the avoided crashes. The parameter "Percent of Crashes Avoided" in the spreadsheet was designed to represent the estimated percentage of the secondary crashes that can be avoided due to the deployment of HELP trucks.

The fuel consumption saving rate was set as 1.719 gallons of fuel per vehicle-hour of saved delay (Mauch, Skabardonis, & McKeever, 2019). The emissions included hydrocarbons (HC), carbon monoxide (CO), and nitrous oxide (NO). Their saving factor and associated price were presented in Table 8.

Table 8: Emission factor and price by type (Zhu, Kim, & Chang, 2012)

Emission Type	*Emission Factor (gram/vehicle-hour)*	*Price Unit ($/ton)*
HC	13.073	$6,700
CO	146.831	$6,360
NO	6.261	$12,875

The overall procedure for calculating the B/C ratio of HELP program was outlined in Figure 3-10.

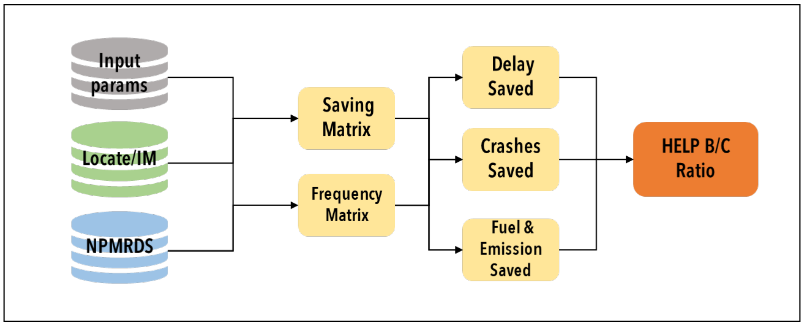


Figure 3-10 Overall procedure for B/C ratio calculation

3.2.3 Risk probability model for PTQ

Traffic queues, especially those caused by unexpected and non-recurrent incidents, pose a great danger to the drivers approaching the end of queue (EOQ) at a high speed. A study conducted by Karlaftis et al. (Karlaftis, Latoski, Richards, & Sinha, 1999) pointed out that for each minute increase of the incident clearance time of the primary crash, the likelihood of a secondary crash is increased by 2.8% without taking any EOQ warning measures. Another recent research conducted by Goodall (Goodall, 2017) first utilized widely available and legally obtained private-sector speed data to fit a logistic regression model examining the relationship between the probability of a secondary crash and other exogenous variables such as clearance time (CLT), season, and day of week etc. The findings suggest that crash odds increased by 0.7% for every 1 additional minute on the scene.

In this project, a risk probability model using logistic regression was proposed for evaluating the likelihood of a secondary crash happening during the worktime of PTQ deployments. The relationship between the secondary crash probability P_i and a series of explanatory variables $\boldsymbol{x}_i$ was shown in following equation:

$$\ln\left(\frac{P_i}{1-P_i}\right) = a + \boldsymbol{b}' \cdot \boldsymbol{x}_i \qquad (4)$$

Commented [ZH4]: The natural log of P-i divided by one minus P-I equals a plus b transpose times x-i

The independent variables $\boldsymbol{x}_i$ depicted the characteristics of the queue occurring in the work zone under the supervision of PTQ working staff. The following three variables were considered to have an influence on the likelihood of secondary crash occurrence:

- Work time (an integer number in minutes): It is generally assumed the likelihood of a secondary crash caused by a traffic queue increases with how long the queue last on the scene. We assumed that during the work time of PTQ trucks, the queue would exist to some extent, and the work time was considered to represent the queue clearance time. The PTQ measures took effects during the worktime.
- Season (a factor variable with four levels: winter, spring, summer, and fall): The prevailing weather conditions for different seasons will affect the driving conditions, which, in turn may have an impact on the driver behavior and the likelihood of a crash occurrence.

- Day of week (a factor variable with two levels: weekday and weekend): This measure was a reflection of traffic volume, vehicle type and possibly driver behaviors.

The data used to fit the logistic model was the PTQ daily working reports (DWR) recorded by TDOT maintenance management system from 2017 to 2019, which was already introduced in section 3.2.

The results of the model showed that, with the deployment of PTQ measures, the crash likelihood decreased by 0.3% for one minute increase in work time with other factors being fixed. This significant finding was one of the most important parameters in the calculation of PTQ benefits. The initial probability used in calculation was 5% (Goodall, 2017), which was subject to change. Figure 3-11 depicted the relationship between the secondary crash occurrence probability and the queuing duration.

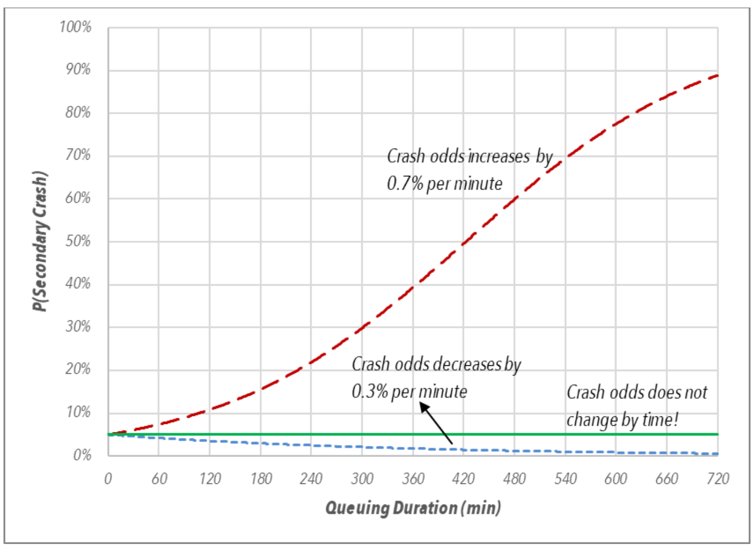


Figure 3-11 Probability of secondary crash with respect to queuing duration

Another assumption was that the number of incidents X occurring within a given period of time followed the Poisson Distribution, where λ is the expected value of the number of incidents:

$$X \sim Poisson(\lambda) \tag{5}$$

Commented [ZH5]: X follows a Poisson distribution with mean value of lambda.

Given the probability of the crash occurrence P_i, the probability of no incident occurring $P(X = 0)$ is given by:

$$P(X = 0) = 1 - P_i = e^{-\lambda} \tag{6}$$

Commented [ZH6]: Probability of X equals zero is equal to one minus P-I, and then equals e to the power of minus lambda.

Thus, the average number of incidents occurring in a given time period is calculated as:

$$\lambda = -\ln(1 - P_i) \tag{7}$$

Commented [ZH7]: Lambda equals minus natural log of one minus P-i.

Therefore, the average number of incidents saved by PTQ program could be derived from the difference between λ_w and λ_{wo}, where λ_w and λ_{wo} are the average number of incidents with PTQ and without PTQ respectively.

This calculation method considered the effect of time accumulation since a tertiary crash be possible to occur if PTQ were not deployed and queue lasted long enough. This should be counted in the number of saved crashes by implementing the PTQ measurements. Figure 3-12 illustrated the relationship between the average number of saved crashes and the queuing duration given that changing rates for crash likelihood with and without PTQ were 0.7% and -0.3% respectively.

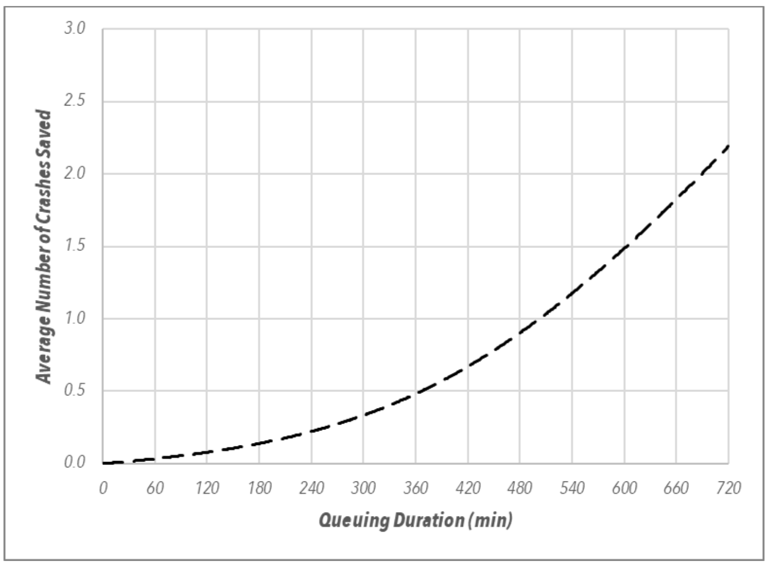


Figure 3-12 Average number of crashes saved with PTQ by the queuing duration length

For each PTQ case, the average number of crashes saved can be obtained by this method. Multiplying this number by the unit cost of crash gives the total benefits of this specific case. Then a summation was implemented based on different region and year to get the annual benefits of PTQ program for each region.

3.2.4 Expansion Scenario for HELP program

In many states, AADT and crash rates are viewed as two leading factors for deploying freeway service patrol. For one thing, the increase in demand on existing roadway capacity that causes congestion, resulting in increased travel time and higher crash rates. For another thing, vehicle crashes not only pose great threat to people’s life and properties, but also disrupt the traffic flow, leading to serious congestion and increasing risk of secondary crashes. Fast response to the crashes is of importance whereas the crash proportion tend to be secondary among all road events, led by disabled vehicles. According to the 2021 Tennessee Statewide incident managed quarterly report[1], near 50 percent of events are disabled vehicles, and near 20 percent of events are crashes (including multi-vehicle crash and single vehicle crash). Experience from the state of Tennessee has shown That 78% of the freeway traffic-related incidents are attributable to disabled and abandoned vehicles. Therefore, the disabled vehicles should also be appreciated on par with crash events on patrol routes. The project employed the AADT and incident rates per million per mile for selecting potential expansion areas.

Firstly, the study followed the AADT criteria that was proposed in 2006 for freeway service patrol expansion (TDOT, 2014 #37). Specifically, the route sections could be viewed as candidate expansion area only where the traffic volume is at least 80,000 on multiple routes or the traffic volume is close to the capacity in large urban areas (equal or greater than 200,000). However, the traffic volume might increase year by year as the extension of lanes, and routes. Therefore, the study attempted to apply multiple the AADT criteria beyond the old AADT threshold. The AADT data of four major urbanized areas in TN are obtained from NPMRDS.

Secondly, the study proposed a series of expansion scenarios based on the AADT and incident rates. The method is based on the knowledge that the larger AADT or incident rates, the higher demand in freeway service patrol. On the other hand, the scale of AADT is not matched with the scale of incident rates. Thus, a severity indicator is proposed based on the multiplication of AADT and incident rates, that is: severity = AADT x annual number of incidents per mile /100,000. Then, the potential expansion areas could be selected by the severity of segments. Due to the limited knowledge of selecting a threshold for identifying the severity/priority level, the study applied an unsupervised learning method that is K-means classification algorithm (Pham, 2005 #38) to automatically classify the priority of patrol area. K-means algorithm has four steps, which are:

Step 1. Randomly initialize K points (e.g., mile markers) as the centroid of K clusters.

Step 2. Compute the distance of other points to those K centroids and assign them to their nearest centroids, separately. The distance is measured by the L1 distance of attributes between two stations. For instance, if the severity at I-24 mile marker 50 is 2.5 and the severity at I-24 mile marker 53 is 1.7, then the distance between these two points is 0.8. This step groups stations with similar severity of crashes and AADT characteristics.

Step 3. Update the centroid by averaging the attribute of points in each cluster. In other words, the new centroids will be calculated as the average of severity of all points within the same group.

Step 4. Repeat Step 2 and Step 3, until the centroids do not change.

Notably, the selection of number of clusters is usually subjective. To choose the optimal K clusters, the research team chose the K value by silhouette coefficient which is a commonly used indicator in determining cluster numbers in machine learning. It ranges from -1 to 1, the larger positive value indicates that clusters are well separated from each other and evidently distinguished (Aranganayagi, 2007 #39). Hence, K value corresponding to largest positive silhouette coefficient is selected for K-means clustering.

[1] https://www.tn.gov/content/tn/tdot/intelligent-transportation-systems/smartway-reports.html

Chapter 4 Results and Discussion

4.1 Exploratory Data Analysis

4.1.1 Locate/IM Incident Data

The Tennessee Department of Transportation (TDOT) deploys HELP trucks on Chattanooga, Knoxville, Memphis, and Nashville's most extensively used roadways. The program was initiated in 1999 with the goals of reducing traffic congestion, enhancing safety, and supporting motorists in need.

The statewide traffic management centers (TMCs) have been using a Web-based traffic incident locator, along with activity and reporting capabilities. This system offers real-time location data, traffic incident reporting, and HELP Truck activities. The program system Locate/IM was integrated with the state's TMCs for TIM control and roadway monitoring. This enables regional and state reporting of incident management actions and performance.

Some exploratory data analysis on over 600 thousand incident record could shed light on the spatial and temporal pattern of incident distribution, more precise incident and response timings, clustering of service call kinds and events, level of service and reaction time in different locations, etc.

The monthly incident frequency distribution across four sites from 2017 to 2021 is displayed in the contingency table in Figure 4-1. The "heatmap" provides a basic depiction of the relationship between incident hotspot occurrence and months. While Chattanooga typically has the fewest incidents, Nashville ranked first among the four cities from 2017 to 2021 in terms of incident volume and density. The four cities consistently experience July as a "hot" month for incident occurrence.

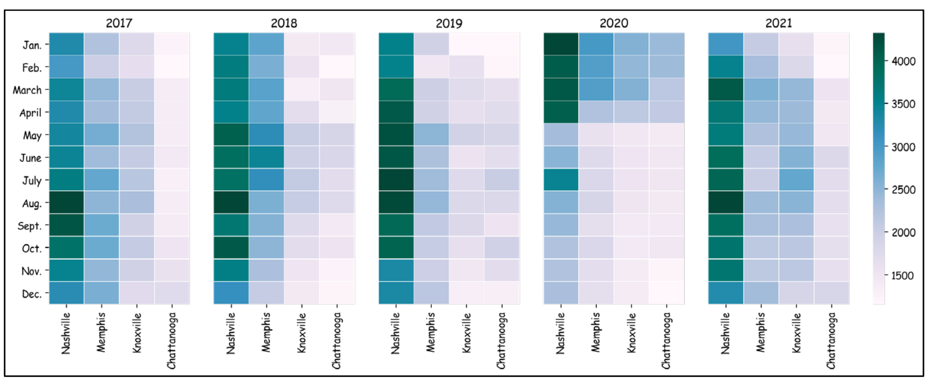


Figure 4-1 Contingency table of incidents across four regions

The 5-year dataset was divided into pre-COVID19 (2017-2019) and post-COVID19 (2020-2021) timespans. Figure 4-2 illustrates the incident count of four sites categorized by different time-of-day. AM_PEAK denotes the early morning peak period from 6:00AM to 09:59AM, MID_PEAK denotes the midday peak period from 10:00AM to 2:59PM. The terms PM_PEAK and OFF PEAK refer to the afternoon peak (3:00–6:59 PM) and the evening off peak (7:00 PM–5:59 AM), respectively. The majority of incidents occur during PM_PEAK, followed by MID PEAK, and OFF PEAK period has witnessed the least number of incidents in the four time windows, notwithstanding the variation in incident number across the four cities before and after COVID19.

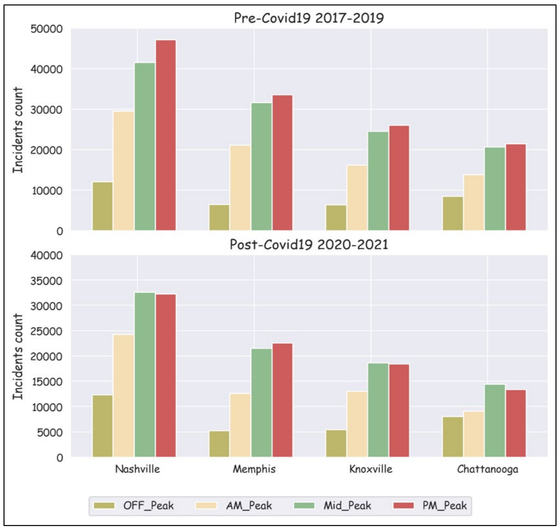


Figure 4-2 Incident count by different time-of-day

The relationships between the number of incidents, the time-of-day of incident occurrence, and the number of lanes blocked on the site are shown in Figure 4-3. A small number of incidents held up four lanes, which had the most detrimental effects on the stability of the traffic flow. The majority of occurrences blocked zero lanes due to the swift traffic management measures, and the impact would dissipate quickly.

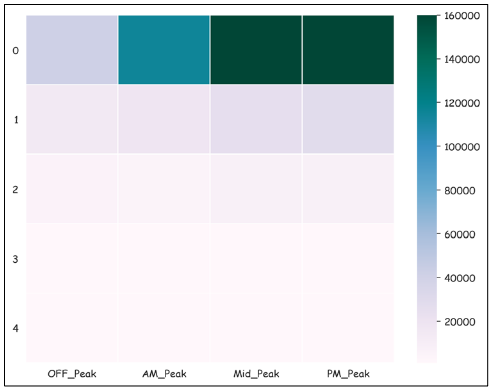


Figure 4-3 Contingency table of number of blocked lanes and time of day

The line plot in Figure 4-4 shows the ratio of reacted incidents to total incident count to provide a clearer picture of the overall performance of HELP trucks in terms of response rate. Memphis has the best overall HELP truck response performance of the four cities, with a stable response rate over 0.9 and the service level only slightly declining after the COVID19 outbreak, while the other three cities are significantly affected by the pandemic with a decline in service rate: Nashville had a good service rate between 0.85 and 0.9 before and it decreased to 0.7; The service rate in Chattanooga is the lowest of the four cities, and this number experiences the most disruption during the epidemic.

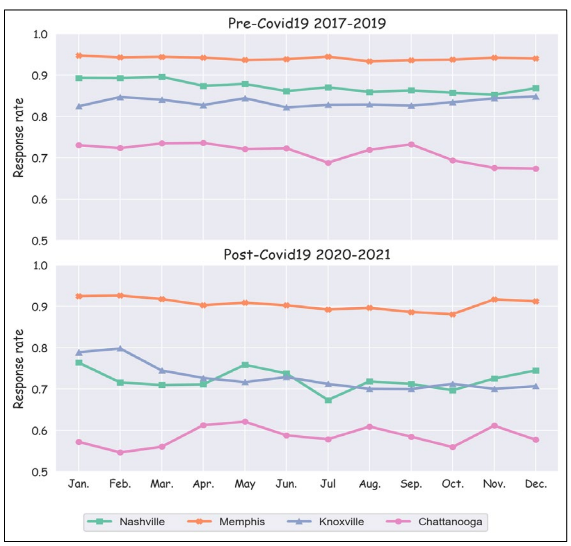


Figure 4-4 HELP truck response rate in four regions

4.1.2 PTQ Service Data

Protect the Queue (PTQ) is a TDOT initiative that emphasizes the necessity of providing upstream traffic with advance notice of an incident occurring downstream to reduce the probability of a secondary accident. The deployment of queue protection vehicles and a buffer zone will facilitate the safe and efficient movement of road users in and around work zones, while safeguarding workers, traffic incident responders, and equipment.

Over 10,000 records of queue protection vehicle deployments are collected in the PTQ dataset. The 5-year dataset was partitioned into pre-COVID19 (2017–2019) and post-COVID19 (2020–2021) time periods and recorded as four regions based on the location where it occurred. Regions 1, 2, 3, and 4 correspond to Knoxville, Chattanooga, Nashville, and Memphis. The monthly frequency distribution of cases across four sites from 2017 to 2021 is depicted in Figure 4-5's contingency table, illustrating the association between the occurrence of case hotspots and the months.

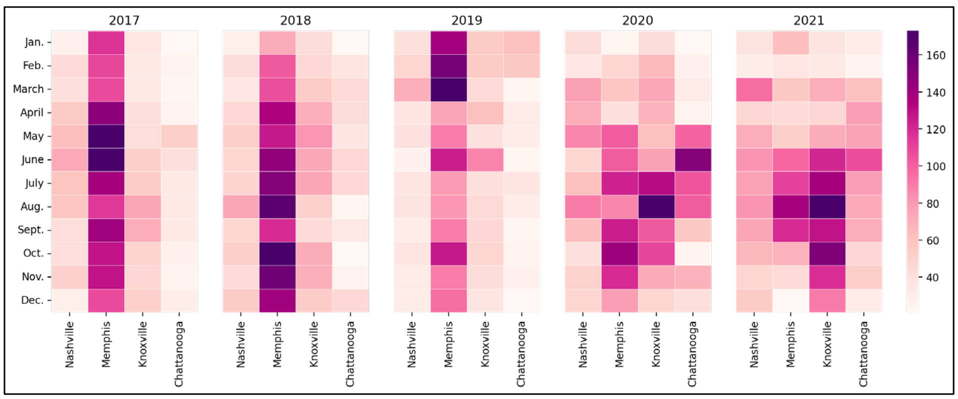


Figure 4-5 Contingency table of PTQ cases across four regions

The data collected during pre-Covid19 time window are more comprehensive and captures more spatial-temporal detail, thus, an exploratory analysis on the accident/non-accident nature of the cases and worktime distribution are presented using the Pre-Covid19 data. Cases involving an accident represent a modest proportion of the overall number of records for all four regions, as shown in Figure 4-6. Region 2 (Chattanooga) placed top among the four regions in terms of the total number of cases, which is larger than the combined total of the other three regions. The distribution of case worktime is shown in Figure 4-7. The majority of PTQ deployments take place in the range of 0 to 600 minutes, and within this time, a sporadic pattern of case occurrences is seen.

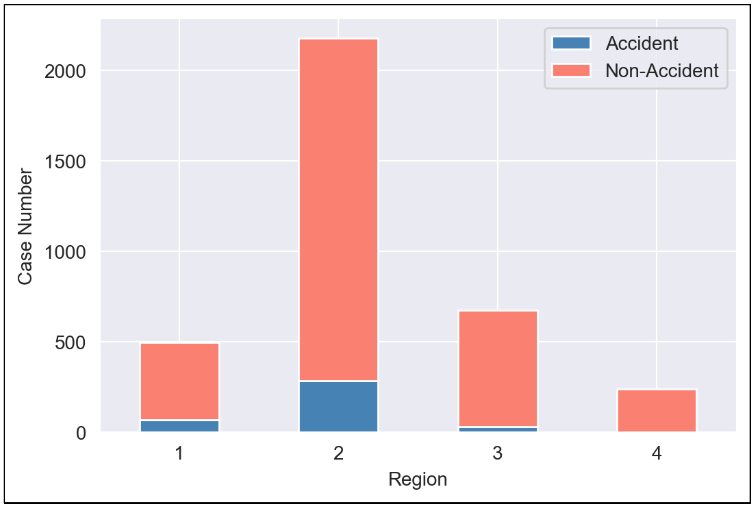


Figure 4-6 Pre-Covid19 Accident and Non-Accident cases

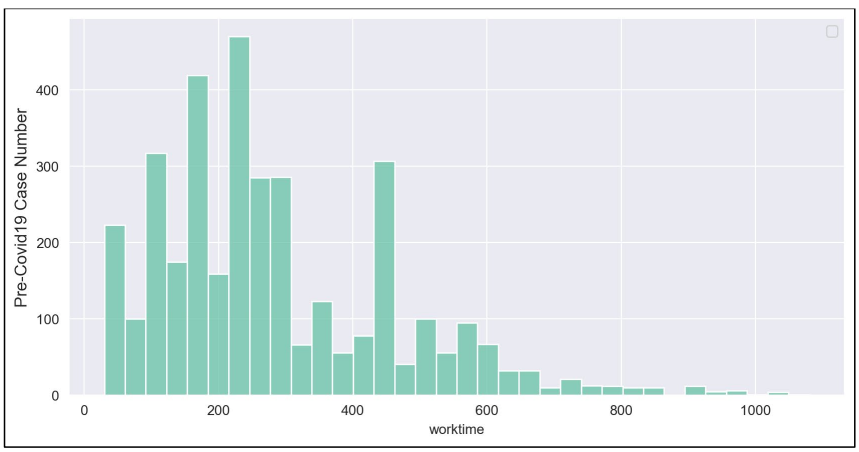


Figure 4-7 Pre-Covid19 Worktime distribution of Cases

4.2 Benefit Cost Analysis for HELP Program

Each incident was categorized into one group based on the four parameters incident type, time of day, queue duration and number of lanes blocked, thus allowing the delay of similar incidents to be estimated based on common criteria. The queue duration, which needs to be derived from NPMRDS data, is the only parameter that is not raw data. In this project, Locate/IM data from 2017 to 2019 are used to calculate the delay saving matrix. New data from 2020 to

2021 is to be applied to the saving matrix as a demonstration of how to use the benefit calculation tool.

Based on the number of features used in classification, three versions of solution, i.e., full, thorough, and quick version, are provided for different application scenarios. The detailed instructions of how to use the three versions of solution will be presented in section 4.5.

Given that we know all the four characteristics (incident type, time of day, queue duration, and number of lanes blocked) of the new incident data, it is appropriate to use the full version, which achieves the most accurate estimation of the benefits while taking most time to preprocess the raw data. The full version requires $8 \times 5 \times 4 \times 4 = 640$ cells of frequency numbers. However, in reality, the queue duration is pretty unreliable due to the limit of data collection technology, so there are usually only three available and reliable features for the new data. The best way of obtaining the queue duration is to capture from the traffic condition data using well-designed algorithms like what has been done for 2017-2019 data.

With these three available features, a thorough version of calculation can be done based on the past years' distribution of queue duration. The coming new incident will be classified based on the three known parameters and then the frequency numbers will be populated according to the past years' distribution, assumed that the distribution of how long the queue lasts remains stable over the time. The number of cells required to be filled in is reduced to $8 \times 5 \times 4 = 160$.

For the purpose of easy use of our calculation tool, a quick version solution is invented to simplify the data preprocessing work. The quick version only needs one number, the number of responded incidents, to be populated into 640 cells base on the past distribution. This version is the quickest and simplest one but can still achieve a relatively accurate estimate of the benefits of HELP program. The margin of errors and comparisons between the three versions will be presented in section 4.2.3.

4.2.1 Full version

Full version is only applicable to the training data from 2017 to 2019 because NPMRDS data and internal algorithms are integrated to obtain the accurate queue duration for each incident that has been responded by HELP trucks. Data from 2020 and 2021 are not involved in the full version of calculations, so the results shown below do not include 2020 and 2021.

Figure 4-8 shows how annual benefits change with year by different regions. Among four urban areas in TN, Nashville has seen the most benefits and a steady increasing rate from 2017 to 2019 while Knoxville remains the lowest level in terms of the annual benefits. Chattanooga and Memphis area gain similar benefits over the three years. This is related to the difference between the number of incidents occurring in each region. There is a steady increase in the annual benefits for all four regions from 2017 to 2019 despite a slight drop was seen in 2019 for Knoxville.

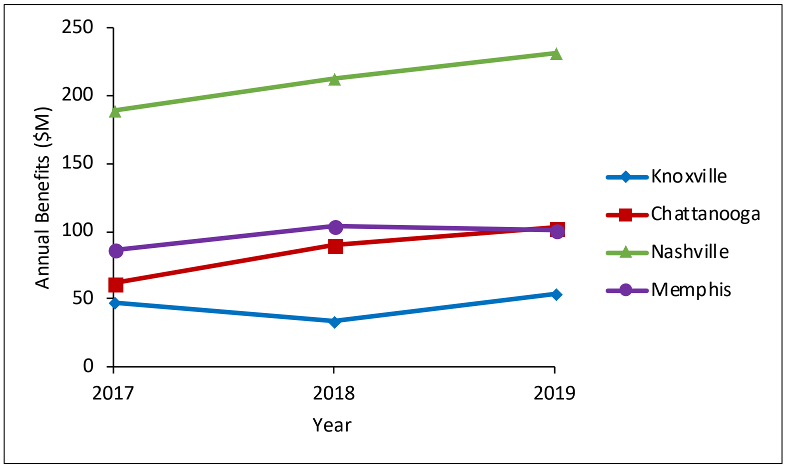


Figure 4-8 Annual benefits of HELP by regions – Full Version

Table 9 provides the full version of annual benefits by regions and years. This becomes the benchmark to be compared with the thorough and quick version of calculations.

Table 9: Annual benefits of HELP by regions ($Million) – Full Version

Region	*2017*	*2018*	*2019*	*3-Year Total*
1 - Knoxville	48.0	33.8	53.7	135.4
2 - Chattanooga	61.7	90.2	102.8	254.7
3 - Nashville	188.9	211.9	231.1	631.9
4 - Memphis	86.0	103.8	100.1	289.8
State Total	384.6	439.5	487.7	1311.8

Figure 4-9 depicts the average annual benefits of 2017 to 2019 by different measurements. Delay saved undoubtedly accounts for the majority of the benefits, while crash saved, fuel saved, emission saved, and goodwill are subject to change with respect to adjustable parameters.

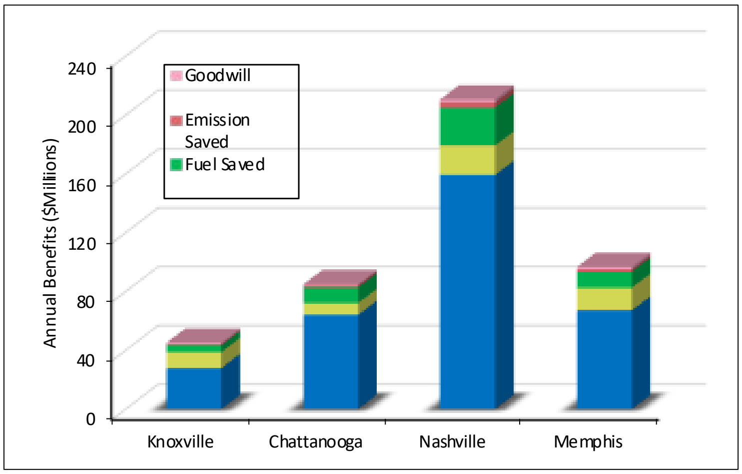
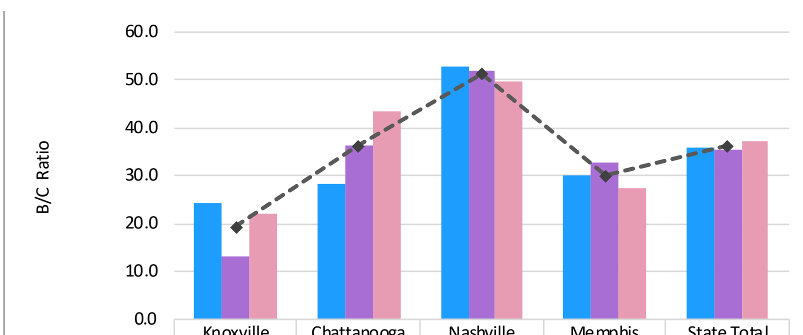


Figure 4-9 Average annual benefits of 2017~2019 by measurements – Full Version

Dividing the benefits by the costs for each region and year, the B/C ratio values can be obtained as shown in Figure 4-10. Note that cost information is one of the inputs which can be adjusted in the Excel tool, so the current values presented here are subject to change with different input information provided. Nashville, Memphis and statewide B/C ratios remain pretty much stable, while Chattanooga sees a steady increase and Knoxville experiences a bit fluctuation from year to year. The main reason for the drop of B/C ratio for 2018 Knoxville is there are more incidents with less than one hour's queue duration which results in a lower total delay saved.



	Knoxville	Chattanooga	Nashville	Memphis	State Total
2017	24.5	28.1	52.7	29.9	35.7
2018	13.2	36.3	51.8	33.0	35.4
2019	22.0	43.4	49.6	27.4	37.2
3Yr Total	19.5	36.2	51.3	30.0	36.1

Figure 4-10 B/C ratio of HELP by region and year - Full Version

4.2.2 Thorough version

In real world, it is often the case that we need to use thorough version due to the lack of queue duration information for incoming new data. Figure 4-11 presents how the annual benefits change with year by different regions. One interesting finding is that all regions except Chattanooga saw a growth on annual benefits for 2020 when the COVID pandemic started to hit the world. This may be because drivers' behaviors become more aggressive when there are fewer cars on the road thus causing more incidents to be responded by HELP trucks. Almost all regions had a steady increase in the annual benefits during the pre-COVID times (2017~2019).

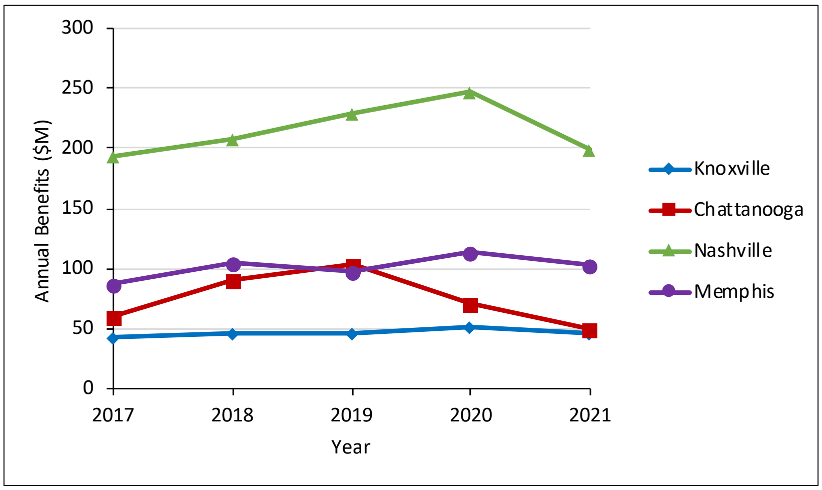


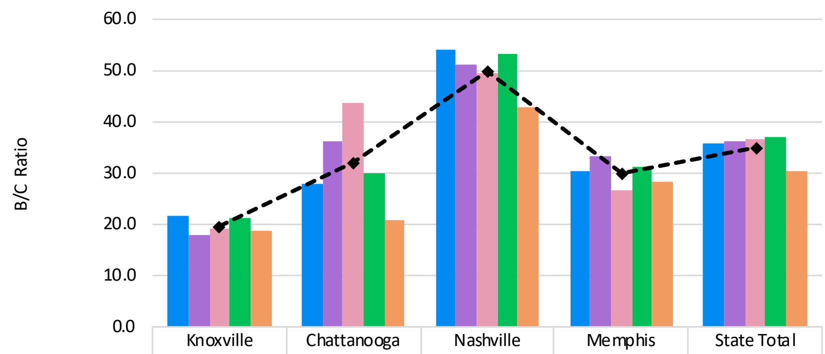
Figure 4-11 Annual benefits of HELP by regions - Thorough Version

Table 10 presents annual benefit numbers for each region from 2017 to 2021, which comes from the thorough version of solution.

Table 10: Annual benefits of HELP by regions ($Million) – Thorough Version

Region	*2017*	*2018*	*2019*	*2020*	*2021*	*5-Year Total*
1 - Knoxville	42.9	45.6	47.0	51.3	45.5	232.3
2 - Chattanooga	61.1	90.0	103.6	70.9	49.6	375.2
3 - Nashville	193.5	208.8	229.6	247.4	199.4	1078.7
4 - Memphis	87.5	104.7	97.6	113.8	103.2	506.9
State Total	385.0	449.0	477.8	483.4	397.7	2193.0

We can obtain the thorough version of B/C ratio by dividing the benefits by associated costs. Note that cost information for 2020 and 2021 was not available at the time of calculation, so numbers from previous years were used as placeholder. Then, the B/C ratios of different years and regions are provided in Figure 4-12.



	Knoxville	Chattanooga	Nashville	Memphis	State Total
2017	21.8	27.8	54.0	30.5	35.8
2018	17.9	36.3	51.1	33.3	36.1
2019	19.3	43.8	49.3	26.7	36.4
2020	21.1	29.9	53.1	31.1	36.9
2021	18.7	21.0	42.8	28.2	30.3
5Yr Total	19.6	31.9	49.9	29.8	35.1

Figure 4-12 B/C ratio of HELP by region and year - Thorough Version

4.2.3 Quick version

The quick version of solution is the easiest one to implement in real practice. All we need is the total number of the responded incidents by HELP. The built-in algorithm is able to distribute the total number into different groups base on the historical distribution. Figure 4-13 and Table 11 display the annual benefits calculated by quick version tool. It appears that 2021 has seen a slight drop on benefits for all four regions. This is probably because more people are back to commuting so that drivers become more careful when driving on the road, thus causing relatively fewer incidents in 2021.

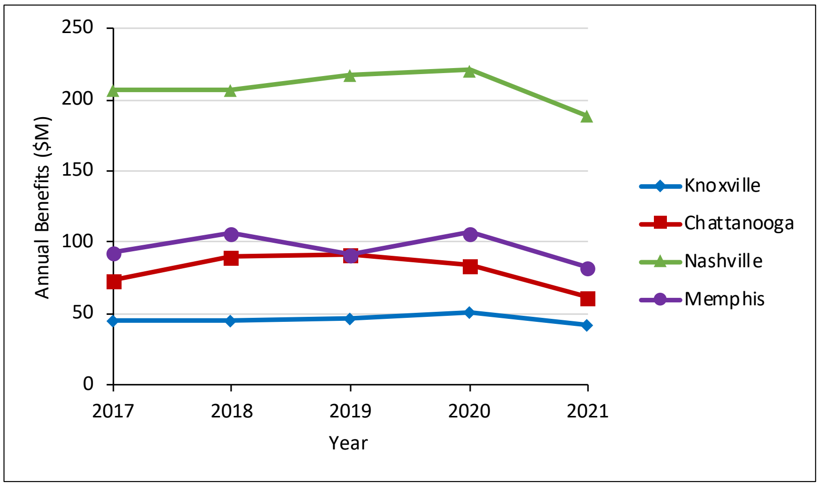
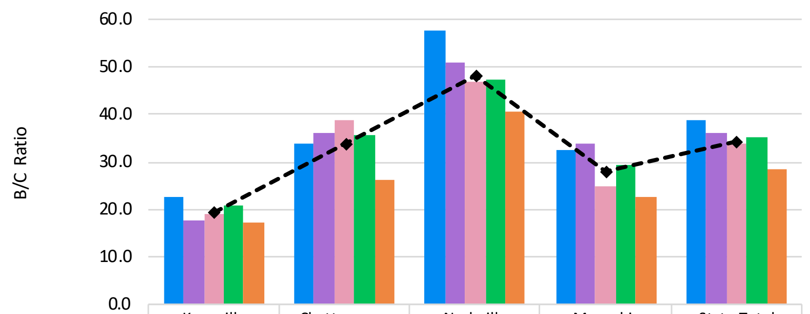


Figure 4-13 Annual benefits of HELP by regions - Quick Version

Table 11: Annual benefits of HELP by regions ($Million) – Quick Version

Region	*2017*	*2018*	*2019*	*2020*	*2021*	*5-Year Total*
1 - Knoxville	44.4	45.1	46.0	50.7	41.8	228.0
2 - Chattanooga	74.1	89.2	91.3	84.2	61.5	400.4
3 - Nashville	206.9	207.2	217.8	221.0	188.3	1041.1
4 - Memphis	92.9	106.0	90.9	107.1	82.3	479.3
State Total	418.3	447.6	446.0	463.0	373.9	2148.7

Figure 4-14 presents the B/C ratio of HELP program acquired by the quick version solution. Overall, Nashville gains most per dollar spent on HELP program. All four regions see a relatively stable level of B/C ratio. Chattanooga saw an increase from 2017 to 2019 and then decrease from 2019 to 2021 while Nashville experienced a pretty much steady decrease of B/C ratio. Both Knoxville and Memphis had a relatively stable level of B/C ratio.



	Knoxville	Chattanooga	Nashville	Memphis	State Total
2017	22.6	33.7	57.8	32.3	38.9
2018	17.7	36.0	50.7	33.7	36.0
2019	18.9	38.6	46.8	24.9	34.0
2020	20.8	35.6	47.5	29.3	35.3
2021	17.2	26.0	40.4	22.5	28.5
5Yr Total	19.3	34.0	48.1	28.2	34.4

Figure 4-14 B/C ratio of HELP by region and year - Quick Version

Figure 4-15 compares the B/C ratios obtained from three versions' calculation by different year and region. It can be noted that both quick and thorough versions achieve a close result compared to the most accurate full version within a 10% margin of error, which justifies the use of quick version estimation method.

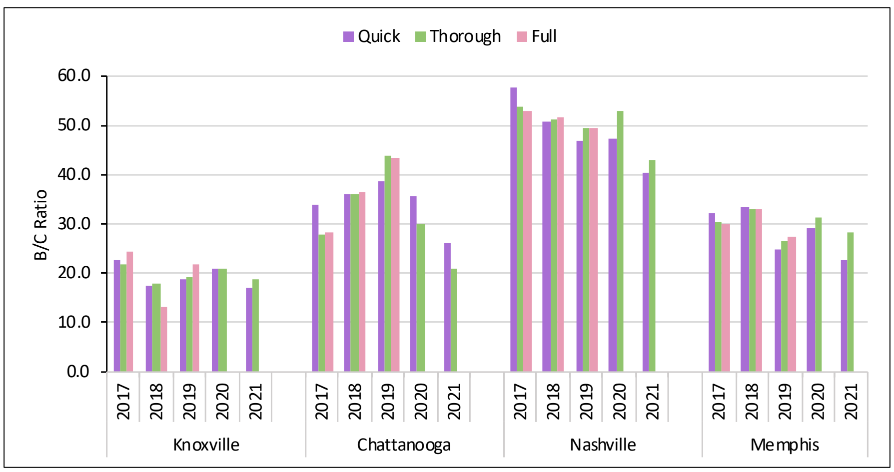


Figure 4-15 Comparison between three versions of B/C ratios of HELP by region and year

4.3 Benefit Cost Analysis for PTQ Program

Figure 4-16 shows the annual benefits of PTQ program by different regions.

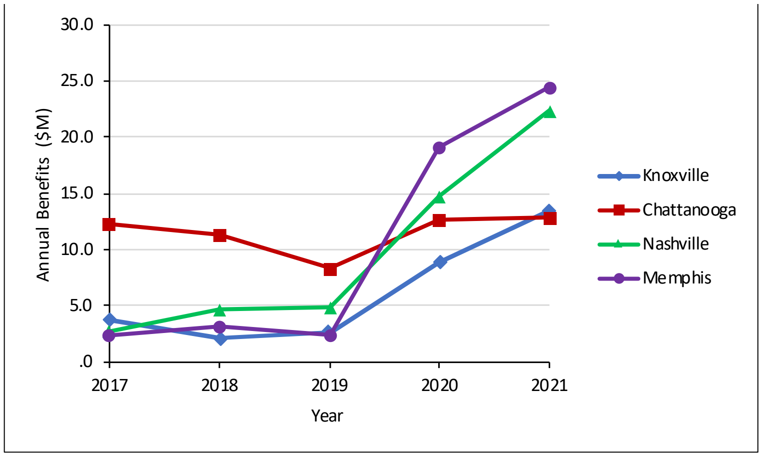


Figure 4-16 Annual benefits of PTQ by regions

Given the cost information of PTQ program, we can calculate the B/C ratio for each year and region. As depicted in Figure 4-16, the B/C ratio saw a dramatic change between 2017~2019 and 2020~2021. This is primarily because data from 2017 to 2019 was acquired from TDOT's maintenance management system which mainly stores call-out PTQ services, while data from 2020 to 2021 was provided by TDOT's construction database strictly focusing on materials and equipment for that specific contract. Therefore, the number of records for two databases does not remain a stable level and the cost breakdown is quite different as well. The maintenance management system spends more on labor cost and the construction group has a higher material and equipment cost.

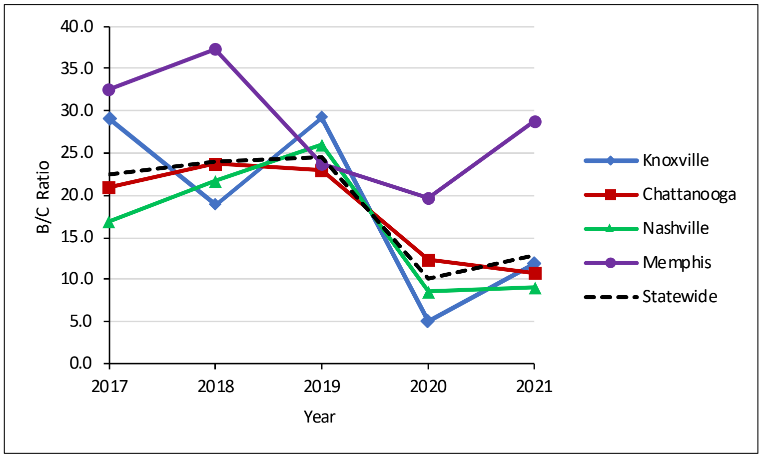


Figure 4-17 B/C ratio of PTQ by region and year

4.4 Automation of B/C Analysis

For the purpose of quick and simple implementation, the team develops a quick version of B/C analysis tool to automate the process of estimating the B/C ratio when new data becomes available. Figure 4-18 illustrates the aggregation and simplification process of the automated workflow for FSSP. Depending on number of features used to categorize the incidents, different levels of aggregation will be implemented. The developed tool only requires the total number of responded incidents and the associated cost information to complete the B/C calculation, which is proved to be a good estimation and extremely easy to be implemented by practioners.

The author provides three versions of analysis of HELP program, among which the quick version is the automated and simplest version to use. The automation tool is developed as an excel spreadsheet containing all raw data, formulas, and instructions to do the B/C analysis. The file name is FSSP-tool.xlsx and the data used is extensive and would be cumbersome to include, so a separate, readable file will be attached to this report. Figure 4-19 demonstrates the user interface of the automation tool of B/C analysis for HELP program. The only input information that needs to be provided by the user in the tab “Input” is the total number of incidents that are responded to by the HELP truck. Then by selecting the city among Knoxville, Chattanooga, Nashville and Memphis, the total number will be populated to different classification based on the historical distribution. And the total benefit will be calculated correspondingly by multiplying the incident number and the delay saving values. The final results will be presented in the first tab “BC Ratio”. The user can adjust the parameter values in the “Parameter Configuration” tab. Figure 4-20 shows how the calculation results will be presented in the format of a pie chart showing the percentage of all subcategories of benefits along with a table displaying all the detailed numbers.

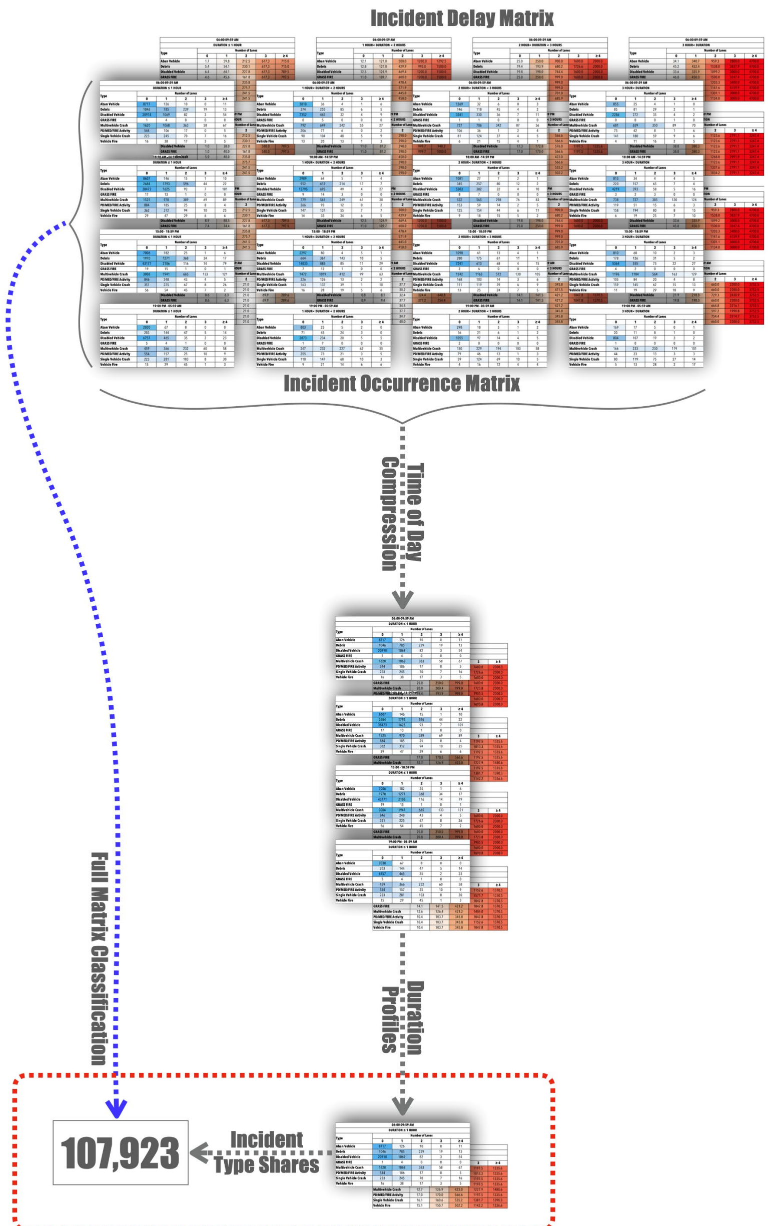


Figure 4-18 Aggregation and simplification process of automated workflow for FSSP

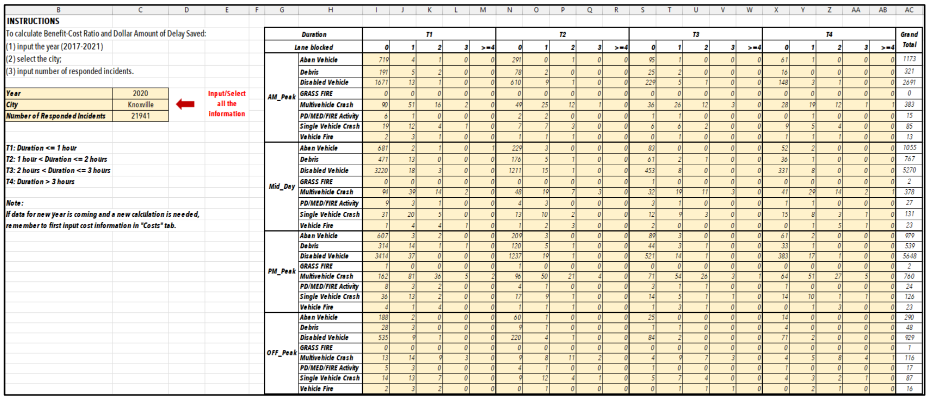


Figure 4-19 User interface of B/C analysis automation tool for HELP program

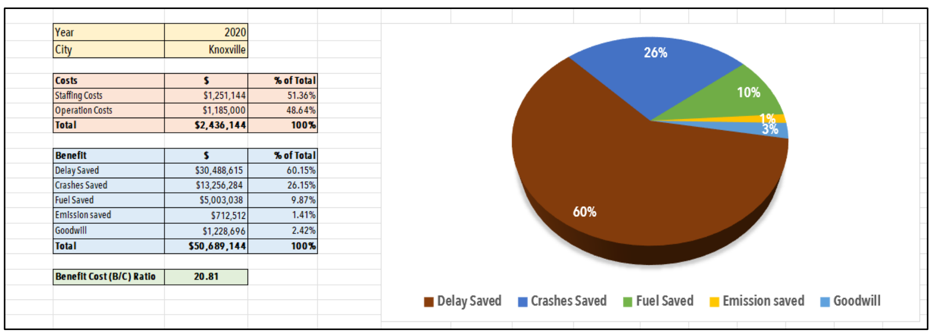


Figure 4-20 Calculation results of the automation tool for HELP program

In a similar manner, the automation tool of B/C analysis for PTQ program is attached in an excel spreadsheet, which will be provided separately. The only information that needs to be input is the number of cases deployed in this region and the associated costs. When new data becomes available, the user can summarize the raw data to get the total number of PTQ deployments for each region and enter the figures in "Effective Worktime Method" tab, then the B/C ratio results will be calculated automatically based on the internal algorithm. Figure 4-21 displays the interface of the automation tool used to calculate the B/C ratio of PT

Region	Average Number of Crashes Saved	Average Effective Worktime (min)	Number of PTQ cases deployed	Benefits ($)	Costs ($)	B/C Ratio
1	0.4404	345		$ -		
2	0.3781	320		$ -		
3	0.4649	354		$ -		
4	0.8503	467		$ -		
Instructions:						
1. Input number of PTQ cases deployed in this region						
2. Input corresponding cost						

Figure 4-21 User interface of B/C analysis automation tool for PTQ program

4.5 Benefit Cost Analysis for HELP Expansion

4.5.1 Expansion results

To correclty represent traffic the of each region, three normal year's traffic volume and incidents (i.e., 2017-2019) data are aggregated. Then, the severity metric at each mile miler of each route is cacluated as the 3-year average AADT X 3-year average incidents /100,0000. Note that the severity also reflects the priority that HELP truck should give to a location. After that, a K-means algorithm was performed to classify the level of severity. The silhouette coefficient suggests 3 clusters for all regions. Therefore, the severity can be labeled as serious, moderate, and mild according to the average severity of each cluster.

Figure 4-22 to Figure 4-25 demonstates the level of patrol prioirty (i.e., severity) at mile markers for region 1 to region 4. The red points reflect the serious situation with either high frequency incidents or high AADT or both. It is not difficult to find that those red dots apears in the centroid of city where the traffic is quite busy and road network is complex. Those red labeled stretch should be given more attention from HELP program than other areas. The yellow dots, representing the moderate sitatution tend to appear at the area perpheral to centroid city. Some of them end by the city boundary (i.e., blue area), like I-40 in west and east of knoxville, I-75 at east of Chattanooga, I-24 at south of Nashivlle and so on. By contrast, it is also found that some moderate roads end within the city, like SR153 in Chattanooga, I-65 in south of Nashville, I-40 in east of Memphis, and so on. Hence, simply relying on the cites' boundary to assign the patrol service is not efficient as some route may not need much attention and help. The detailed patrol boundary to mile marker can be found in Appendix.

4.5.2 Other Expansion considerations

The proposed metric only considers the traffic exposure and incidents, which are of importance to HELP truck's decision. However, there are many other important factors that decision makers or HELP crews should consider when they expand the patrol area. For instance, the benefit cost in expanded area. When expanding the patrol area, we need to consider the how many benefits users can gain from the expansion and how many extra crews and resources need to be assigned. The benefits tend to be unknown until the expansion is conducted. The other factor should be considered is the time. The proposed expansion only considered the spatial distribution of patrol area, while the traffic exposure and incident occurrence have both spatiotemporal characteristics. Understanding the temporal incident characteristics would help operators better distribute their resoureces. To this end, the crowdsourced Waze data be utilitzed to monitor the temporal road service demand. For instance, Figure 4-26 a shows the frequency of traffic jam and accidents report on I-24, Nashville, the apparent spatiotemporal variation was found. The peak hours (green shaded area in figure a) generates many more reports then other periods, accounting for 63.7% reports in total. Figure 4-26 b can also tell crews where to patrol for next help as the percentage of spatiotemporal freqeuncy explicitly represents the probability of incident occurrence at a time and location.

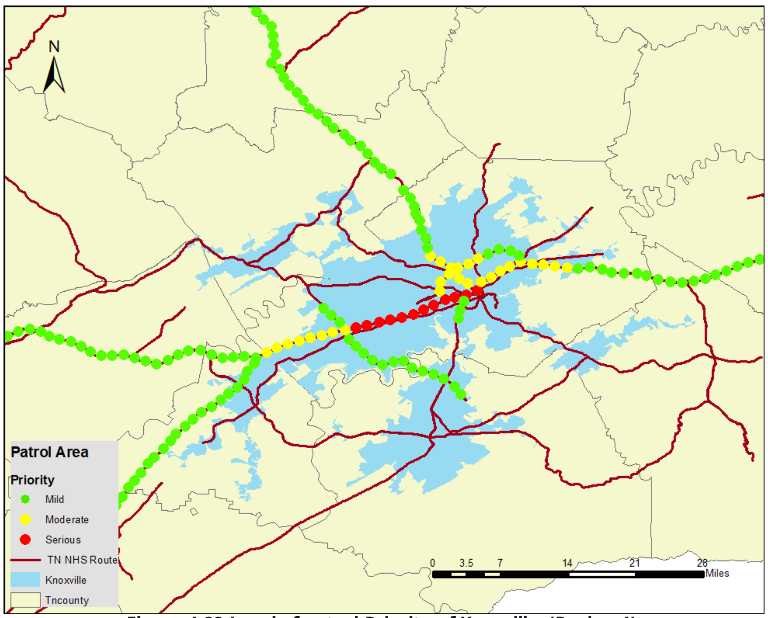


Figure 4-22 Level of patrol Priority of Knoxville (Region 1)

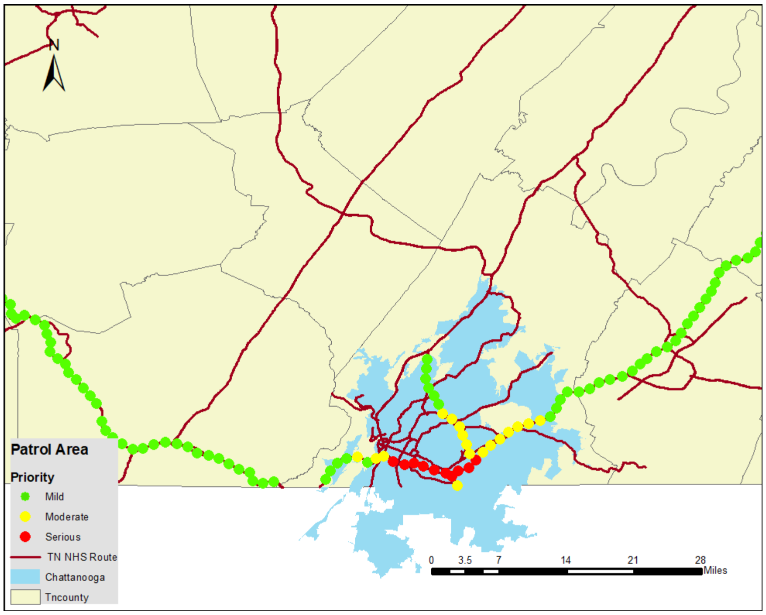


Figure 4-23 Level of patrol Priority of Chattanooga (Region 2)

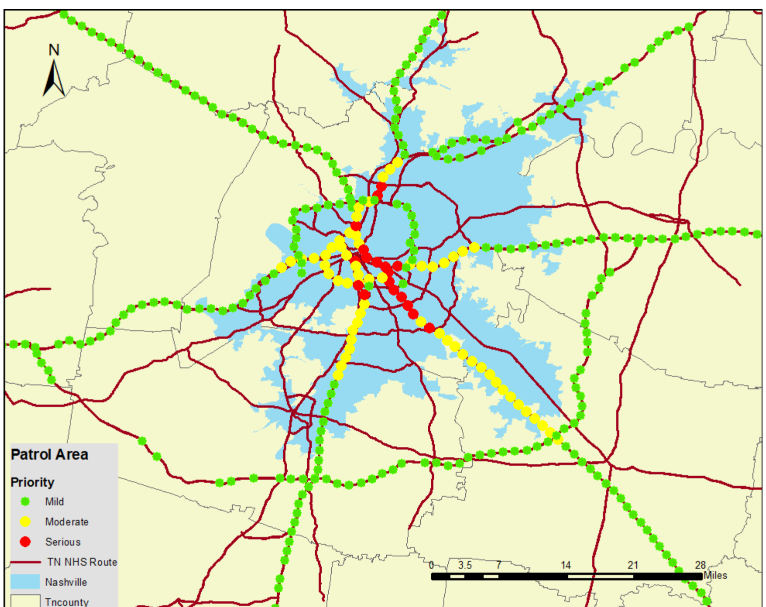


Figure 4-24 Level of patrol Priority of Nashville (Region 3)

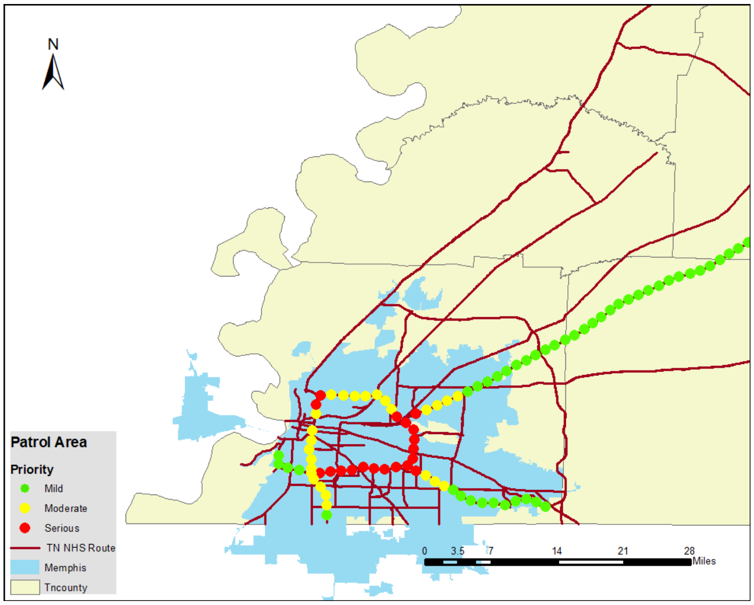
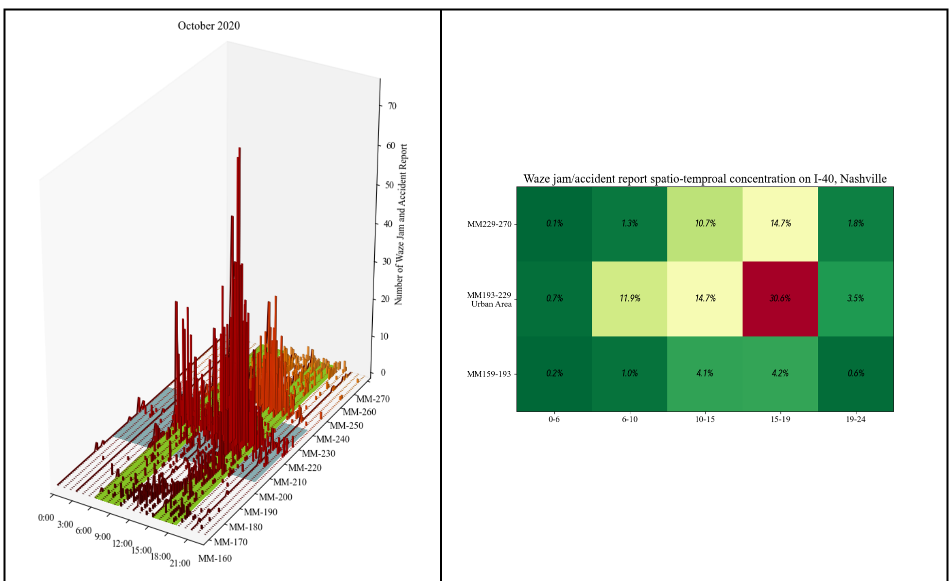


Figure 4-25 Level of patrol Priority of Memphis (Region 4)



(a) Spatiotemporal report frequency | (b) Spatiotemporal percentage of report

Figure 4-26 A example of Waze data in reflecting the road service demand on I-40, Nashville

Chapter 5 Conclusions

The primary purpose of this study is to better understand and quantify the impact of FSSP programs such as HELP and PTQ services through an objective data-driven analysis.

This project provides a thorough literature review of state-of-the-art practice of evaluating the impact of traffic incident management program and proposes a framework for quantifying benefits for HELP and PTQ service. Furthermore, the calculation process has been automated to facilitate the future application of the proposed method. The estimated B/C ratios for HELP program ranges from 20 to 50, providing a solid support for TDOT to make investment decisions on TIM programs.

This study provides three versions of B/C ratio calculations for HELP program based on different data aggregation level, thus allowing users to determine which version to use according to the available data granularity. The automation of the quick version analysis enables TDOT users to apply simply and directly to new data without needing to do complicated reprogramming. A simple output in the format of spreadsheet and standard charts can be generated automatically for quick visualization and easy implementation.

The deliverables of this study will provide factual statistics backed by sound data-driven analysis to assist CMAQ application strategies. The B/C reports for HELP and for PTQ program facilitate TDOT to make important investment decisions to best serve the motoring public in Tennessee. The automated workflow for generating B/C reports will achieve the goal of comprehensive performance monitoring. In addition, the incorporation of crowdsourced data like WAZE into TDOT's existing TIM framework will result in a better understanding of incident spatiotemporal characteristics and more efficient and timely incident management.

This study deals with empirical incident events and realistic traffic data on Tennessee's highway system. All reports and deliverables can be used by TDOT readily and directly. The procedures can be used for benefits resultant from savings in travel delay, emission, fuel consumption, and secondary crash for a wide range of programs beside incident management. Results from this study will be readily implementable for the entire State, any region, or even individual counties. The B/C analysis for a rural HELP program can be quite useful for securing CMAQ or other type of funding sources.

There are also challenges and issues encountered in this study, which in turn points to the future direction of investigation and research. The trade-off problem between computation cost and accuracy in calculating B/C ratios for HELP program deserves further attention and analysis. The higher the aggregation level leads to a more accurate estimation while costing more computational and preprocessing efforts. The output will also be more complex to use by practitioners.

Another big issue is the unreliability and low quality of the raw incident service data. While enormous data is being stored every day, cases are rare when people pay more attention to the assurance and control of data quality. For instance, errors are often seen in the blockage duration and incident clearance time from Locate/IM database. A large portion of raw data has a record of 0, 9999, or even a negative value. This largely undermines the practical value of Locate/IM data.

The problem in dealing with data from PTQ program is the inconsistency of the databases. Data from 2017 to 2019 comes from maintenance management system which focus more on labor cost and stores on-call service data. In contrast, 2020 and 2021 data are retrieved from construction database, in which data tends to have higher material and equipment cost. This type of consistency leads to an instinct difference of B/C ratios between two groups. For future studies, a unified and vertically managed databases for PTQ program is essential and necessary to better understand and analyze the influence.

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Appendices

Appendix A – FSSP Tool.xlsx

Appendix B – FSSP Summary.xlsx

Appendix C – FSSP Expansion.xlsx

Appendix D – PTQ.xlsx