FUNCTIONAL RESILIENCE EVALUATION OF ROAD TUNNELS THROUGH STOCHASTIC EVENT SIMULATION AND DATA ANALYSIS

FINAL PROJECT REPORT

by
Sandeep Singh Khetwal[1]
Dr. Shiling Pei[1]
Dr. Marte Gutierrez[1]
[1] Colorado School of Mines,

November 30, 2020

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

1. Report No. UTC-UTI-006	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle FUNCTIONAL RESILIENCE EVALUATION OF ROAD TUNNELS THROUGH STOCHASTIC EVENT SIMULATION AND DATA ANALYSIS		5. Report Date November 30, 2020
		6. Performing Organization Code
7. Author(s) Sandeep Khetwal (Orcid.org/ 0000-0003-3993-6730) Shiling Pei (Orcid.org/ 0000-0002-6458-3124) Marte Gutierrez (Orcid.org/ 0000-0001-5070-8726)		8. Performing Organization Report No. UTC-UTI-006
9. Performing Organization Name and Address University Transportation Center for Underground Transportation Infrastructure (UTC-UTI) Tier 1 University Transportation Center Colorado School of Mines Coolbaugh 308, 1012 14th St., Golden, CO 80401		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. 69A355174711
12. Sponsoring Agency Name and Address United States of America Department of Transportation Research and Innovative Technology Administration		13. Type of Report and Period Covered Final Project Report
		14. Sponsoring Agency Code

16. Abstract
Resilience of tunnels can have significant impact on the efficiency of the entire transportation network. The ability to assess resilience of tunnels accurately is important for tunnel owners and stakeholders when they evaluate the cost-benefit of the investment made and the monetary value of future maintenance and upgrade activities. In this thesis, a simple and direct measurement metric for tunnel functionality was proposed with the focus on the usage of road tunnels. An ideal data collection framework for tunnels was proposed to support the calculation of tunnel functionality, as well as additional data-driven analysis that can be conducted to seek correlation between tunnel design and operation parameters with its resilience. As an example, existing tunnel operational data collection practice in a large tunnel in Colorado was summarized and compared with the proposed framework. Data analysis was performed for Eisenhower Johnson Memorial Tunnel (EJMT), Colorado. Since the data for the tunnels was found to be insufficient and incomplete to perform a completely data-driven analysis, a stochastic simulation model to predict tunnel resilience over time was developed by simulation of individual disruptive events. The model was a combination of modules representing disruptive events namely, accident, vehicle fire, hazmat platooning, maintenance and operations. This model was validated to the extent that is realistic using limited data from EJMT. Further, a parametric sensitivity analysis was performed to identify the impact of tunnel parameters, associated with disruptive events, on the tunnel functionality loss and resilience. The parametric study was also expanded to conduct a preliminary correlation assessment of tunnel key parameters and their performances using 22 major road tunnels in the United States.

17. Key Words		18. Distribution Statement
Tunnels; Functionality; Resilience, Databases; Stochastic simulation; Accidents; Maintenance and Inspection; Disruptive events; Sensitivity.		No restrictions.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No of Pages	22. Price
Unclassified	Unclassified		NA

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Resilience of tunnels can have significant impact on the efficiency of the entire transportation network. The ability to assess resilience of tunnels accurately is important for tunnel owners and stakeholders when they evaluate the cost-benefit of the investment made and the monetary value of future maintenance and upgrade activities. In this thesis, a simple and direct measurement metric for tunnel functionality was proposed with the focus on the usage of road tunnels. An ideal data collection framework for tunnels was proposed to support the calculation of tunnel functionality, as well as additional data-driven analysis that can be conducted to seek correlation between tunnel design and operation parameters with its resilience. As an example, existing tunnel operational data collection practice in a large tunnel in Colorado was summarized and compared with the proposed framework. Data analysis was performed for Eisenhower Johnson Memorial Tunnel (EJMT), Colorado. Since the data for the tunnels was found to be insufficient and incomplete to perform a completely data-driven analysis, a stochastic simulation model to predict tunnel resilience over time was developed by simulation of individual disruptive events. The model was a combination of modules representing disruptive events namely, accident, vehicle fire, hazmat platooning, maintenance and operations. This model was validated to the extent that is realistic using limited data from EJMT. Further, a parametric sensitivity analysis was performed to identify the impact of tunnel parameters, associated with disruptive events, on the tunnel functionality loss and resilience. The parametric study was also expanded to conduct a preliminary correlation assessment of tunnel key parameters and their performances using 22 major road tunnels in the United States.

CHAPTER 1 INTRODUCTION

1.1 Background

Road tunnels are an important part of modern transportation infrastructure. The construction of tunnel infrastructure is relatively expensive and time-consuming as compared to other transportation infrastructure. However, once completed, a tunnel is generally a very efficient solution to transportation needs spatially and environmentally. A functional road tunnel often serves as critical link in a transportation network, while a tunnel that has to be shut down will negatively impact the efficiency of the traffic system significantly. With the increasing level of urbanization and environmental considerations, society and the transportation network are expected to become increasingly dependent on tunnel infrastructure. Hence, the continuous operation of tunnels at its design capacity and their quick recovery from disruptive events (i.e. tunnel resilience) is essential to the design and management of tunnels.

The functionality of a tunnel can be defined as its traffic capacity over time. Tunnel resilience is the ability of a tunnel to minimize and recover from functionality loss due to disruptive events. The goal of engineering for better transportation infrastructure should be targeted at optimizing design, construction, and operation to maximize the traffic capacity of the tunnel in an uninterrupted manner. As the tunnel operating conditions are not standardized, its functionality is dependent on the occurrence of many planned and random disruptive events, to which the tunnel is exposed. These events could be triggered by intrinsic factors, such as design flaws, construction shortcomings, deterioration of components, and regular maintenance, or extrinsic factors that are not directly related to the construction/design of the tunnels, such as random events including traffic accidents, fire, and natural hazards.

Worldwide, tunnels have been constructed and designed for centuries. Usually, the knowledge of engineers has increased as we learn from operational interruptions. Thus, design and construction of road tunnels has evolved, and many new technologies have been added to tunnel construction and maintenance practices. There are some advanced technologies, such as smoke and fire detectors and suppression systems, have become common in recent tunneling projects. All the advancement in technology and design are done with the main objective in mind, that is, to provide a safe and reliable passage to the vehicles using the tunnel. Generally, the design of tunnels follows this same philosophy, however, the design can vary based on the geometry of the tunnel, its length, location, traffic volume and other parameters. While the impact of a particular design innovation or improved component to its corresponding performance was studied in detail (such as the reduction in fire load caused by fire suppression system, benefit to strength and durability of lining segment from new material or construction design, etc.), there is currently no systematic approach to evaluate the resilience of the whole tunnel with respect to the type of design and use of new technology. The optimization of tunnel resilience through improvements in design, maintenance and operation can only take place once the tunnel resilience as a whole can be accessed.

It is important to estimate the tunnel functionality quantitatively in order to access the tunnel performance accurately. This can be achieved by either a data-driven study which would rely on large amount of realistic data collected during tunnel operation or through stochastic simulation-based models. The data-driven approach requires large amount of data collected over years on

multiple tunnels with a readily accessible format, which was found during this study to be difficult to obtain. On the other hand, a simulation model must also be validated through realistic tunnel performance data, while the amount of data needed was less than a full-fledge data-driven approach. Nonetheless, both approaches require data collection at the tunnel level which in turn will benefit from a unified data collection framework universal to all road tunnels.

In recent years there has been emphasis on tunnel asset management in terms of recording of disruptive events and reorganizing tunnel maintenance and operations. The corresponding actions to the highlight on tunnel asset management has resulted in data collection recommendations which seldom include aspects related to tunnel functionality. In fact, tunnel functionality has not been defined in any recommendation or report and due to incongruity in these reports a unified tunnel data collection framework has not emerged yet. Currently, although large quantity of data was collected in major crew-operated tunnels, it is difficult to conduct performance analysis or to quantify tunnel resilience because (1) most of these data collection efforts lack uniformity and (2) there is no commonly adopted metric for tunnel functionality.

Ahmed and Dey (2020) described a comprehensive overview of highway resilience and proposed vulnerability to be the most explored resilience indices. Resilience quantification for emergency management of a city network was proposed by Liao et al. (2019) where traffic condition in terms of capacity and time before and after the disasters were evaluated. Twumasi-Boakye and Sobanjo (2018) developed identification metrics using high speed differences to locate high-impact-zone location and implemented it to identify the areas affected by bridge closures. Vehicle distance traveled computed as the product of the traffic volume and distance and vehicle hours traveled computed as the product of traffic volume and time were used to estimate the transportation network resilience based on bridge damage. Chen and Miller-Hooks (2012) quantified the resilience of intermodal freight transport network due to natural and human-caused disaster using topological and operational attributes with budget constraint. The post-disaster recovery actions for road-bridge transportation network using resilience-based framework was proposed by Zhang et al. (2017). The method incorporates network topology, redundancy, traffic flow, damage level and available resources into stochastic simulation model to measure the total recovery time and efficiency of the restoration strategies.

Nassif et al. (2017) studies the impact of Hurricane Sandy on bus transit system in New Jersey and used travel time over time and traffic volume over time to study resiliency of the system. Zhang et al. (2010) studied resilience of freight vehicle transportation post Hurricane Katrina for Mississippi DOT. Resilience indicators such as travel time, average trip length, percentage of vehicles traveling under acceptable speed, percentage of total length of highway open in the network and proportion traffic that can maintain schedule were considered in the study. Sun et al. (2018) has done a comprehensive review of the different metrics used for resilience measurement. Most of these studies are related to measuring network resilience rather than a component. According to Mackie et al. (2006), bridge functionality can be measured in terms of the traffic load-carrying capacity, lane closures, allowed axle loads and speed limits. Padgett et al. (2007) defines the bridge functionality as the traffic carrying capacity of the bridge. Bocchini et al. (2012) proposes an index for functionality for highway segment based on a performance index.

Most of the studies talk about functionality or functionality loss to define resilience but very few studies as tend to quantify functionality. Also, most of the transportation resilience studies are related to the network resilience.

Therefore, in this study a baseline data collection framework was proposed in order to support future tunnel data collection and quantifying road tunnel performance. The objective was to identify the minimally required data to collection during tunnel operation to assess the tunnel resilience with respect to disruptive events. Further, a simple tunnel functionality metric is developed which can be used to evaluate the resilience of the tunnel.

After developing the tunnel data collection framework and functionality metric, a stochastic simulation model to predict tunnel functionality (also resilience) over time was developed through simulation of individual disruptive events that are main contributors to tunnel functionality loss. The model focused on shortlisted event types, namely vehicle accident, vehicle fire, hazardous material platooning in case of restrictions, tunnel maintenance and tunnel operations. The simulation can generate disruptive events based on probabilistic occurrence model and then simulate the magnitude of the event. Eventually the model associates the magnitude of event to event duration and the corresponding tunnel functionality loss. The simulation parameters in the model were estimated through public data and literature information about these events, together with reasonable assumptions. The objective of the simulation tool is to be used as a guide to decision making related to tunnel design, management, and maintenance. The model was applied to a mountain tunnel on the I70 artery which has years of operation data to be used for comparison. The comparative study served as a preliminary validation for the accuracy of the simulation model developed.

Finally, a parametric sensitivity study was carried out using the model to study different design and configuration parameters' impact on tunnel resilience. The sensitivity study was conducted using a baseline case identical to the mountain tunnel used in initial model validation. Furthermore, this study showcased the proposed simulation tool as an automated performance evaluating tool for tunnel owners using a correlation study between tunnel resilience to tunnel design, age, location and other tunnel parameters. The cases used for the correlation study was extracted from the National Tunnel Inventory which contains some basic information of all road tunnels in the U.S. While the data in NTI was very basic and not detailed, assumptions were made to make this analysis possible. The sensitivity study and correlation analysis provided a glimpse into the potential of the simulation model in future tunnel asset design and management if more data can become available and with better uniformity. The application of the developed tool can help provide answer to questions like the possible worst-case scenario functionality loss event or the more efficient type of tunnel design and management practice.

1.2   Research objective

The main objective of the research is to develop a quantitative method to assess relationship between the functional resilience of road tunnels and its intrinsic and extrinsic parameters. These design and environmental parameters reflect the design and location of the tunnel, operation management strategies, and external influential events (such as hazardous events like crash and vehicle fire). This objective will be achieved by developing a stochastic event simulation tool that

will simulate the downtime of a tunnel. This simulation tool will be validated and calibrated using a limited amount of function data from real road tunnels. The following are the specific objectives of the dissertation:

I.   Develop a uniform data collection framework for road tunnel that will support quantitative analysis of tunnel resilience.

II.   Develop a stochastic event simulation model/tool to quantitatively predict road tunnel downtime and resilience given tunnel parameter inputs.

III.   Conduct a parametric sensitivity study using the prediction model results to better understand the relationship between critical events and tunnel functionality

1.3   Thesis organization

The thesis comprises of five chapters. Three of these chapters are technical paper manuscripts that have been or will be submitted for publication in peer-reviewed technical journals and conferences. This is an acceptable format for graduate thesis based on Graduate School requirement at Colorado School of Mines. Therefore, each chapter has its own abstract, introduction, main body, results and conclusions. There are some level of repetition in the introduction and background portion of these chapters.

The chapters are organized as research objectives defined before. Chapter 2 is dedicated to achieving Objective 1 wherein data framework is developed while Chapter 3 proposes stochastic simulation model as per Objective 2. Sensitivity analysis which is Objective 3 is discussed in Chapter 4, with Chapter 5 giving the overall conclusion and summary of the research and its recommendations for future use.

1.4   References

Ahmed, S. and Dey, K. (2020). Resilience modeling concepts in transportation systems: a comprehensive review based on mode, and modeling techniques. *Journal of Infrastructure preservation and resilience*, volume 1, 8. https://doi.org/10.1186/s43065-020-00008-9

Bocchini, P., and Frangopol, D. M. (2012). Optimal resilience- and cost-based post-disaster intervention prioritization for bridges along a highway segment. *Journal of Bridge Engineering*, volume 17(1), 117–129.

Chen L. and Miller-Hooks E. (2012). Resilience: An indicator of recovery capability in intermodal freight transport. *Transportation science*, volume 46, no.1, pp 109-123

Liao, T.Y., Hu, T.Y., Ko, Y.N. (2018). A resilience optimization model for transportation networks under disasters. *Natural Hazards*, volume 93, no. 1, pp 469-489

Mackie, KR, Stojadinović, B. (2006). Post‑earthquake functionality of highway overpass bridges. *Earthquake Engineering and Structural Dynamics,* volume 35(1): 77‑93.

Nassif, H., Ozbay, K., Deka, D., Lou, P., Na, C., Mudigonda, S., Zhu, Y., Faruk Morgul, E., Bartin, B., and El-War, A. (2017). Performance Measures to Assess Resiliency and Efficiency of Transit Systems. Mineta National Transit Research Consortium

Padgett, J.E., DesRoches, R. (2007). Bridge functionality relationships for improved seismic risk assessment of transportation networks. *Earthquake Spectra*. 23:115–130.

Twumasi-Boakye, R. and Sobanjo, J.O. (2018). Resilience of regional transportation networks subjected to hazard-induced bridge damages. *Journal of transportation engineering, part A: systems*, ASCE, pp 04108062-1-13. DOI:10.1061/JTEPBS.0000186

Zhang, L., Wen, Y., Huang, Z., and Mingzhou, J. (2010). Framework of Calculating the Measures of Resilience (MOR) for Intermodal Transportation Systems. Jackson, Mississippi Federal Highway Administration and Mississippi Department of Transportation.

Zhang, W., Wang, N. and Nicholson, C. (2017). Resilience-based post-disaster recovery strategies for road-bridge network. *Structure and infrastructure engineering*, Taylor & Francis group, pp 1-10. http://dx.doi.org/10.1080/15732479.2016.1271813

CHAPTER 2 A UNIFIED DATA COLLECTION FRAMEWORK FOR QUANTITATIVE RESILIENCE ASSESSMENT OF ROAD TUNNELS

2.1 Abstract

Road tunnels often represent one of the most critical links in a transportation network. The performance and functionality of tunnels can significantly affect regional transportation network. It is common for major large tunnels to have a dedicated management crew and some level of data collection and monitoring during tunnel operation. There is currently no standard approach on how data should be collected for tunnel management, leaving available data from individual tunnels without standardization. While a uniform data collection framework for tunnel operation is not a necessity for individually managed tunnels, having such a standard will be of great value to the development of generalized data-driven tools to enable better tunnel management practices. A practical tunnel data collection framework is proposed in this study with the aim of enabling quantitative assessment of tunnel resilience. A simple user-oriented tunnel functionality and resilience metric is also suggested. The proposed framework is divided in categories associated with different aspects of the tunnel and the variability of the data over time. The proposed framework was compared with the management and data-collection practices at two major tunnels in Colorado, USA.

2.2 Introduction

Road tunnels are an important component in a transportation infrastructure. Tunnels play a similar role as bridges of connecting two points on a road across an obstacle such as a mountain, a river or urban infrastructure. Although tunnels are more costly to build, they do not create a visual obstruction, help in generating free space on the surface and usually are the shortest path in connecting two points spatially. The alternative by-pass for tunnels is typically long and inconvenient, making tunnels critically important to the efficient functioning of local transportation infrastructure. Hence, the continuous operation of tunnels at their design capacity and their quick recovery from disruptive events (i.e., tunnel resilience) is vital. In order to accurately assess tunnel performance and optimize design and management decisions to minimize losses, it is imperative to study a functionality of tunnels in a quantitative manner. Two fundamental steps must be taken in quantitative tunnel functionality studies. The first step is to systematically collect the tunnel performance data in a format that can be used to derive quantitative functionality metrics. Functionality metrics can then be used to quantify tunnel resilience against disruptive events such as accidents, malfunction of equipment or natural disasters. The ability to quantitatively assess tunnel resilience will enable the next step to investigate correlations between the tunnel design features and management decisions with its resilience metric. Such a study can be data-driven, which rely on large amount of realistic tunnel performance data collected, or simulation-based using computerized models.

Regardless of the approaches taken, a unified data collection framework for tunnel operation and performance is one of the most fundamental needs in streamlining resilience studies for tunnels. Currently, there is no such a baseline standard across different tunnels. Some modern tunnels have very comprehensive management and data collection systems built in as part of the physical tunnel infrastructure (e.g. State Route 99 Tunnel in Seattle was opened in 2019 has centralized

Supervisory Control and Data Acquisition (SCADA) system), while other older tunnels rely on hand-written notes to record events and disruptions. At the most fundamental level, while data collection is conducted in most of the large tunnels, there is no guideline on what type of data should be recorded and at what frequency.

In this study, in order to get a systematic quantification of tunnel performance, a baseline data collection framework was proposed for large (crew-operated) tunnels. The objective of the study is to address the question: "what is the minimum amount of information about a tunnel that should be collect to assess resilience or calibrate a simulation model?" In modern tunnels, while an owner/manager may be overwhelmed by the amount and types of data that can be collected daily, the focus should be put on data that is most relevant to the quantification of tunnel functionality. In this paper, a simple tunnel functionality metric is developed and applied to two example tunnels in Colorado, USA. to illustrate the gap between current practices and the proposed framework.

2.3   Literature Review

A large transportation tunnel is a very complicated system consisting of a range of inter-dependent geotechnical, structural, drainage, mechanical, and electronic systems. The functionality of these components/sub-systems will affect the functionality of the tunnel. Data collected based on individual tunnel component is useful but lacks uniformity because tunnels can be different regarding their components. It is difficult to come up with a generalized policy for data collection for all tunnels. In the following section, reviews were conducted of existing practices and recommendations on tunnel management and data collection, as well as literature related to resilience concept applied to tunnel systems.

2.3.1   Tunnel Data Collection Recommendations

Richards (1998) emphasized the usefulness of data for determining long term performance of tunnels. It was pointed out that well-structured tunnel inspection, maintenance and repair program should be put in place by inspecting the cost of maintenance, age and under-capacity of tunnels, water leakage, aggressive environments, tunnel lining and construction methods as part of data collection. Asakura and Kojima (2003) proposed a data framework for tunnel inspection to rationalize diagnosis methods and make informed decisions. Furthermore, that study proposed a maintenance strategy in which primary inspection is conducted every 2 years, detailed inspection is recommended every 10-20 years. These two studies were some of the earlier efforts emphasizing the need for data collection for tunnel operation and maintenance.

While there has not been any recommendation for tunnel data collection and management dedicated to resilience or functionality evaluation/prediction, there are a few data collection guidelines published by different agencies around the world. Some of the recommendations from the prominent agencies are given in Table 2.1. Since tunnel data collection has only gained some moderate interest recently, there are limited studies that utilized any of the collected tunnel data. Some of the example studies using collected tunnel data were summarized in Table 2.2.

Table 2.1. Existing recommendations on tunnel operation and maintenance data collection.

Agency (year)	Title	Data Type / Technique	Objective and Limitation/ Comments

PIARC committee on road tunnel operation C5. (2005)	Good practice for the operation and maintenance of road tunnels	• The report suggests:
		  ▪ Compiling database of maintenance data like repetition intervals, planned and incidental tasks.
		  ▪ Keeping historical record of data.
		  ▪ Application of statistical techniques to overcome lack of data
			Emphasis on data-based maintenance system to optimize operation and maintenance.
			
			The report does not propose the methodology for data acquisition.

PIARC technical committee C.4 – road tunnel operations (2012)	Recommendations on management of maintenance and technical inspection of road tunnels	• Maintenance strategy based on average cost of component per annum using statistical data (defining lifetime cost) of tunnel component
		• Inspection plan based on data collected from:
		  ▪ Technical manuals
		  ▪ Drawings and safety documents
		  ▪ Tasks and their intervention procedures.
		  ▪ Recording all equipment data with detailed description of interventions, defects and repairs
			Optimization of maintenance closure frequency and duration.
			
			The report does not consider the quantification of the impact of maintenance closures.

PIARC technical committee C3.3 road tunnel operations (2008)	Urban road tunnels recommendations to managers and operating bodies for design, management, operation and maintenance	• Collecting component specific failure data • Data Collection by research specialists to rate tunnel operation and services • Use SCADA data for tunnel maintenance • Provide tunnel closure recommendations	States challenges and recommendations of operation and maintenance in urban road tunnels considering urban traffic conditions.
FHWA (Federal Highway Administration, 2009)	Technical manual for design and construction of	• Recommends tunnel inspection database to be maintained • Data obtained from field book that comprises of: ▪ General information,	Covers major aspects of road tunnel like planning, design,

Agency (year)	Title	Data Type / Technique	Objective and Limitation/ Comments
	road tunnels-civil elements	▪ Defects in the tunnel components recorded in data forms and related photography or videos.	construction and rehabilitation. This manual is not specific for data collection of existing road tunnels.
US Department of Transportation (2015)	National Tunnel Inspection Standards (NTIS), Federal register (2015)	• The inventory data include the items related to: ▪ Tunnel identification, ▪ Age and service, ▪ Classification, ▪ Geometric, ▪ Structure type and material	Robust data collection on condition and operation of tunnels to prevent any structural, geotechnical and functional system failures. The standard specifically mentions the use of maintaining an inventory of the data for determining the time schedule and frequency of inspections and their priorities.
FHWA (Federal Highway Administration). (2015)	Specifications for the National tunnel Inventory (SNTI, 2015)	• Data in forms to record and maintain the inventory data • Inventory data with addition of the condition state of elements like: ▪ Electrical, ▪ Civil, ▪ Mechanical systems, ▪ Fire safety, ▪ Signs and ▪ Protective systems among other	Provides qualitative assessment of the condition of tunnel components. Based on recommendation given in NTIS. Basis for National Tunnel Inventory (NTI)
Colorado Department of Transportation (CDOT) (2018)	Colorado tunnel inventory & inspection manual	Similar to SNTI	Specifically adapted for Colorado tunnels.
FHWA (Federal Highway	Tunnel operations, maintenance, inspection, and	• Provide inspection data collection forms. • Define tunnel operations and emergency procedures	Provides a guide to tunnel operation, maintenance inspection

Agency (year)	Title	Data Type / Technique	Objective and Limitation/ Comments
Administration) (2015)	evaluation (TOMIE, 2015) manual	• Define maintenance activities and strategies Guidelines for developing tunnel inspection program. • Emphasis on a data-driven, risk-based approach to optimize performance	and evaluation. Based on NTIS recommendations. The inspection data will be recorded in NTI database.
German Tunnelling Committee (ITA-AITES), (DAUB) (2018)	Recommendations for the determination of lifecycle costs of road tunnels	• Use of manufacturer's data for: ▪ Repair and maintenance, ▪ Lifecycle cost of technical equipment • Data from available documents from various countries and international organizations include ▪ Germany, United Kingdom, Austria and Switzerland ▪ PIARC	Calculation of life cycle cost of tunnel comprising of maintenance and repair and operating costs for service life. Proposed an investigation framework for lifecycle cost analysis.

Table 2.2. Studies using operation and maintenance data.

Agency/ Author (year)	Document	Data details / Techniques	Comments
Transportation Research Board of The National Academies of Sciences, Engineering, and Medicine (2015)	NCHRP Report 816	• Assess the tunnel system for preservation actions • Proposes a metric for prioritizing preservation action • Use of qualitative ratings	Uses SNTI condition states for risk-based urgency score.
Transportation Research Board of The National Academies of Sciences, Engineering, and Medicine (2019)	NCHRP 14-27A	• Implementation of NCHRP Report 816	Cases study on CDOT tunnels
Hasan and Elwakil (2019)		• Assess the dummy patterns in NTI for predicting tunnel conditions using regression	

2.3.2 Tunnel Incident Database

While it is not clear how functionality loss events were recorded routinely for major tunnels in the past, there were a number of specific post-disaster study reports developed for some major tunnel

accidents (Khetwal et al., 2019) which led to a long-term closure (functionality loss) for large tunnels. For example, on July 10, 2006, a suspended ceiling panel collapsed on the roadway in the I-90 connector tunnel. This led to a fatality and the tunnel was closed for 6 months. The traffic had to be diverted from a longer route and this led to traffic delays and productivity loss. A similar event caused due to tunnel ceiling collapsed occurred in the Sasago Tunnel (2012) in Japan, leading to fatalities and long tunnel closures for repair and investigation. Similarly, fires in Gotthard (2001) and Mont Blanc (1999) tunnels which caused tunnel closures in the order of months including injuries and fatalities have been recorded extensively. Some of these major events have caused decision makers across the globe to develop recommendations for recording and analyzing similar incidents regardless of their magnitude. Some of these recommendations are listed in Table 2.3. In the past decade since the collection of incident data started, a few studies have taken place to find the likelihood (probability) of accident occurrences in road tunnels. Some of such notable studies are recorded in

Table 2.4.

Table 2.3. Existing recommendations for recording tunnel incident data.

Agency	Document title	Data details / Techniques	Objective and Limitations / Comments

PIARC committee on road tunnels (1995)	Road safety in tunnel	• Traffic data on basis of
		  ▪ Gradient,
		  ▪ Location,
		  ▪ Unidirectional or bi-directional
			To assess the accident rates used to provide safety measures

PIARC Technical committee C.4 – Road tunnel operations (2012)	Assessing and improving safety in existing road tunnels	• For performance and reliability assessment of mechanical and electrical equipment Data regarding incidents in tunnel • Traffic analysis, • Incident reports, • Interviews with key personnel	It is used to evaluate the effectiveness and relevance of emergency response plan
PIARC technical committee 3.3 – road tunnel operations (2009)	Tools for tunnel safety management	• Data regarding incidents in tunnel • A list is suggested to collect the minimum information of any incident with additional information in case of fire	To evaluate the frequency and causes of significant incidents for risk analysis caused due to different events like collision and fire

PIARC Technical committee 3.3 – road tunnel operations (2017)	Experience with significant incidents in road tunnel	• Local and network level data collection for tunnel incidents
		• Collection of data using different equipment like
		  ▪ CCTV,
		  ▪ Phone calls,
		  ▪ Radio communication along with the SCADA records.	

PIARC Technical committee C.3.3 –	Improving safety in road tunnels through real-time	• Real-time data collection from radio or traffic message channel	Improvisation in the safety measures

Agency	Document title	Data details / Techniques	Objective and Limitations / Comments
Road tunnel operations (2016)	communication with users	• Clear indication based on the severity of the situation is given to effectively utilize the communication system.	
PIARC committee on road tunnel operation (C 5) (2004)	Traffic incident management systems used in road tunnels	• Vehicle count and speed data, to detect fire incident and air quality and visibility • Cameras and closed-circuit video equipment (CCVE), • Fire detected using linear heat detection system, • Air quality is monitored using carbon monoxide, nitrous oxide and • Beam detectors are used for visibility.	To detect the traffic incident that causes slowdowns or possible damage to the tunnel structure. Data collection system does not provide closure time and quantitative estimation of traffic incident

Table 2.4. Studies using incident data.

Author (year)	Study objective	Data details	Other details
Kohl et al. (2014)	Upgrading Austrian Tunnel Risk Model TuRisMo	• Data collected on tunnel accidents and fires in Austrian road tunnels since 2006.	An update on the risk-based study to minimize risk due to accident and fires.
Ren et al. (2019)	Statistical analysis of tunnel fire accidents (TFAs) in China	• Data collected from: ▪ State Administration of Work Safety (SAWS), ▪ governmental query system, ▪ those reported by police, ▪ tunnel management center of freeway at different province, ▪ news archives and literature	Observed that no systematic official statistics data set is established
Naevestad and Meyer (2014)	Tunnel fire accidents in Norway	• Data from: ▪ Five Norwegian road traffic centrals' (RTS) system ▪ Road traffic central personnel ▪ Norwegian Public Road Administration (NPRA) personnel ▪ Fire services in municipalities and news archives	Found recorded data over represent heavy vehicle fires and subsea fires in Norway Observed that since, not all fires are recorded hence the literature representing major international tunnel fires shows more harm to people than actual
Casey (2020)	Analyze the fire safety performance of Australian road tunnels	• Data was obtained from Austroads tunnel task force (ATTF) that comprises of: ▪ Australasian Tunnel Operators Group (ATOG), ▪ Australian Tunnelling Society (ATS) and ▪ Australasian Fire Authorities Council (AFAC)	Data was collected for 11 tunnels with similar physical characteristics, at heavily trafficked urban locations and with similar fire safety features having 78 fire incidents.

2.3.3   Tunnel Resilience

Resilience is a concept widely adopted in hazard mitigation research to describe the ability of a system to recover its functionality from disruptive events. For civil structures, resilience of the

structure is its ability to restore its function at a certain service level after the occurrence of extreme events (Bocchini et al., 2014). Quantitative analysis of seismic resilience was conceptualized by Bruneau et al. (2003) through a quantitative metric, Q(t), defined to assess the functionality of the infrastructure. The capability of the system to minimize the loss of Q(t) after an event is termed as the seismic resilience. This concept can be illustrated using a "resilience triangle" shown in Figure 2.1. Attoh-Okine et al. (2009) proposed a resilience index of urban infrastructure using discrete belief function incorporating the strong interdependencies amongst them. Chang and Shinozuka (2004) suggested a probabilistic approach using loss of performance and length of recovery for evaluating resilience. For tunnel structure, there has only been very limited studies addressing resilience, even fewer assessing tunnel resilience quantitatively. A data-driven resilience approach is discussed in NCHRP synthesis 527 (2018) wherein data was collected from three distinct sources namely literature review, state department of transportation surveys, and case examples. The report suggested that insufficient data and lack of discrete framework make it difficult to justify the necessity of resilience mitigation measures. The analysis of tunnel resilience for fire by Rinaudo et al. (2016) used data that were readily available, although the source of the data was not mentioned, and collected by sensors installed along the tunnel cross section. Huang and Zhang (2016a); Huang and Zhang (2016b) used the measured convergence data to estimate the lifetime performance of tunnel lining under extreme surcharge. Overall, there is currently no consensus metric for tunnel functionality quantification, thus it is impossible to quantify the recovery of functionality, i.e. resilience for tunnels.
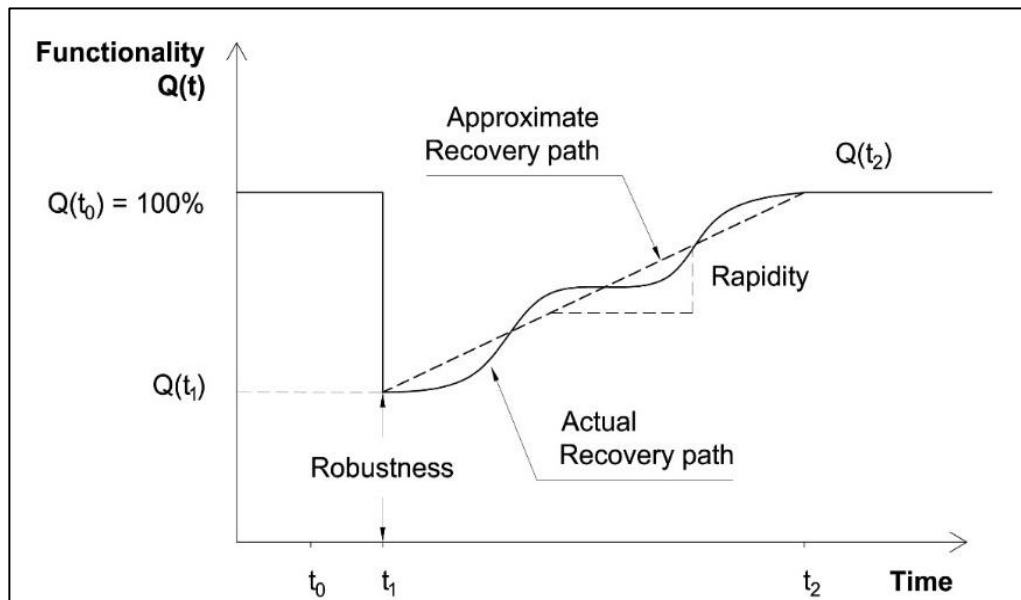
Figure 2.1. Resilience triangle.

2.4   Tunnel Functionality Metric

In this study, the functionality Q for any traffic tunnel is quantified as the ratio of available traffic capacity to the maximum design traffic capacity (Khetwal et al., 2019). The tunnel functionality metric has been calculated as:

$$Q(t) = \left(\frac{\text{\# of open lanes } (L_n(t))}{\text{Total \# of lanes } (L_{tot})} \right) \times \left(\frac{\text{Reduced speed limit } (S_n(t))}{\text{Normal speed limit } (S)} \right) \tag{2.1}$$

where $L_n(t)$ is the number of lanes that are open to traffic at time t, L_{tot} is the total number of lanes, $S_n(t)$ is the assigned speed limit in the tunnel at t, and S is the design speed limit for the tunnel, t is time, which signifies the time dependent nature of tunnel functionality.

This simple definition has several major advantages. Firstly, Q is solely a state of tunnel operation status independent of traffic condition. For example, a perfectly functional tunnel could have low vehicle pass rate during heavy traffic conditions caused by incidences miles away, such incidences should not be considered in tunnel resilience analysis. Secondly, the simple form of this metric enables the evaluation of tunnel functionality at any time with very basic monitoring data (speed limit and lane open condition), making it ideal as a baseline functionality metric. If a more comprehensive data collection plan is to be implemented, this simple metric can then be linked to other performance data types. Finally, this functionality metric is defined based on end-user experience, directly addressing the needs and experiences of the public utilizing tunnels, thus more relatable to the public. Once the functionality metric is defined, calculation of functionality loss and resilience can be conducted using recorded or simulated data. Figure 2.2 illustrates a hypothetical example of tunnel functionality curve during a planned inspection or repair activity with one Lane closure (partial closure of tunnel), in a unidirectional, 2 lanes tunnel. The key points that can be identified from the curve during the closure include:

a)   The whole tunnel is closed to set taper for crew safety (t_1).

b)   One lane opened with speed lower than the maximum allowable speed limit (t_2).

c)   The task, which causes closure, is performed (e.g., tasks like washing of walls, inspections, replacements, etc.)

d)   Both lanes of the tunnel are closed again for safety of crew while removing taper (t_3).

e)   The whole tunnel is opened with lower than normal speed (t_4) and then transitioned to normal speed (t_5).

The curve in Figure 2.2 represents the tunnel functionality (y-axis), which is a dimensionless unit (Q, in percentage), over time (x-axis). The shaded region with green hatch represents the resilience of the tunnel during the event which starts at time t_1 and ends at t_5. The sum of all the shaded regions between t_0 and t_n represent resilience (R_n) of the tunnel over a period of $t_n - t_0$. Where R_n is

$$R_n = \sum_{i=0}^{n} (t_{i+1} - t_i) \frac{Q_{i\_i+1}}{100} \tag{2.2}$$

The unit of resilience (Q – time) is unit of time (because Q is unitless). The weighted average functionality ($\bar{Q}$) over the duration of an event or period can also be defined as resilience index (Attoh-Okine et al., 2009), where $\bar{Q}_n$ for duration $t_n - t_0$ is

$$\bar{Q}_n = \frac{R_n}{t_n - t_0} \tag{2.3}$$

In case the tunnel system consists of more than one tunnel (multiple bores) then the combined resilience of the system can be calculated by considering all the lanes of the system as L_{tot}, the total number of lanes.
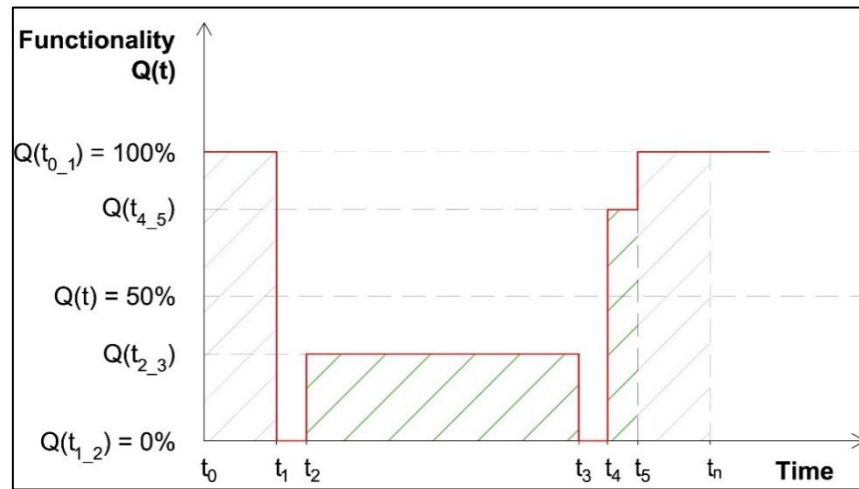
Figure 2.2. Functionality loss event in the tunnel versus time.

2.5   Tunnel Data Collection Framework

As demonstrated in the previous sections, while there are several studies and reports regarding suggestions on tunnel data collection for specific objectives in tunnel management, there is currently no uniform way to collect tunnel data to support functionality and resilience quantification. With most of major tunnels conducting case-specific data collection, the data sets resulted from these tunnels cannot be easily combined to support data-driven analysis approaches or calibrate simulation models for tunnel functionality/resilience assessment or prediction.

The first step towards systematic quantification of tunnel performance or functionality is to establish a "baseline" data structure that can be implemented in most tunnel operation management cases. The data structure (i.e., framework) is meant to support the assessment of resilience (a metric of functionality during a hazardous event), as well as to improve further data-driven analysis when more data becomes available.

Road Tunnel Data Collection Framework							
Category	Static Data		Dynamic Data		Functionality Data		
Type	General Information	Design / Construction	Operation	Maintenance	Events Details	Functionality Loss Data	Recovery Detials
Sub-Type	Identification Age Ownership	Geometric Data Geotechnical Data Structural Data Drainage System Data Electro Mechanical Systems Data	Tunnel Operation Details Traffic Details	Component Maintenance Detials Equipmet Replacement Details	Event Type Magnitude of Event Injuries / Fatalities	Lane Opening Information Speed Limit Information	Planning / Execution Detials Cost of Restoration

Figure 2.3. Schematic chart of a tunnel data collection framework.

This study proposes a tunnel data collection framework as shown in Figure 2.3. The data collection framework was developed considering end goal of quantifying resilience and tunnel functionality. Therefore, the data types included in the proposed collection framework include both the needed data for functionality metric Q(t) calculation and the physical management information about the tunnel that can potentially affect tunnel resilience. This framework can be divided into three categories, namely Static Data, Dynamic Data, and Functionality Data.

2.5.1   Static Data

Static data are defined as the design and configuration specification of the tunnel system that do not change over a long duration unless a major upgrade or retrofit happens. Static data can be categorized into general information, design parameter, and construction information. These data can be extracted from sources such as preliminary studies, design documents and as-build records. The amount of information in these documents could be immense. Although it is possible to have as much data as possible, the user should decide the level of details suitable for each project. The key objective is to achieve a level of detail that can later be used to assess the impact of different design decision on tunnel functionality.

Static data can be broadly divided into basic information and specific information. Most of the basic information, as shown in Table 2.5, is simple information about the tunnel attribute and systems that should be available for any tunnels. Basic information is usually constant over time and consists of tunnel geometric data, structural data, electromechanical system data, geotechnical setting of tunnel and regional transportation network setting. As an example, a basic set of static inspection data is readily available for all U.S. public tunnels in National Tunnel Inventory (NTI) based on Specifications for the national tunnel inventory(SNTI, 2015) and Tunnel operations, maintenance, inspection, and evaluation (TOMIE manual, 2015) as shown in Table 2.1.

Table 2.5. Static data: Basic tunnel information.

Type	Sub-Type	Data / Information
General Information	Identification	Tunnel Name; Location; Highway (NHS) or Road ID
	Age	Build Year
	Classification	Jurisdiction / Owner; Designer Contractor
Design / Construction	Geometry	Length; Finished Diameter (Width); Average Slope; No. of Bores; No. of Lanes per Bore; Vertical Clearance; Roadway Width; Sidewalk Width Right Side; Sidewalk Width Left Side; Cross Passage Spacing; Tunnel Shape; Portal Shape; Invert Shape
	Structural	Lining Type; Lining Thickness; Ceiling Type; Invert Lining Type; Invert Thickness
	Drainage	Waterproofing; Ground Water Drainage Capacity; Surface Water Drainage Capacity
	Electro-Mechanical Systems	Pumping System Capacity; Ventilation System Type; Fire Suppression System Type; Lightning Type; Power Supply # of Sources; Emergency Generator (Y/N); Data Acquisition System Type
	Geotechnical	Geological Ground Condition; Primary Support System; Excavation Methods

Static Data contain specific tunnel information including details of structural component, equipment and zoning. A tunnel component is defined as a semi-permanent element in a tunnel such as structural components or lining segment, which is often repaired if found defective; while equipment or device is a mechanical element that is generally replaced if it malfunctions. Specific information of tunnel components and equipment consist of details like number ID, service life, location, cost, etc. Furthermore, a tunnel can be divided into different zones based on management

decisions. Zoning helps in identifying the location in the tunnel and a subsequent zone-specific response by operator. All the static data/information provided a basis for the operation and maintenance of a tunnel. While Static Data is likely constant throughout the lifespan of the tunnel, it may change or require update in case of retrofitting or upgrade of elements. For example, upgrading of ventilation system of an old tunnel may result in change in the type or the number of ventilation components.

2.5.2   Dynamic Data

Dynamic data are defined as the operational parameters of tunnel that can be changed during the life of the tunnel due to change in environment or management decisions. This includes adoption of new technology (permanent major upgrade should be recorded as changes in Static Data), traffic demands, the deterioration condition of tunnel components, and tunnel operation and maintenance strategies. These data are time dependent and can be updated as changes happen. Some operational data are recorded more frequently, such as hourly traffic volume, while other data can only be updated through inspection, which may happen on yearly basis. Collection of Dynamic Data is a continuous process and is critical in understanding the impact of operational and maintenance strategies in terms of tunnel functionality.

Dynamic data can be broadly divided into operational data and maintenance data. The definition of maintenance and operation can depend on the management style of the tunnel, and its meaning varies from one country to another (Good practice for the operation and maintenance of road tunnels, 2005). A simplified approach is used in this study where, operational data is defined as the data collected related to tunnel operation on daily basis associated to trivial activities which are handled by the on-site tunnel operator requiring minimal technical expertise like tunnel wash or changing of light bulbs. Maintenance data is defined as the data collected during planned maintenance activities, such as inspection and repair activities which require experts and external contractors instead of the onsite tunnel crew. Table 2.6 listed some typical data types for dynamic data in roadway tunnels.

Table 2.6. Dynamic data: Operation and maintenance.

Type	Sub-Type	Parameter
Operations	Traffic	Average Daily Traffic; Hourly Traffic Volume; Direction of Traffic; Detour Length; Highway Speed Limit (at Tunnel Location); Tunnel Speed Limit; Highway Vehicle Spacing; Hazmat (Hazardous Material / Dangerous Goods) Restriction; Hazmat Restriction Removal Reason; Highway Settings (Alternate Route, Detour Length)
	Tunnel Operations	Operation; Operation Interval (months); Unit work; Number of units; Time taken per Team for Unit work (minutes); Number of Teams/ Staff; Closure Type; Activity Season (Time of year); Mean Closure Time (minutes)
Maintenance	Component Maintenance	Inspection Interval (months); Maintenance Interval (months); Initial Element Condition States; Inspection Time per Element (minutes); Rate of Deterioration (per month); Percentage of Element Repaired; Percentage of Elements Replaced; Time of Repair per unit (minutes); Time of Replacement per unit (minutes); Inspection Season (Time of year); Maintenance Season (Time of year); Inspection Closure Type (Partial/Full); Maintenance Closure Type (Partial/ Full); Inspection Teams; Repair Teams
	Equipment Replacement	Actionable Number of Failures; Time per Replacement per unit (minutes); Average Planning Time; Closure Type; Staff / teams;

As shown in Table 2.6, component maintenance data consist of inspection, repair and replacement information of the tunnel components and equipment. Inspection data of a component entails a record of the time of inspection, condition state (CS) of elements (Specifications for the national tunnel inventory (SNTI, 2015)), duration of inspection and type of tunnel closure. Rate of deterioration can be estimated by service life of component or by regression of previously recorded inspection data. Repair and replacement information is the record of the number or percentage of components repaired or replaced during a maintenance season. Further, the information states the number of teams / staff available, average time of repair/ replacement per unit and the type of closure involved (i.e., partial closure or full closure of tunnel).

Equipment replacement details contains maintenance information of the equipment and devices that cannot be repaired. This type of event occurs after a minimum (actionable) number of equipment fail. This event like other operation and maintenance event is planned. The data recorded also include key operation parameters such as the actionable (minimum allowable) number of equipment failures, average time taken to replace an equipment, average number of

days to plan the event after minimum failures, the number of teams /staff available for replacement and the type of closure to be done in case of equipment replacement. These parameters affect the resilience of the tunnel when an accident happens and can be changed depending on the resources dedicated to tunnel operations.

2.5.3   Functionality Data

Functionality data record any incident (planned or random) that affects the functionality of the tunnel. It is ideally organized and stored as individual events in time. Within each event record, the information can be sub divided into three types, namely event details, functionality loss data and recovery details. Typical data that can be recorded from these events are given in Table 2.7. Event details consists of type of event, its corresponding magnitude defining the impact on tunnel functionality and injuries/fatalities during the event defining societal impact. Magnitude of an event should be recorded because it will directly or indirectly relate to the duration and type of closure during an event. The lane closure times of tunnel during an event should be recorded, which can be used to calculation tunnel functionality loss and generate recovery curves.

Table 2.7. Functionality data details.

Type	Sub-Type	Parameter
Event Details	Event Type	Accident; Fire; Hazardous Material Release; Maintenance; Operation
	Magnitude of Event	Damage States; Duration of Alternate Route Closures (minutes); Number of Component/ Equipment Failures; Tunnel Partial Closure Time (minutes); Tunnel Full Closure Time (minutes); Total Duration of Closure (minutes)
	Injuries / Fatalities	Number of people injured or dead
Functionality Loss Data	Lane Opening Information	Number of Open Lanes
	Speed Limit Information	Reduced Speed Limit
Recovery Details	Planning / Execution Details	Contractor; Equipment; Manpower (Teams / Staff)
	Cost of Restoration	Cost of Repair; Economic Damage to Society

Additional information related to the events and consequences should be logged in functionality data under a separate category. This category might include planning/ execution details and cost of restoration. The planning / execution details consist of the contractor information, equipment used for recovery and manpower required including tunnel operation staff. While it is difficult to estimate the indirect financial loss to the entire society due to an event, as recording the direct cost of repair will be valuable to future decision making.

The data collection framework described here can serve as a powerful tool for tunnel owners and engineers to manage and assess tunnel functionality and resilience. Although most of large tunnels already have ad-hoc logging or traffic management systems which record the data described in the

proposed framework, it will take significant effort to implement a new data structure described. The challenges in implementing the proposed data collection framework using an example tunnel located in Colorado are demonstrated here. It can be shown that although it is possible to extract needed data for tunnel resilience assessment from an ad-hoc non-integrated data collection system, such effort is not scalable thus the situation necessitates some fundamental changes in the tunnel management community to collect better quality and easier-to-use data with this proposed framework in mind.

2.6   Example of existing data collection practice

2.6.1   On-Site Data Collection for an Existing Tunnel

In this study, the Eisenhower-Johnson Memorial tunnel (EJMT) located in Colorado, USA, is used as an example to demonstrate typical data collection practices in an existing large tunnel. EJMT consists of twin bore tunnel, serving Interstate highway I-70. Eisenhower bore was first opened in 1973 with a length of 2725 m and Johnson bore was opened in 1979 with a length of 2731 m. Most of the design and construction documents of the tunnel are from the 70's and kept as hard copy documents, with some been scanned electronically. The data related to organizational setup of the tunnel is available from CDOT, which include staff list and roles, as well as inventory of fixed and mobile equipment. The tunnel goes through regular inspection checks according to TOMIE Manual (2015), thus some of the Dynamic Data on components were recorded in the National Tunnel Inventory (NTI). Most of the Static data and a large portion of Dynamic data from early inspections are almost exclusively hard-copy documents that has never been digitalized until this study.

The daily operational data is recorded in form of manually generated logs. These logs were initially handwritten on logbooks. Recently (in 2018), EJMT management started to use excel spreadsheet to replace hard-copy logbook (the recording is still done manually by the onsite crew in three 8-hour shifts). Examples of the manually filled excel logs are shown in Figure 2.4. Information recorded in these log files include hourly traffic count, carbon monoxide readings, fan operation status and continuous flow metering. Most of the operation activities regarding the activities of the crew are also recoded in these logs. Further, recording of traffic interruption due to fire, accident and hazardous material are also recorded in the logs manually. These logs are based on visual monitoring via cameras, data collection via sensors and oral confirmation by the crew in the tunnel by phone.

COLORADO DEPARTMENT OF TRANSPORTATION EJMT TUNNEL OPERATIONS LOG					FAN OPERATIONAL STATUS																												Crew: "B"
Day : Mon. Date: 08.7.17	Traffic Count		CO Reading		North Tunnel																South Tunnel												
					East Ventilation Building								West Ventilation Building								East Ventilation Building						West Ventilation Building						
Time	North Tunnel WB	South Tunnel EB	North Tunnel WB	South Tunnel EB	Supply				Exhaust				Supply				Exhaust				Supply			Exhaust			Supply			Exhaust		
					1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	5	6	7	5	6	7	5	6	7	5	6	7
14:00					N	L	N	N	L	N	N	N	N	N	N	L	L	N	N	N	L	N	N	N	L	N	L	N	N	N	L	N
	1313	1456																															
15:00		2769	16	13																													
	1250	1792																															
16:00		3042	14	11																													
	1098	1448																															
17:00		2546	16	9																													
	904	1406																															
18:00		2310	12	10																													
	727	956																															
19:00		1683	14	11																													
19:30	706	710			N	L	N	N	L	N	N	N	N	N	N	L	L	N	N	N												
20:00		1416	18	9																													
	503	535																															
21:00		1038	13	11																													
	396	390																															
22:00		786	13	8																													
					N	L	N	N	L	N	N	N	N	N	N	L	L	N	N	N	L	N	N	N	L	N	L	N	N	N	L	N

EP: J. Quintana @ 1000 | WP: M.Kelly @ 1345 | R/E:D. Martinez CGW B.Trigg & R.Hemphill @1345 | CRO: Stf @ 1345

Time	Beginning Shift 10-13's	EP: +45DEG 4/5	WP:+49DEG Cldy 4/5
13:45	Relieved "C" crew, 50 mph both tunnels, EVB NT Sup & Ex 600s T, reservior 12'2", "Wat 4 Rox" "St Gr" "Trkr Spd 35" exit NT, OHs enabled, 213e VMS offline, E & W emer equip checked, MB#10 offline		
14:37	Trigg & Hemphill into NT supply duct to insulate downspout Sg. #156-#157./ 1450 Glycol recycled SW boiler rm, 1 bag btrash to dumpster		
15:08	EB hazmat Rawhide trk 12k Flam3 Ut 966ZR Mr. Northstrom denied./ 1530 S.Ludolph fini gather trash EVB fan deck & 10-42, 1qt oil #70003732./		
18:08	LRR occupied MB #1 NT & Chain Staion overview per JOA disp, 1qt oil./ 1826 906 10-42		
18:36 W5	*Semi stoppage NT R/L Zn#6, WB held,Quintana Trigg enroute./ *1841 WB rls 5mins, pulled out E. Wrecker, Platinum trk Il P947242, Blown radiator hose./		

Figure 2.4. Example logs from Eisenhower-Johnson Memorial Tunnel.

Because EJMT was constructed in 1970's, the tunnel does not have an automated equipment monitoring and data collection system such as SCADA. Recently in 2015, the tunnel was upgraded to include a modern fire suppression system which resulted in a separate monitoring system dedicated to fire equipment. Therefore, the integration of the sprinkler operation data (when activated) will have to be manually integrated with other parts of the operation data (e.g. fans). This presents a general challenge in older tunnels that went through separate upgrades.

For EJMT, almost all dynamic and function data was recorded in the log files but mixed. The issue with the manual log recording is the lack of consistency in the language, style, and level of details. It is understandable because the tunnel crew has changed over the service life of the tunnel and there is no standards for recording. There is no consistency on what should be recorded and how it should be recorded using what language. For example, in one instance partial closure of tunnel was mentioned but reopening of the lane was not recorded simply because it was not deemed important at that time. The log was generated as a voluntary practice in tunnel management; thus, the format of the recorded data is not developed with extensive datamining in mind. As a result, the data from these logs were very difficult to extract in large volume because every inquiry must be done manually. The authors extracted 4-month of functionality loss data from copies of handwritten logs from May to August of 2017 (Figure 2.5). Moreover, eight months of data from

September 2017 to April 2018 was extracted from excel log files. In addition, critical details such as lane closure and speed limit were missing in most of the cases. It is assumed that these stoppages/closures are complete tunnel shutdown in case of missing information, resulting in the functionality of the tunnel (Q) to be either 100% or 0%.

Eisenhower Johnson Mountain Tunnel (West Bound)									
Event No.	Date	Time of Closure	Time of Opening	Stoppage Time (min)	Tunnel Zone	Comments	Reason	Category	Hourly Traffic Count
1	1-May-17	6:00	6:08	8		Held	For Hazmat	9	355
2	1-May-17	7:00	7:09	9		Held	For Haz-mat	9	754
3	1-May-17	8:00	8:08	8		Held	For Haz-mat	9	785
4	1-May-17	9:00	9:06	6		Held	For Haz-mat	9	979
5	1-May-17	10:00	10:06	6		Held	For Haz-mat	9	961
6	3-May-17	2:48	2:57	9		Held	Clear icicles	7	87
7	3-May-17	6:36	7:11	35		Held	Rollback cleared, Fuel	1	676
8	3-May-17	23:30	23:34	4		Held	Set taper	2	186
9	4-May-17	1:00	1:05	5		Held	To knock down icicles	7	123
10	4-May-17	5:14	5:21	7		Held	Clear icicles again	7	248
11	5-May-17	1:47	1:57	10		Held	To clean cameras by hand	7	118
12	5-May-17	2:27	2:37	10		Held	To clean remaining cameras	7	95
13	5-May-17	23:55	23:58	3		Held	Set taper	2	256

Figure 2.5. Extracted information from the tunnel logs.

2.6.2   Colorado Traffic Management System (CTMS)

Specifically, in Colorado, there is another source of tunnel performance data for EJMT from a system not designed for tunnel data collection, but for the general highway system. CDOT's traffic management system CTMS is a web-based traffic data collection and management system launched in 2013, serving as a universal data management platform for CDOT. This system is used to report, respond to and manage accident events as it happens in real time. CTMS data is collected via sensors, cameras, radars, weather stations, vehicle tag readers, State patrol and CDOT crews that handle the accidents. The data structure in CTMS was designed with a focus on traffic incident reporting and resolution instead of focusing on infrastructure component. It is not dedicated for tunnel traffic but fits well with the function data collection objective proposed in the framework. Any event that causes disruption of traffic will initiate a record either by the monitoring crew or emergency responder. The management center will dispatch needed resources and crew to resolve the incident and keep updating the event record as more information becomes available. As the event gets resolved, the parties involved (e.g. contractor) are supposed to report necessary details (time, action taken, resources, etc.) back to CTMS to complete the event data, which gets saved in the CTMS database. An example of CTMS call log is shown in Figure 2.6. More conveniently, the CTMS system also records planned maintenance work and their impacts on traffic.

Direction	Roadway Closure	Event Type	Event Sub Type	Event Severity	Event Start Date	Event End Date	Partial Closure Duration	Full Closure Duration	Total Duration
West	Partial Closure	Planned Event	Road Work	**Moderate**	Apr 30, 2017 11:36:00 PM	May 1, 2017 9:30:00 AM	15 hours 3 minutes		9 hours 54 minutes
West	Partial Closure	Planned Event	Road Work	**Moderate**	May 2, 2017 1:47:00 AM	May 2, 2017 3:02:00 PM	13 hours 11 minutes		13 hours 15 minutes
West	Partial Closure	Planned Event	Road Work	**Moderate**	May 3, 2017 11:16:00 PM	May 4, 2017 5:00:00 AM	5 hours 44 minutes		5 hours 44 minutes
West	Partial Closure	Planned Event	Road Work	**Moderate**	May 5, 2017 11:39:00 PM	May 6, 2017 4:37:00 AM	4 hours 56 minutes		4 hours 58 minutes
West	Full Closure, Partial Closure	Incident	Accident	**Severe**	May 8, 2017 2:05:00 PM	May 8, 2017 3:44:00 PM	1 hour 14 minutes	9 minutes	1 hour 39 minutes
West	Partial Closure	Planned Event	Road Work	**Moderate**	May 11, 2017 2:55:00 AM	May 11, 2017 10:35:00 AM	7 hours 37 minutes		7 hours 40 minutes
West	Full Closure	Incident	Safety Closure	**Severe**	May 14, 2017 3:36:00 PM	May 14, 2017 5:58:00 PM		1 hour 51 minutes	2 hours 22 minutes
West	Partial Closure	Planned Event	Road Work	**Moderate**	May 17, 2017 10:58:00 AM	May 18, 2017 12:29:00 AM	13 hours 31 minutes		13 hours 31 minutes

Figure 2.6. Extracted CTMS data log of Eisenhower tunnel.

Because Eisenhower tunnel is part of the CDOT roadway system, the events happening in the Eisenhower tunnel are also recorded by the CTMS in this manner. Since 2013 (when CTMS system started), there are in total 3944 events associated with the Eisenhower tunnel (identified with the mileage marker information) till 2019. Out of these, 1607 events are recorded as incidents and 645 events as planned events.

Unintentionally, CTMS data is a good source for tunnel functionality loss and recovery data. However, the event data structure can still be improved to facility large-scale automated data extraction. For example, the event details also include many manually written entries on closure and reopen details, which must be extracted manually. It will be much easier if there is a system with searchable data keys for resilience related calculations (e.g., creating a table entry or tag to record lane closure and reopen time history that can be automatically queried). In addition, CTMS data does not include (in a synchronized manner) the dynamic data or equipment and component data recorded by the tunnel itself. Thus, the synchronization and correlation of tunnel operation data and functionality loss data will take extra effort and can only be done manually at this point.

2.7   Data Analysis: Eisenhower Tunnel (EJMT)

As it is clearly demonstrated in the previous section, the current data collection practice for EJMT is a result of historical practices and limitations on technology used. Even when advanced data management system like CTMS is used, there is no dedicated effort to adjust the system to make tunnel resilience data mining scalable and efficient. This is not anyone's fault as all these systems were set in place without a tunnel data collection standard or framework for reference. With that said, the following section described the procedure took in this study to extract the raw data embedded within the EJMT and CTMS records and re-organize them into the framework format proposed in this study. This practice will demonstrate that: (1) the data types proposed in the framework is not anything new that will require significantly more effort than what has been done

routinely for large tunnels (i.e. the data is already there); (2) once extracted, a quantitative analysis of tunnel functionality and resilience can be performed. Note that it is not ideal to conduct data extraction as demonstrated in this section because it is very labor intensive. It is the hope of this study to demonstrate the efficiency that can be achieved on tunnel data mining in the future if the proposed data collection framework were to be adopted.

2.7.1   Steps taken to extract EJMT Data according to Proposed Framework

Following steps were taken to extract and map data from the EJMT data sources (basic data, logs, CTMS) to the data categories outlined in the proposed framework:

Step 1: Basic tunnel information consisting of basic tunnel parameters such as tunnel geometry was collected from NTI database.

Step 2: Specific tunnel information about the tunnel was collected from available tunnel documents and information provided by tunnel operators. Further information like average service life of equipment and components were adopted from report provided by German Tunnelling Committee (DAUB).

Step 3: Hourly traffic volumes were provided in daily tunnel logs. Normal speed limits were recorded during site visits. Highway setting details like detour length and hazmat restrictions were extracted from NTI.

Step 4: Tunnel Operation Data was collected from the weekly operation schedule provided by the operator and data extracted from CTMS.

Step 5: Maintenance details consisting of component and equipment information like inspection and maintenance intervals and time of inspection were provided by the tunnel operator. Other details like conditions states were extracted from NTI.

Step 6: Event details like damage states were defined based on the tunnel data from CTMS. In case of rare events like large fires which occur a few times in the service life of the tunnel literature review of similar fires were considered. Closure intervals for various events were extracted from event data provided in CTMS and tunnel logs. Injury and fatality data were generally not available from CTMS.

Step 7: Lane closure data was mostly extracted from CTMS records. Reduced speed limits during events were sometimes recorded in CTMS data or in daily tunnel logs.

Details of recovery from event were currently not available. Some of the sources from where the Eisenhower tunnel data was collected were EJMT tunnel operator (CDOT), CTMS, National Tunnel Inventory (NTI) and other national databases for traffic, fire and accident, as shown in Table 2.8.

Table 2.8. Data collection sources.

Data Description	Type	Source (major sources)
General Information	Static Data	National Tunnel Inventory (NTI)
Design / Construction	Static Data (Basic Information)	National Tunnel Inventory (NTI)
Design/ Construction	Static Data (Specific Information)	Tunnel Operator (CDOT); German Tunneling Committee (DAUB)
Traffic Details	Dynamic Data	Tunnel Operator; NTI
Operation Details	Dynamic Data	Tunnel Operator; Colorado Traffic Management System (CTMS)
Maintenance Details	Dynamic Data	Tunnel Operator; NTI
Event Details	Function Data	Tunnel logs; CTMS; Literature review
Functionality Loss Data	Function Data	Tunnel logs; CTMS

In the end, from 2015 to 2019, a total of 5 years of data associated to EJMT was extracted from CTMS, resulting in approximately 400,000 minutes of partial closure (lane closure) and 10,000 minutes of full tunnel closure due to 477 recorded maintenance and operation activities. 54 accidents were recorded in CTMS during this period resulting in 2,305 minutes of closures. Furthermore, 6 fire events within the tunnel and 3 fire events near tunnel portal were recorded causing 748 minutes of closures. The fire and accident events are shown in Figure 2.7 and Figure 2.8, respectively, where the number of events on interstate I-70 are plotted against the mile markers (MM) containing the tunnel (MM 213.651–215.340). More fire events are noted to happen on the west side (WB) of the tunnel than east side (EB). Greater number of fire events occur inside and near the tunnel than on the tunnel approaches. Conversely, less accidents happen in the tunnel than the approaches. Since some of the events have occurred at the tunnel portals, some of them are

counted as incidents occurring at tunnel based on the proximity to the tunnel. This proximity was determined by reading the incident reports recorded in CTMS. Controlled removal of hazardous material restrictions (Hazmat events) which happen at the tunnel due to Loveland pass closure during heavy snowfall were not recorded explicitly in CTMS. This data was extracted from tunnel logs which contained 428 closures from May 2017 to April 2018 with total closure time of 2670 minutes. Since, one year of comprehensive data of all type of events was available so, a comparison of number of events and tunnel closures per year is shown in Figure 2.9.
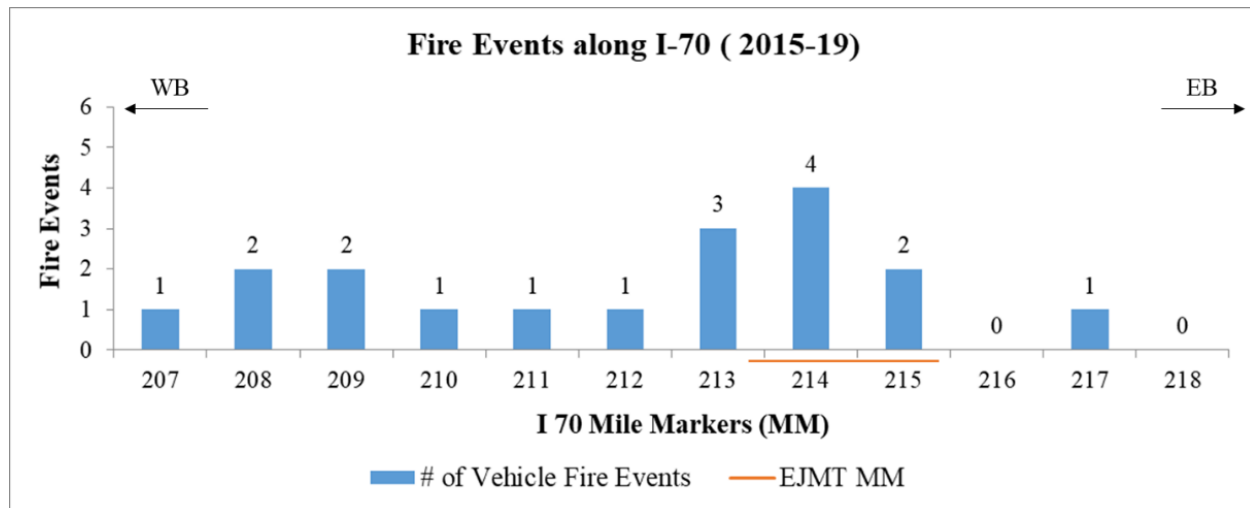
Figure 2.7. Fire events on I-70 along Eisenhower Tunnel over 5 years.
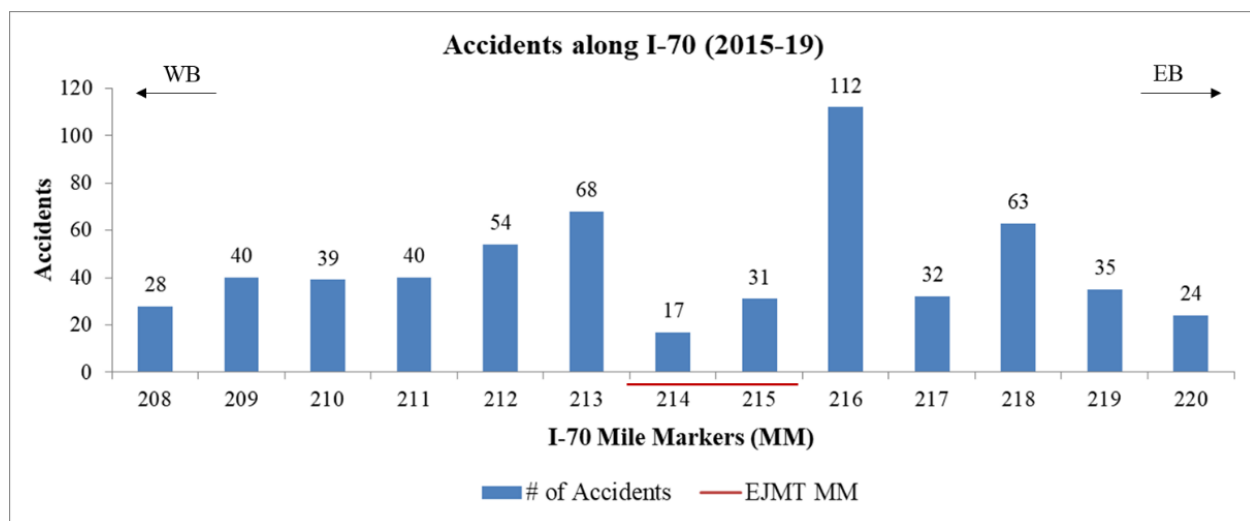
Figure 2.8. Accident events on I-70 along Eisenhower Tunnel over 5 years.
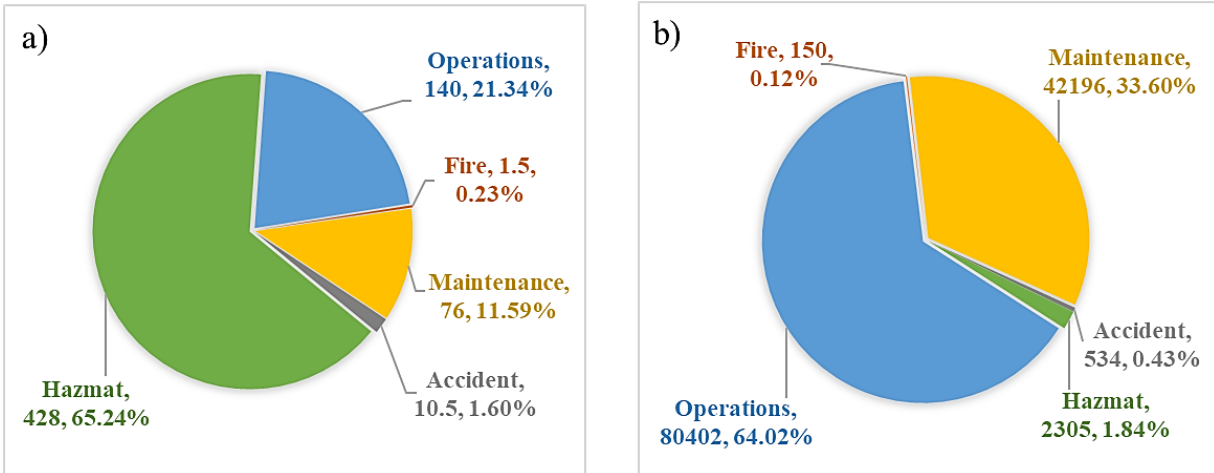
Figure 2.9. a) Number of events per year by type; b) Total time of closure due to events per year.

2.7.2 Preliminary Data Analysis Using Extracted Data

With the data extracted, very informative data sheets and plots that reveal interesting aspect of tunnel performance metrics can be generate. The functionality value for the event is based on the Q metric proposed in this study, by using equation (2.1). Since the tunnel system consist of 2 tunnel bores (Eisenhower and Johnson) functionality value was calculated accordingly.

Figure 2.10 shows tunnel functionality during a typical fire event at EJMT which occurred on September 4, 2019. This event was recorded in CTMS. Fire was detected on the eastbound tunnel on at 7:12 p.m. Both the tunnels were shut down. Once pedestrians who had crossed over by cross passages were evacuated from westbound tunnel, it was opened at 8:12 p.m. Left lane of eastbound was opened at 10:08 pm and right lane remained closed for further 19 minutes to check damage due to fire. All lanes were opened by 10:27 p.m. The tunnel resilience during this fire event spanning 195 minutes is 72.25 Q - mins thus the resilience loss is 122.75 Q - mins while the resilience index is 37%. The lower value of resilience index states higher functionality loss during the event.
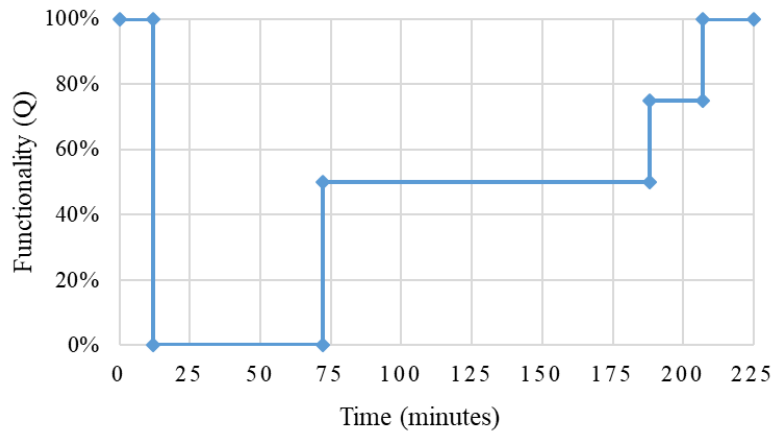
Figure 2.10.Example tunnel functionality history during a fire event at EJMT (September 4, 2019).

Figure 2.11 shows functionality of the tunnel during a single vehicle accident that occurred in the eastbound tunnel at EJMT on April 11,2019. Like the fire event this event was also recorded in CTMS. The tunnel was shut down as the accident was detected at 6:24 p.m. The vehicle was disabled in right lane with debris in the tunnel. Left lane was open at 6:45 p.m., with right lane closure for towing of vehicle. Both lanes were opened at 6:55 p.m. The tunnel resilience during the accident is 18 Q - mins with an event duration of 31 minutes thus the resilience loss is 13 Q - mins while the resilience index is 58%.
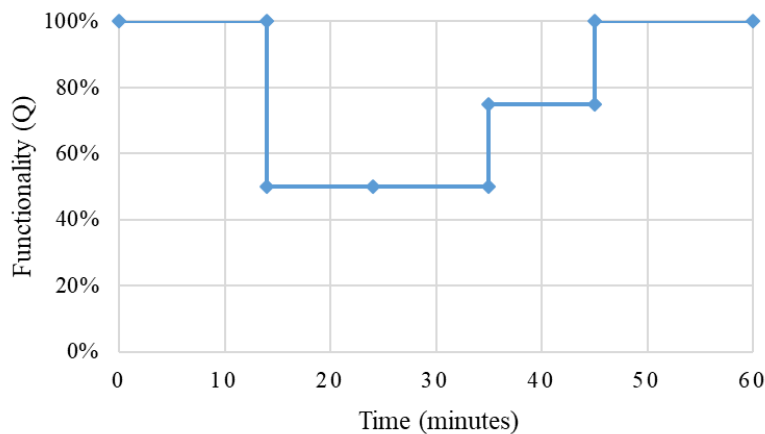
Figure 2.11.Example tunnel functionality history during an accident at EJMT (April 11, 2019).

Figure 2.12 represents a tunnel maintenance event of fire suppression testing in eastbound tunnel of EJMT starting on September 5, 2019. This was recorded as a planned event CTMS. Eastbound interstate highway I-70 was completely closed at 11:09 p.m. and the traffic was diverted through Loveland pass. After fire suppression testing was over at 5:03 a.m. on September 6, 2019 the crew started clearing the tunnel. By 5:31 a.m. right lane was cleared for traffic and by 5:37 a.m. both

lanes inside the tunnel was open. It is important to note the two lanes of north tunnel / westbound (Eisenhower tunnel bore) were always open during this event. Therefore, the tunnel system maintained a minimum functionality of 50% throughout the process. The tunnel resilience during the event is 195.5 Q – mins with an event duration of 388 minutes thus causing a resilience loss of 192.5 Q – mins with a resilience index of 50%.
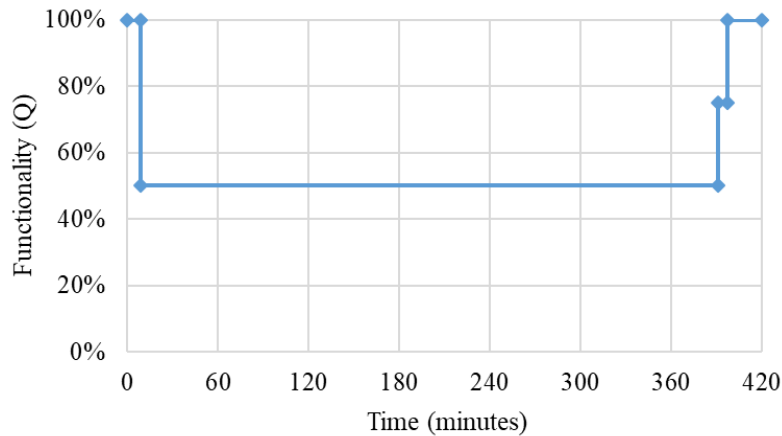
Figure 2.12. Example tunnel functionality history during a maintenance event at EJMT (September 5, 2019).

Full and partial closure in Table 2.9 means all lanes and single lane closure respectively of a tunnel bores which consist of two lanes each. Since it is a twin tunnel system full closure of single bore is equal to 50% functionality of the tunnel system (assuming the open bore is running at its maximum allowed speed limit). In case of partial closure of single bore, the reduced speed limit of the bore is assumed 80% (based on data from EJMT). Therefore, the functionality of the system is calculated to be 70%. Since, the functionality is different in case of different type of events, the impact of the event varies not only with the total time of closure but also with the value of tunnel functionality during the event. Random events like fire and accident occur rarely, as shown in Figure 2.9, but their resilience index, based on equation (2.3), is low as they cause longer full closures than partial closures. In contrast, operation events have high resilience index. Thus, even if the time of closure due to these events is longer their resilience loss is relatively low, as shown in Figure 2.13.

Table 2.9. Resilience loss due to events.

Event	Time Period	Number of Events	Partial Closure	Full Closure	Total Time	Total Resilience Loss	Overall Resilience Index
type	years	range	minute	minute	minute	Q - min	during events
Fire	5	6 - 9	229	519	748	328.2	56.1%
Accident	5	51 - 54	886	1419	2305	975.3	57.7%
Hazmat	1	428	0	2670	2670	1335	50.0%
Maintenance	1	76	34371	7825	42196	14223.8	66.3%
Operations	1	140	78762	1640	80402	24448.6	69.6%
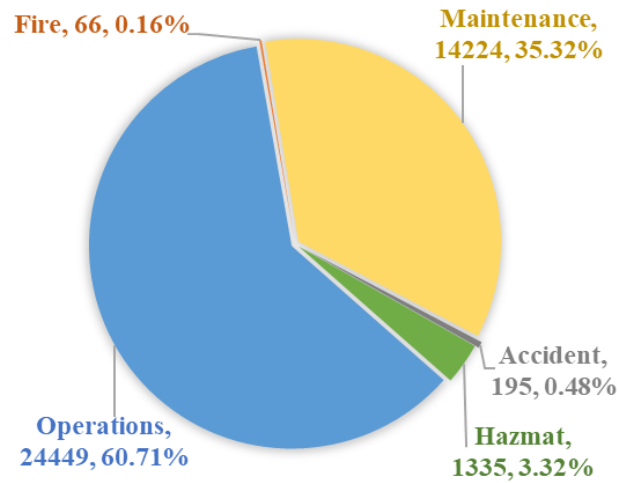
Figure 2.13.   Resilience loss per year by event type.

2.8   Conclusions

The United States has around 500 road tunnels (NTI). Approximately 80% of these tunnels are more than 30 years old. Apart from random disruptive events these tunnels are also impacted by long functionality loss events due to operation and maintenance. In this paper, a tunnel resilience metric was introduced to evaluate the functionality loss of tunnel due to various disruptive events. The simplicity of the metrics can be realized by the fact that by use of limited data it was possible to generate functionality charts for various events. Thus, calculating the functionality loss and resilience of the tunnel.

During the study it was established that the simple data to quantifying functionality loss is seldom collected. Therefore, in order to evaluate events with respect to the resilience of the tunnel it is necessary to collect tunnel data. Consequently, a tunnel data collection framework was developed to collect and store tunnel data that will assist in evaluating the tunnel resilience as a function of events. The larger goal of proposing the framework is to predict the loss of tunnel resilience in terms of various in tunnel parameters and strategies.

The data collected from the EJMT shows that the data is insufficient to understand the impact of events. In case of random events, the data sample is too limited to provide the real bounds of the impact that the events can have on the tunnel functionality. If a large event of some magnitude has not occurred in the small sample space, that does not mean that a large event cannot occur in the tunnel. Hence, it is important to look at the literature apart from the tunnel data to find the possibilities that can impact the tunnel. In case of operation and maintenance events the data recorded at the tunnel in operation logs and in system like CTMS do not match all the time. This incongruity in data collection makes it difficult to estimate the frequency and impact of operation and maintenance event on tunnel functionality. Hence, this framework provides a baseline for tunnel operators to bring uniformity in the data collection.

The next part of the research is to estimate the functionality loss by simulating the physical processes and operational procedures during and after disruptive events. This simulation will use the parametric information collected based on the tunnel data collection framework. Random samples of functionality loss parameters will be generated for various events. The distributions of these generated samples will be compared to the collected functionality loss data to validate the simulation model.

2.9   Acknowledgments

2.10   References

Asakura, T. and Y. Kojima (2003). Tunnel maintenance in Japan. *Tunnelling and underground space technology*, volume 18, pp 161-169

Attoh-Okire, N, O., Cooper, A.T., Mensah, S.A. (2009). Formulation of resilience index of urban infrastructure using belief functions. *IEEE systems journal*, volume 3, no. 2, pp 147-153. DOI: 10.1109/JSYST.2009.2019148

Bocchini, P., Frangopol, D. M., Ummenhofer, T., Zinke, T. (2014). Resilience & Sustainability of Civil Infrastructure: Toward a Unified Approach. *Journal of Infrastructure Systems* 20(2), 1–16.

Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O'Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A., Von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra* 19(4), 733–752.

Casey, N. (2020). Fire incident data for Australian road tunnels. *Fire safety journal*, volume 111, pp 1-11. https://doi.org/10.1016/j.firesaf.2019.102909

CDOT (Colorado department of transportation). (2008). *Colorado 2035 Statewide Transportation Plan: Intelligent Transportation System (ITS) Technical Report*: CDOT.

CDOT (Colorado department of transportation). (2018). *Colorado tunnel inventory & inspection manual*: CDOT.

Cedergren, A. (2011). Challenges in Designing Resilient Socio-technical Systems: A Case Study of Railway Tunnel Projects. *Resilience Engineering Symposium*, 2011

Chang, S. E., Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. *Earthquake Spectra* 20(3), 739–755.

DIN EN 13306. (2018). *Maintenance – maintenance terminology*. Beuth Verlag, Berlin.

FHWA (Federal Highway Administration). (2015). *Federal register*. Volume 80, No. 134, part V, Washington D.C.: FHWA.

FHWA (Federal Highway Administration). (2015). *Specifications for the national tunnel inventory (SNTI)*. (Publication no. FHWA-HIF-15-006). Washington D.C.: FHWA

FHWA (Federal Highway Administration). (2009). *Technical manual for design and construction of road tunnels-civil elements*. (Publication no. FHWA-NHI-10-034). Washington D.C.: FHWA.

FHWA (Federal Highway Administration). (2015). *Tunnel operations, maintenance, inspection, and evaluation (TOMIE) manual*. (Publication No. FHWA-HIF-15-005). Washington D.C.: FHWA

German Tunnelling Committee (ITA-AITES) (2018). *Recommendations for the determination of lifecycle costs of road tunnels*, Cologne, Germany: DAUB.

Hasan, S. and Elwakil, E. (2019). Cluster based regression modeling for predicting condition rating of highway tunnels. *CSCE annual conference, Growing with youth*, Laval, Greater Montreal, June 12-15, 2019, pp 305-1-305-10

Huang, H. and Zhang, D. (2016a). Resilience analysis of shield tunnel lining under extreme surcharge: characterization and field application. *Tunnelling and underground space technology*, volume 51, pp 301-312

Huang, H. and Zhang, D. (2016b). Resilience of operated tunnels under extreme surcharge: field study. Japanese geotechnical society special publication. *The 15th Asian regional conference on soil mechanics and geotechnical engineering*, pp 1492-1496. http://doi.org/10.3208/jgssp.ATC6-06

Khetwal, S.S., Pei, S., Gutierrez, M. (2019). Operational resilience of traffic tunnels: An example case study. In: Proceedings of the *WTC 2019 ITA-AITES World Tunnel Congress*, Naples, Italy, May 3-9 (2019).

Khetwal S., Pei S., Gutierrez M. (2020) A Data-Driven Approach for Direct Assessment and Analysis of Traffic Tunnel Resilience. In Correia A., Tinoco J., Cortez P., Lamas L. (eds) Information Technology in Geo-Engineering. *ICITG 2019*. Springer Series in Geomechanics and Geoengineering. Springer, Cham, pp. 168-177.

Kohl, B., Forster, C., Weisholzer, S. (2014). Upgrading of the Austrian tunnel risk model TURISMO – Methodical and practical aspects. *7th International Conference on Tunnel Safety and Ventilation*, Graz, pp 170-179

Manca, D. and Brambilla, S. (2011). A methodology based on the analytic hierarchy process for the quantitative assessment of emergency preparedness and response in road tunnels. *Transport policy*, volume 18, pp 657-664. doi:10.1016/j.tranpol.2010.12.003

Nævestad, T.O. and S. Meyer (2014). A survey of vehicle fires in Norwegian road tunnels 2008–2011. *Tunnelling and Underground Space Technology*, 41(1), pp 104–112.

NCHRP 14-27A. (2019). *Implementation of report 816: a guide for the preservation of highway tunnel systems,* Gannett Fleming, Inc., Camp Hill P.A..: Transportation research board

NCHRP Synthesis 527. (2018). *Resilience in transportation planning, engineering, management, policy, and administration*, Washington D.C.: Transportation Research Board.

NCHRP Report 816. (2015). *Guide for the preservation of highways tunnel systems*, Washington D.C.: Transportation Research Board

PIARC Technical committee C.3.3 – Road tunnel operations. (2016). *Improving safety in road tunnels through real-time communication with users*, Cedex, France: World Road Association (PIARC)

PIARC Technical committee 3.3 – road tunnel operations. (2017). *Experience with significant incidents in road tunnels*, Cedex, France: World Road Association (PIARC)

PIARC Technical committee C.4 – Road tunnel operations. (2012). *Assessing and improving safety in existing road tunnels*, Cedex, France: World Road Association (PIARC)

PIARC technical committee C.4 – road tunnel operations (2012). *Recommendations on management of maintenance and technical inspection of road tunnel*, Cedex, France: World Road Association (PIARC)

PIARC committee on road tunnels (1995). *Road safety in tunnels*, Cedex, France: World Road Association (PIARC)

PIARC technical committee 3.3 – road tunnel operations (2009). *Tools for tunnel safety management*, Cedex, France: World Road Association (PIARC)

PIARC committee on road tunnel operation (C 5) (2004). *Traffic incident management systems used in road tunnels*, Cedex, France: World Road Association (PIARC)

PIARC committee on road tunnel operation C5. (2005). *Good practice for the operation and maintenance of road tunnels*, Cedex, France: World Road Association (PIARC)

PIARC technical committee C3.3 road tunnel operations (2008). *Urban road tunnels recommendations to managers and operating bodies for design, management, operation and maintenance*, Cedex, France: World Road Association (PIARC)

Richards, J.A. (1998). Inspection, maintenance and repair of tunnels: international lessons and practice. *Tunnelling and underground space technology*, volume 13, no.4, pp 369-375.

Rinaudo, P., Paya-Zaforteza, I. and Calderon, P.A. (2016). Improving tunnel resilience against fires: a new methodology based on temperature monitoring. *Tunneling and underground space technology*, volume 52, pp 71-84.

Zhang, W., Sun, K., Lei, C., Zhang, Y. and Li, H. (2014). Fuzzy analytic hierarchy process synthetic evaluation models for the health monitoring of shield tunnels. Computer-aided civil and infrastructure engineering, volume 29, pp 676-688. DOI: 10.1111/mice.12091

CHAPTER 3 STOCHASTIC EVENT SIMULATION MODEL TO QUANTITATIVELY PREDICT ROAD TUNNEL DOWNTIME

3.1   Abstract

Given the importance of road tunnels in a transportation network, it is essential to quantitatively assess and predict functionality loss of tunnels due to disruptive events. In this study, a stochastic event simulation model was developed to evaluate the resilience of tunnel infrastructure, quantified using a functionality metric as a function of loss in traffic capacity and its duration. The model consists of individual modules to account for disruptive events that cause tunnel closures. In this paper, the mechanism and probabilistic models used for each simulation module are presented. A simulation for Eisenhower tunnel, Colorado, was conducted using the proposed method as a validation case-study. The results showed that the proposed model could simulate realistic tunnel operation status. While the validation was made for a specific tunnel, the model was designed to be applied to the resilience analysis of any road tunnel once their design and operation parameters are defined.

3.2   Introduction

A road tunnel will experience numerous functionality loss events (i.e., partial or complete shutdown) during their service life. A functionality loss event was defined in this study as any event that causes a decrease in the tunnel's ability to accommodate traffic. Some of these disruptive events randomly occur while others may be planned maintenance. Given the importance of tunnels in road transportation infrastructure, it is essential that a tunnel effectively operates at its design through-pass capacity and can recover quickly from disruptive events (i.e., high level of resilience). There has been a recent emphasis on tunnel asset management to record the details of events happening in the tunnel and use these data to improve the efficiency of the tunnel. Despite this interest, there is a lack of systematically collected tunnel performance data that encompasses all aspects of functionality loss events. Even when such data can be extracted from large tunnel operational data recordings, it is challenging to conduct sensitivity analysis on tunnel resilience without a model for tunnel functionality loss. Therefore, a stochastic simulation model to predict tunnel functionality over time was developed in this study through simulation of individual disruptive events, their occurrence, and severity, and the efforts need for tunnel functionality recovery. This simulation tool can be used as a guide to decision making related to tunnel design, management, and maintenance.

Tunnel functionality loss events have a variety of randomness associated with them. The occurrence of accidents and equipment malfunction can be modeled as probabilistic events dependent on tunnel design and traffic conditions. The magnitude of disruptive events also varies greatly. Planned maintenance or management events (e.g., tunnel inspection, cleaning, or hazardous vehicle platooning) are more predictable but still have uncertainty associated with their duration and level of traffic disruption. Engineers and owners need to understand how different design and management decisions can affect the occurrence and impact of all these events over the tunnel's service life. Because any change in tunnel design (through retrofit) or management can potentially be very costly, it is beneficial to develop a simulation method for predicting tunnel resilience under various potential design and management scenarios. This can be accomplished by

combining all significant contributors to tunnel functionality loss using existing probabilistic simulation tools. While the concept of such a simulation framework is not novel by itself, there has not been any comprehensive and generalized procedure to simulation tunnel resilience in the existing literature. This provided the impetus of this study.

In this study, significant events impacting the tunnel functionality were shortlisted based on their duration and intensity. Key parameters affecting these events were identified, including intrinsic parameters (e.g., the geometry of the tunnel, type of tunnel equipment and component, the operation and maintenance strategies, etc.) and extrinsic environmental parameters (e.g., vehicle type composition of the through traffic, the average frequency of accidents on the highway segment, etc.). Several simulation modules were developed to compute the number of events in a given time and the duration of these events and closures. These modules were then combined to calculate a comprehensive functionality loss history over a predefined period. A detailed description of the modeling mechanism of these modules was introduced in the following sections. Eventually, this model is validated through a comparative study using five years of realistic tunnel operation and functionality data from the Eisenhower Johnson Memorial Tunnel (EJMT) located in Colorado, USA.

3.3   Literature Review

While it is difficult to identify any study that explicitly aims at predicting or simulating tunnel downtime, several studies provided data and insight on disruptive events in tunnels. Accurate modeling of the frequency of disruptive event occurrence and their impacts on tunnels is an essential first step for tunnel resilience prediction. There are works of literature on tunnel fire and accident, most of which aimed at estimating the frequency of event occurrence through either a probabilistic prediction model or direct estimation using recorded data. There are also other types of functionality loss events that have not been studied in the past. These include platooning of Hazmat vehicles through the tunnel when alternative routes for these trucks are closed due to weather. Several accident and fire studies related to tunnel functionality loss were referenced in this study, with their brief information outlined in this section.

Caliendo et al. (2013) developed a model to estimate the frequency of accident occurrence, using the Italian road tunnel data collected from 2006 to 2009. Earlier, Caliendo and De Guglielmo (2012) had used the same data to compute the average rate of accidents in road tunnels. Amundsen and Ranes (2000) calculated accident rates in a road tunnel and showed that the accidents vary within the tunnel. Kohl et al. (2014) based on the data collected form Austrian road tunnels, estimated a rate of collision and speed of fires initiated by collision.

Nævestad and Meyer (2014) studied the tunnel fire data in Norway collected between 2008-2011 to describe fire characteristics. Rattei et al. (2014) compares the vehicle fire dataset to the accident dataset from Austria and computes vehicle fires, the rate of fire from spontaneous ignition, and accident. Nelisse and Vrouwenvelder (2016) calculate the probability of a massive fire in road tunnel based on statistical data collected in the Netherlands. Ren et al. (2019) did a statistical analysis of the tunnel fire data collected in China. They found out the percentage of causes of fire, seasonality of fire events, fire percentage by type of vehicles involved, and frequency of fire. Casey

(2020) analyzed the performance of Australian road tunnels in terms of fire frequency and the response to the fire by the operator. Tunnel fire data form reports by PIARC (Design Fire Characteristics for Road Tunnels, 2017), National Fire Protection Association (NFPA) (NFPA 502, 2017), Ingason (2003), and NCHRP Synthesis 415: Design Fires in Road Tunnels (Maevski, 2011) were referenced to estimate the magnitude and damage caused due to fire.

Another reason for tunnel functionality loss was partial or full closure of tunnel traffic for necessary maintenance and inspection operations. Most of the studies in tunnel operation and maintenance are associated with life cycle cost estimation. Some studies are related to specific tunnel components, like tunnel lining deterioration. Lastly, many research efforts were focused on maximizing efficiency and accuracy through the use of new technology for inspection (Montero et al., 2015). Richards (1998) emphasized the importance of inspection, maintenance, and repair in the tunnel due to lining deterioration but the critical aspect which was pointed out is the tunnel outage (functionality loss) due to inspection, maintenance, and repair. Mashimo and Ishimura (2006) suggest that the inspection intervals should be evaluated and decided based on quantitative data. The report, Good practice for the operation and maintenance of road tunnels (2005) recommends collecting operation and maintenance data and using statistical techniques to overcome the lack of data. Still, it does not explain how to do it. To the authors' knowledge, no study has yet simulated the tunnel maintenance occurrence for different components and equipment in a single integrated model. Although there are some studies related to tunnel maintenance, no analysis has been found for routine tunnel operation activities, like tunnel washing, drainage cleaning, etc., let alone operation simulation. In this study, any event that will affect tunnel functionality is comprehensively considered in predicting tunnel functionality loss (outages or downtime), whether the event was random or planned.

Because this study aims at quantitatively predicting tunnel functionality, a numerical metric for tunneling functionality must be defined first. The author adopted a tunnel functionality metric from a previous study (Khetwal et al., 2019) that can be calculated as:

$$Q(t) = \left(\frac{\# \text{ of open lanes } (L_n(t))}{\text{Total \# of lanes } (L_{tot})} \right) \times \left(\frac{\text{Reduced speed limit } (S_n(t))}{\text{Normal speed limit } (S)} \right) \qquad (3.1)$$

where $L_n(t)$ is the number of lanes that are open to traffic at time t, L_{tot} is the total number of lanes, $S_n(t)$ is the assigned speed limit in the tunnel at t, and S is the design speed limit for the tunnel, t is time, which signifies the time-dependent nature of tunnel functionality. The simplicity of this metric makes it easy to be recorded by the tunnel operator. Further, this metric is independent of traffic conditions. It just presents the state of the tunnel defined by the traffic volume, which the tunnel can support at a given time. Note that this metric is intrinsic to tunnel design parameters and operational status (i.e., a maximum possible through-traffic capacity), rather than the actual traffic pass-through rate, which can be affected by overall road conditions outside of the control of tunnel designers and operators.

3.4   Simulation Methodology

The objective of this study is to develop a Monte-Carlo type probabilistic simulation model that will generate functionality loss events and corresponding tunnel closure duration. To achieve the goal, major functionality loss events occurring in tunnels are simulated, including traffic accidents,

fire, hazmat platooning (grouping a number of hazmat trucks and guide them cross tunnel while stopping regular traffic temporarily), maintenance activities (inspection, repair, and replacement of tunnel components, replacement of equipment) and routine tunnel operations (e.g., tunnel wash, road sweeping, washing lights, drainage cleaning, etc.). These events can be divided into two groups.

The first group is called random events as their occurrence cannot be planned but can only be statistically estimated. These are accident, fire, and hazmat platooning. Random events induced functionality losses can vary significantly. A vehicle fire has a very low chance of occurrence in the range of a few events per year, but each event can have a large impact. In contrast, hazmat restrictions lifting (hazmat platooning), based on alternate route closures, has high frequency annually, but the duration of closures per event is relatively small. If a longer period like 5 to 10 years is considered, both the events might have a similar total impact on tunnel resilience. This can be seen from Figure 1, which presents data from EJMT for 5 years from 2015 to 2019 as an example showing resilience loss per event for necessary event type based on their occurrence and impact.

The second group of events is the operation and maintenance of the tunnel, which occur based on some level of planning and active management. These events can be termed as planned events, although some aspects of their occurrence and severity are related to random factors such as deterioration of tunnel components and equipment. Additionally, the magnitude of the events can also vary due to reasons like availability of personnel, parameters of components, equipment to be maintained, and operation activity.
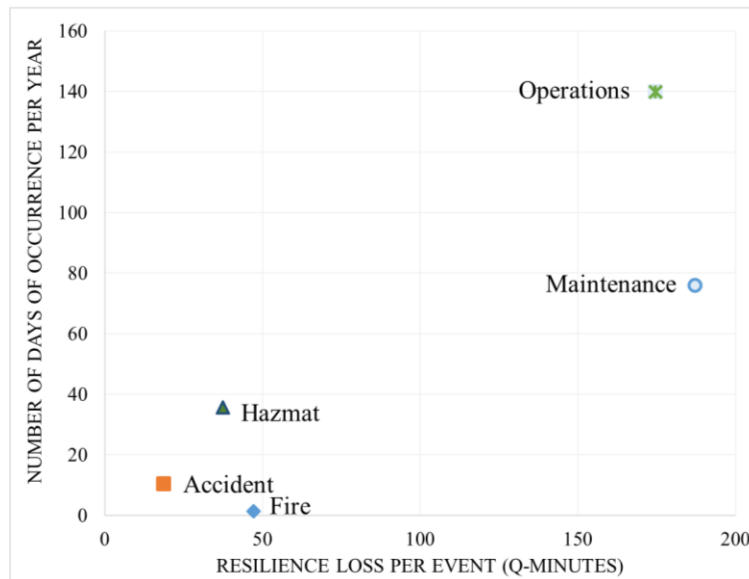
Figure 3.1. Frequency and impact of functionality loss events based on example tunnel data.

The simulation methodology to generate these events and their impacts contains several steps. The first step is to develop a probabilistic occurrence model with parameters that can be estimated

using readily available data (e.g., traffic data from the highway, equipment deterioration data from history, etc.). These probabilistic models can be implemented using Monte-Carlo simulation to generate event occurrence for the time duration of interest. If the event occurs, the second step is to simulate the magnitude of the event based on another probability model, given the characteristics of the event. This can typically be idealized as a conditional probability function given the nature of the event. Finally, the event duration and impact in terms of tunnel functionality loss can be estimated by knowing the magnitude of the event through a fragility function. The detailed methodology used in developing major event types is presented below.

3.4.1 Traffic accident and fire events

Accidents and fire in a road tunnel are randomly occurring disruptive events, causing functionality loss of the tunnel. In this study, both events were modeled using a similar method. The first step is to model the frequency of event occurrence. The basic assumption applied for this step is that the probability of events on any segment of the highway (including tunnels) is related to the time of the day and season (e.g., accidents are more likely during night hours). This relationship can be expressed in terms of probability of event occurrence as:

$$P_T(t) = P_H \times \chi(t) \tag{3.2}$$

where P_T is the time-dependent probability of an accident or fire event in the tunnel per hour, P_H is the random variable for the annual probability of a vehicle in accident or fire event on the highways (this overall rate for the US interstate is available), $\chi(t)$ is a time-dependent random variable generated as the product of vehicles count at the tunnel in an hour (NV) and the weighted probability of an event by month, day and hour at the tunnel.

The values of the dataset used for probability distribution fitting for the random variable P_H is calculated for each year between 2004 and 2018 using data set of VMT (vehicle – miles traveled per year) by all vehicles on a highway in the United States, (data: Highway Statics Series), AVS (miles/hour) which is average vehicle speed on the United States highways that year (data: National Traffic Speeds Survey), A_H that is the number of crashes on all interstate highways (in the US) per year (data: Fatality and Injury Reporting System Tool), and F_H is the number of vehicle fires on all highways per year (data: National Fire Protection Association), respectively, for accident and fire. The value of P_H is calculated by using parameter V_{use} , which is the average number of vehicles in use on all highways at any given time over the year, and A_H or F_H in case of accident or fire, respectively.

$$V_{use} = \frac{VMT}{AVS\left(\frac{365 \times 24 \ hr}{year}\right)} \tag{3.3}$$

$$P_{H_A} = \frac{A_H}{V_{use}} \tag{3.4}$$

$$P_{H_F} = \frac{F_H}{V_{use}} \tag{3.5}$$

where the suffixes A and F correspond to accident and fire, respectively.

Furthermore, a discrete random variable, NV, must be estimated to calculate $\chi(t)$. The mean or rate parameter (λ_{NV}) of Poisson distribution for NV changes with traffic volume arriving at the tunnel (TV) in a given hour. TV is a time-dependent random variable that follows a Nakagami distribution. This distribution is chosen as the best fit for the traffic volume data at the tunnel recorded over a year. Its parameters vary with time depending on the hour of the day and the day during a week. NV is also dependent on TL, the tunnel length (in meters), and HL, the length of the highway (in meters) on which the hourly traffic volume at the tunnel is spread. λ_{NV} is estimated as

$$\lambda_{NV} = \frac{NB \times TV \times TL}{(HL + TL)} \tag{3.6}$$

where

$$HL = 1000 \left(1 - \left(\frac{TL}{1000}\right) \frac{1}{SLT}\right) SLH \tag{3.7}$$

In equation (3.6), NB is the number of tunnel bores, and in equation (3.7), SLT is the traffic speed limit inside the tunnel (km/h), and SLH is the traffic speed limit on the highway (km/h) containing the tunnel. Finally, using NV, $\chi(t)$ for accident ($\chi_A(t)$) and can be estimated as:

$$\chi_A(t) = \frac{NV(t) \times M_p \times Hr_p}{Days\ in\ the\ month \times 12 \times 24} \tag{3.8}$$

where $M_p/12$ is the weighted probability for accidents occurrence by month, $Hr_p/24$ is the weighted probability for accidents occurrence by the hour. These weighted probabilities are estimated using the accident occurrence data along a segment of the highway containing the tunnel. $\chi(t)$ for fire ($\chi_F(t)$) can be estimated as:

$$\chi_F(t) = \frac{NV(t) \times M_{pf} \times Dow_{pf} \times Hr_{pf} \times 12}{365/7} \tag{3.9}$$

where M_{pf} is the weighted probability for fire occurrence by month on a highway, Dow_{pf} is the weighted probability for fire occurrence by day of the week on a highway, Hr_{pf} is the weighted probability for fire occurrence by hour on a highway. In this study, the weighted probabilities were taken from data published by the United States Fire Administration (USFA).

Generally, the time needed to recover from an accident is dependent on the number and size of the vehicles involved in the accident. This is due to the amount of towing required in the clearing and re-opening of the tunnel. Accordingly, the parameter associated with the magnitude of an accident is the total weight of the vehicles. Further, it is observed that the accident clearing time can be significantly affected by the type of vehicle and whether the vehicles rollover or not. Therefore, instead of the total weight of vehicles, their effective weights are calculated (considering only partial weights of the upright vehicles in the accident) that serve as the parameter to define the magnitude of the accident. This information was extracted from the 'Fatality and Injury Reporting System Tool' (NHTSA, version 2.0.1, 2020). In this study, the vehicle weight was assumed to follow Gamma distribution with two parameters (Table 3.1) that were determined by fitting the

probability distribution to the vehicle weight ranges by vehicle class as described by Federal Highway Administration (FHWA). The rollover of a vehicle was assumed to follow a Bernoulli distribution, the probability of which is given in Table 3.2.

Table 3.1. Vehicle weight by vehicle type.

Vehicle type	Weight range	Gamma distribution parameters	
	(kg)	α	θ
Small passenger car	1200 - 1800	300.0	5.0
Passenger car (SUV)	1500 - 2400	190.0	10.0
Van / Pickup	3000 - 8200	35.0	151.1
Bus	8200 - 14200	157.1	70.0
Small loaded lorry	11600 - 15400	669.1	20.0
Large loaded lorry	15000 - 27600	136.7	150.0

Table 3.2. Probabilistic accident attributes by vehicle type.

Vehicle type	Weighted probability of vehicle types per accident	Probability of rollovers for each vehicle type
Car	0.506	0.19
Pickup / Utility / Van	0.336	0.40
Bus	0.002	0.07
Truck	0.156	0.09

The magnitude and severity of a fire event depend on the number and type of vehicles that catch fire. The number of vehicles catching fire is dependent on the probability of fire spread (Carvel et al., 2005) (it is assumed that fire always starts from a point source), which is a function of the size of the current fire and the distance between the vehicles in the tunnel. The distances are less if the fire originates from a collision and/or the traffic density is high. The weighted probability of choosing a type of vehicle is proportional to the general highway traffic data (some classes are adjusted if there are restrictions such as for hazardous material trucks). Each vehicle type is associated with a peak heat release rate in case of fire, which is modeled using a Lognormal

distribution. The iterative process of spread of fire follows a Bernoulli trial and can be expressed as:

$$M_n = aM_{n-1} + m_n \tag{3.10}$$

$$M_{max} = \begin{cases} M_n, & if\ M_n > M_{max-1} \\ M_{max-1}, & if\ M_n < M_{max-1} \end{cases} \tag{3.11}$$

where M_n is the cumulative heat release rate *HRR* (in Megawatt) of current vehicles on fire, M_{max-1} is previous maxima of the cumulative heat release rate, m_n is the peak heat release rate of the nth vehicle, and a is a factor dependent on the time lag between the vehicle fire peaks (in this case generated randomly due to lack of data). The parameter defining the magnitude of the fire event is M_{max} which is the maximum heat released during the period of fire.

Once the total towing weight from an accident or the maximum HRR for a tunnel fire is determined (or simulated in this case), the fragility-based method was implemented to estimate the tunnel functionality loss in terms of the magnitude of the event. A fragility function (curve) is a cumulative distribution function (CDF), which states the probability that a tunnel reaches or exceeds a limit (damage state) as a function of a demand parameter (loading condition). The fragility function F_d for damage state d is defined as:

$$F_d(x) = P[D \geq d | X = x] \quad d \in \{1,2,3,4,5\} \tag{3.12}$$

where X is the demand parameter (random variable), D is an unknown damage state, P is the conditional probability such that the damage state d is reached or exceeded when the value of X is x, a specific value of demand X. The same format can be used in the functionality loss estimation of different events. For example, the demand parameter in case of an accident is the effective weight of vehicles or the amount of towing required; and in case of fire, the demand is the maximum HRR during the fire (Table 3.3). Damage state, d is defined by the type of closure (number of lanes closed) and the duration of recovery (partial and full) associated with the demand parameter.

Table 3.3. Heat release rate by vehicle type.

Vehicle type	Heat release rate range (MW)	Lognormal distribution parameters	
		☐	☐
Small passenger car	1 - 4	0.89	0.25
Passenger Car	2.5 - 9	1.59	0.20
Van / Pick up	8 - 23	2.69	0.17
Bus	15 - 35	3.21	0.12
Small loaded lorry	20 - 50	3.55	0.12
Large loaded lorry	45 - 110	4.24	0.13
Tanker	120 - 300	5.18	0.17

In this study, the Gamma function was used for these fragilities. The parameters of these fragility functions are listed in Table 3.4. Accident data from the highway tunnel can estimate the parameters of probability distribution functions for the demand parameter (effective weight), as shown in Figure 3.11. The resilience loss for a damage state is a combination of functionality loss (depending on the number of lane closure), response time, and time of recovery. Response time, assumed to be a constant value, is the time taken by the tunnel operator to reach the site of the event. However, the time of recovery for each type of damage state is different and varies with the number of the lane closure. The time of recovery from vehicle accidents follows a gamma distribution. It is estimated like the demand parameter by considering accident data from the highway corresponding to the tunnel, as shown in Figure 3.11.

Table 3.4. Fragility parameters for accident damage states.

Parameter		Damage state					
		DS0	DS1	DS2	DS3	DS4	DS5
Accident Condition		Single (passenger car/ utility) vehicle pushout	Two vehicle pushout	Multi vehicle pushout	Single rollover	Multi vehicle accident with one or two rollovers	Multi vehicle accident CMV/ truck rollovers
Demand parameter (Gamma distribution)	μ (kg)	870	1975	4200	9500	14400	22500
	α	9.5	23.2	23.5	47.5	95.0	90.0
	θ	90.9	85.0	178.0	200.0	152.0	250.0
Functionality loss (%)	Level 1	50	50	50	50	50	50
	Level 2	34	34	34	34	34	34
Response Time	(minutes)	5	5	5	5	5	5
Time of Recovery (Gamma distribution) — t_f	μ (minutes)	4	8	12	25	60	180
	α	0.5	2.0	8.0	15.0	25.0	15.0
	θ	8.0	4.0	1.5	1.7	2.4	12.0
Time of Recovery (Gamma distribution) — t_p	μ (minutes)	5	10	20	40	90	150
	α	1.0	2.5	10.0	20.0	30.0	13.0
	θ	5.0	4.0	2.0	2.0	3.0	11.5

Figure 3.2. Fragility curves for damage states due to accident.

For fire, events with magnitude greater than 100 MW are infrequent based on Design Fire Characteristics for Road Tunnels (2017). The probability of such an event during the service life of a tunnel is generally low, depending on the tunnel parameters. For large fires, parameters of probability distribution functions for the damage states and the demand parameter were estimated based on historical fires (Design Fire Characteristics for Road Tunnels, 2017) (Henke & Galiardi, 2004) in tunnels. In the case of smaller fires, data available from the tunnel is used to estimate the parameters. Fragility curves generated for fire are shown in Figure 3.3. The resilience loss for a damage state is similar to the accident, which is a combination of functionality loss (equation (3.1)) (depending on the number of lane closure), response time, and time of recovery. The time of recovery follows a lognormal distribution (Table 3.5).

Table 3.5. Fragility parameters for fire damage states.

Parameter		Damage States					
		DS0	DS1	DS2	DS3	DS4	DS5
Fire condition		No Lining Damage	No Lining Damage	Negligible Lining Damage	Minor Spalling	Concrete Lining Spalling	Support Lining Damaged
	μ (MW)	0	4	15	50	100	200

Demand parameter (Lognormal distribution)	σ	0	0.6	0.5	0.3	0.2	0.12
Functionality loss (%)	Level 1	50	50	50	50	50	50
	Level 2	34	34	34	34	34	34
Response Time	minutes	5	5	5	5	5	5
Time of Recovery (Lognormal distribution)	t_f — μ (minutes)	10	30	90	450	7200	64800
	σ	0.5	0.45	0.35	0.25	0.2	0.2
	t_p — μ (minutes)	0	90	300	1800	32400	129600
	σ	0.4	0.45	0.35	0.25	0.2	0.2
Repair Cost	μ (in USD)	1000	10000	100000	1000000	10000000	100000000
	σ	0.48	0.48	0.48	0.48	0.48	0.48
Fire Duration	minutes	2	10	25	60	90	120
Remarks		Only Vehicle Pushout	Only Vehicle Pushout	Tunnel closed for 1 - 2 hours, one lane blocked for 2 - 5 hour	All lanes blocked for 5 - 10 hours, one lane closed for 12 - 48 hours	Tunnel fully blocked for 2 - 10 days, repair work 15 - 30 days	Tunnel fully blocked for 1 - 2 months, repair work for 2 - 4 months
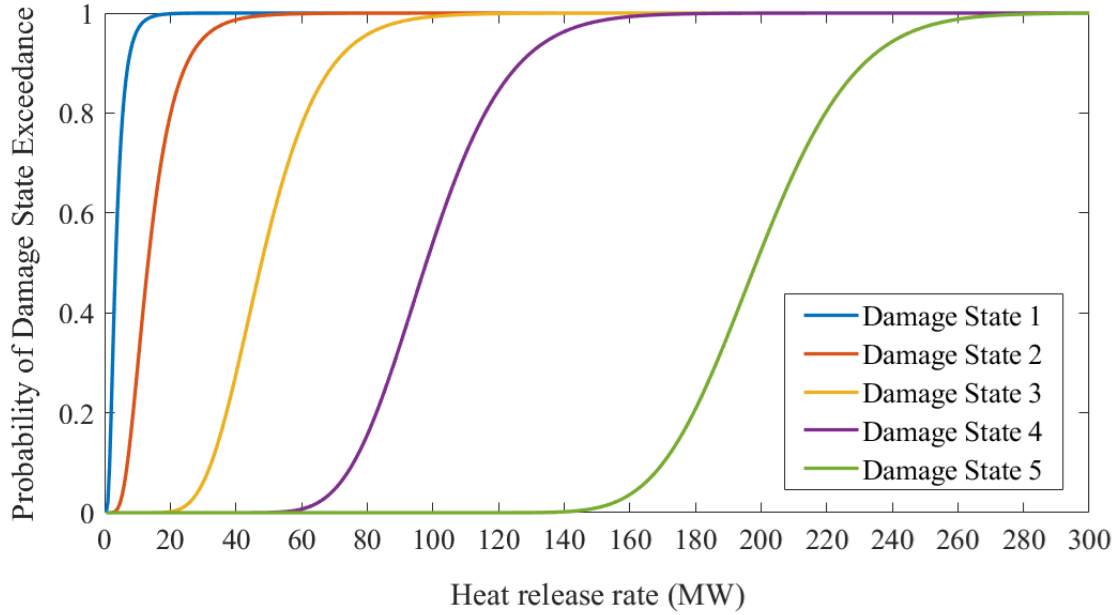
Figure 3.3. Fragility curves for damage states due to fire.

The tunnel closure can be partial closure (lane closure) or full closure (bore closure) or both for accident and fire. The closure type also depends on the damage state and is defined by the level of functionality loss. Level 1 is complete bore closure, and level 2 is partial bore closure. Generally, both type of closures occurs during the event to a certain degree depending on the damage state. The duration of partial closure t_p and full closure t_f are random samples generated from a distribution whose parameters are dependent on the acquired damage state D as given in Table 3.4 and Table 3.5.

3.4.2   Hazardous Material Restriction (Hazmat platooning)

Most of the tunnels have restrictions on the transportation of hazardous material (Hazmat). This is done to reduce the risk to health, safety, and property associated with hazardous materials. Hazmat trucks are typically forced to take an alternate route (detour) to bypass the tunnel (not allowed). Sometimes it is not possible to completely shut off hazmat trucks for some tunnels because of the inaccessibility of alternative routes. This can happen when the other routes are not there or closed due to weather conditions (e.g., snow, flood), accidents, landslides, construction, etc. When such a condition happens, the tunnel management will typically collect hazmat trucks at the entrance of the tunnel and let them pass as a platoon while shutting down the tunnel for normal traffic. To simulate this type of event, a model was developed considering alternate route closure and platooning. The temporary closure of the tunnel to regular traffic can be calculated based on this model to evaluate resilience loss.

In this study, a Gamma distribution is considered to encompass all the possible reasons for the closure of alternate routes whose random variable is the number of alternate route closure events

per year. If detailed information on reasons for alternate route closure events for a specific tunnel is available, then a detailed model can be developed instead of a single distribution. Because of the validation case study discussed later, a special case for hazmat platooning being affected by adverse weather conditions is discussed here. Probabilistic forecasting based on previously collected weather data is used to estimate the frequency and magnitude (duration) of alternate route closure, triggering hazmat platooning event at the tunnel. The duration of alternate route closure (T) is a function of weather event intensity (d), which can be represented by a parameter ($\{d \mid 0 < d \leq d_{max}\}$), like the amount of precipitation, expressed as:

$$T = \begin{cases} f(d), & if \ d \geq d_{cr} \\ 0, & if \ d < d_{cr} \end{cases} \tag{3.13}$$

where d_{cr} is the critical value of the weather event intensity representing the beginning of closure. For example, in the case of snow, d_{cr} is the minimum depth of snow that can cause alternate route closure.

Tunnel closure due to Hazmat platooning happens during time T in a discrete manner depending on platooning management practices of the tunnel. Typically, the tunnel will be shut down for platooning at a set interval (generally hourly) to let the Hazmat trucks collected during this interval to pass. The number and duration of closure depends on the number of hazmats arriving at the tunnel (N_{Haz}) and traffic volume at the tunnel during the interval. Hazmat arrival (N_{Haz}) is a function of the number of vehicles $g(nv)$ arriving at the tunnel, which is normally distributed. The number of allowable closures per hour (n_{ac}) are given as:

$$n_{ac} = a \ (nv - \overline{nv})^2 + n_{ac(max)} \tag{3.14}$$

$$a = - \frac{n_{ac(max)}}{\overline{nv}^2} \tag{3.15}$$

$$N_{Haz} = g(nv) \tag{3.16}$$

where nv is the traffic volume per hour having variable mean and standard deviation for every hour of the day, $\overline{nv}$ is the overall mean of traffic volume per hour, and a is a negative coefficient. Here, n_{ac} increases as the number of Hazmat increase but starts to decrease if the nv increases over a critical value ($\overline{nv}$) because the priority is to avoid traffic congestion along the tunnel. Considering n_{ac} as the rate parameter actual number of closures per hour n_c can be sampled randomly using Poisson distribution.

The duration of tunnel closures (t) will not only depend on the number of Hazmat vehicles cued up at the portals and on the number of closures (n_c) but also tunnel management practices, such as the maximum duration of closure permissible at one time. In this study, individual tunnel closure event duration t is a random sample generated from a Gamma distribution for closure intervals at the tunnel. The summation of the closure duration during time T is the sum of time taken by Hazmats to cross the tunnel. Since a tunnel is completely shut down for vehicles during hazmat platooning, as per equation (3.1), functionality loss will be 50% if platooning happens in one direction and 100% if platooning occurs in both directions assuming the tunnel is twin-bore unidirectional.

3.4.3 Tunnel Maintenance

Modern road tunnels are complex systems consisting of concrete structural elements, ventilation, lighting, other electrical and mechanical systems, interconnecting cross passages, signs, sensors, alarms, etc. Components are different parts of a tunnel (e.g., lining, hydrants, ceiling, sprinklers, roadway, etc.) that are vulnerable to aging and failure. Some components deteriorate over time and can be retrofitted and maintained as long as the deterioration is not very severe, such as tunnel lining segments under various chemical and physical stresses (mostly due to water leakages, Richards, 1998). Such components can be inspected from time to time and assigned different condition states, which lead to them being either repaired or replaced. On the other hand, some equipment or devices do not have intermediate deterioration states, such as a light bulb or ventilation fan. Once they fail, the management will notice, and they must be replaced. The maintenance processes of inspection, repair, and replacement of elements of different systems in the tunnel can lead to lane closures causing tunnel functionality loss. While these two types of maintenance process are similar in function, the models used to represent them differs slightly. Components and equipment are divided into single units called elements. For example, the component lining is divided into a one-meter square (1 m²) of lining as its element.

For the repair and replacement category (components can be inspected and repaired), each component i has n_i elements, these can be in four condition states (CS), namely CS1, CS2, CS3, and CS4. These states are defined for individual components based on the description given in Specifications of National Tunnel Inventory (SNTI) (details not included in this paper due to length limitation). In a new tunnel, all the elements will be in condition state 1 (CS1). For old tunnels, the condition state of each component at a given point in time can be different, which can be defined as initial states. It is assumed that the elements of an element will deteriorate with a mean rate of deterioration λ_{ij} following a Poisson distribution for condition state number j. The rate is deterioration is the inverse of service life. The expected mean number of state change over time t is defined by $n_{ij}\lambda_{ij}t$, where n_{ij} is the initial number of elements in state j. The confidence level of the state change of the number of elements of the component c_{ij} is attained for the expected mean of the number of state changes. The probability of exceedance P_e of the number of state changes of elements and new number n'_{ij} of elements in a condition state j are expressed in terms of Poisson cumulative distribution function ($F_{Poisson}$) as

$$P_e = 1 - F_{Poisson}\left(c_{ij}, n_{ij}\lambda_{ij}t\right) \tag{3.17}$$

$$n'_{ij} = n_{ij} + c_{i(j-1)} \tag{3.18}$$

This process, as shown in Figure 3.4, repeats over the inspection interval defined by the tunnel operator (as an input to the model). Each inspection is followed by repair and replacement events. The duration of examination is a factor of the number of elements n_i to be inspected and their quantity in different states. The duration of repair or replacement depends on the number of elements in the vulnerable states, usually CS3 and CS4. The amounts to be repaired or replaced c'_{ij} at a time, which depends on the tunnel operator's decision based on the financial constraints or/and time requirement. The repair and replacement of elements can be expressed as:

$$n_{ij}^{''} = n_{ij}^{'} + c_{i(j'-j)}^{'} \tag{3.19}$$

where $n_{ij}^{''}$ is the new number of elements in the state j after repair and/or replacement, j' is the previous state of the element.
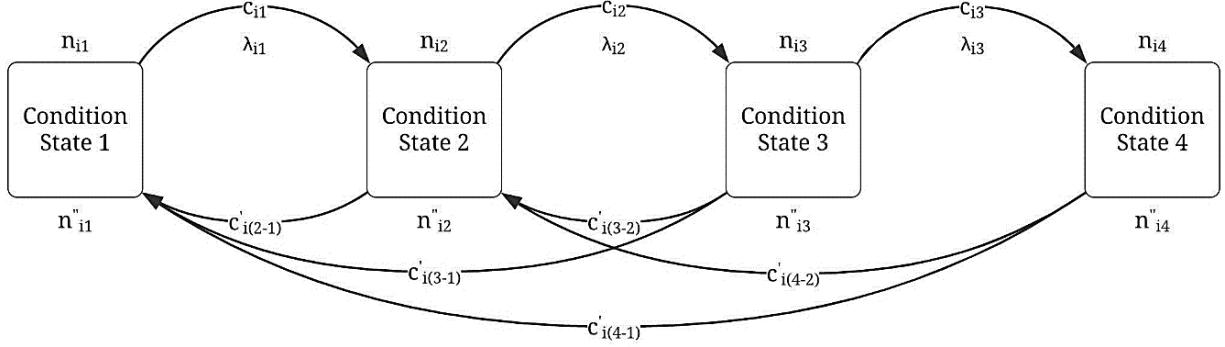
Figure 3.4. Element deterioration and repair/ replacement model.

In the second maintenance category, element status only consists of two states: working and failed state. These are mostly for mechanical or electrical elements. There is no need for planned inspection, and the only option is replacement after a failure is detected. Intervention to replace elements is prepared when the maximum allowable number of elements fail. An example is when replacing light bulbs in a tunnel will not happen every time a single light goes out but will depend on the safety criteria followed at the tunnel about how much light is needed to be safe. Then all failed elements are replaced in a single operation. The functionality loss at the tunnel is equivalent to the total time taken to replace the equipment. The expected mean number of equipment failures is defined by $n_i \lambda_i t_a$, where n_i is the total number of equipment i, λ_i is failure rate (average number of events per interval per equipment), which is the inverse of the service life of the equipment, and t_a is the length of the interval over which the allowable number of failures occur. The probability of exceedance of loss is the same as P_e in equation (3.18).

For both maintenance models, the total time of closure for an activity T_{ci} (inspection or repair/replacement) on a component/equipment is the product of the number of elements of component/equipment to be inspected or replaced/repaired. t_{ij} is a random variable of a Poisson distribution with an average time of activity per element $\overline{t_{ij}}$ as a rate parameter. The average time of the activity depends on the state of the element. For the first maintenance model, this can be expressed as:

$$T_{ci} = \sum_{j=1}^{4} n_{ij} t_{ij} \tag{3.20}$$

The type of tunnel closure is associated with the kind of element (component or equipment) and the activity. The tunnel bore closure could be partial t_p or full tunnel closure t_f. Further, the setup and removal of workforce and equipment for the event might require complete tunnel bore closure t_f for safety reasons. Random sample t_p and t_f are generated for each event based on the time

distribution parameters for each type of equipment. The summation of all types of closures for an activity for each component/ equipment is equal to the total time T_{ci} required.

3.4.4 Tunnel Operations

Tunnel operation is defined as the routine maintenance activities which do not require outside expertise and are organized by the onsite tunnel operator to keep the tunnel in a good physical state and functional, like washing and sweeping of tunnel. These activities are mostly planned but also take place in case of emergency or as required. Although the activities generally follow a pattern and are organized seasonally, their occurrence may vary within the season, depending on weather conditions or another random or maintenance event. In general, the level of uncertainty in these events is lower than maintenance. Thus, they are much more predictable for well-managed tunnels.

The occurrence of an event can be estimated based on the fixed time interval for events and seasons when they are organized. The magnitude of activities is related to the geometric dimensions of the tunnel, the equipment used for the activity, the organizational capabilities of the tunnel operator/staff, and the type of closure (all lanes/ some lanes) required for the activity. The tunnel can be divided into units based on the number of lanes, zones, width, and length of the tunnel, thus accounting for the geometry of the tunnel. The time taken to complete one unit of work is a function of equipment and the organizational capabilities of the operator. In this study, the total time T_c taken to complete one activity is the product of the units of work n_u and Poisson random sample with the average time taken to complete one unit of that work $\bar{t}$ as a rate parameter. Like maintenance, the total time is divided in partial t_p, and full t_f closures, depending on the type of activity and full closures for safety during the setup and removal of equipment and workforce involved in the activity.

3.5 Model implementation

The probabilistic model presented in the previous section was implemented using the Monte Carlo simulation. In this study, a five-module program was developed in MATLAB to conduct the simulation of tunnel functionality time history considering random and planned disruptive events. The overall structure of the program is shown in Table 3.5. Each of the five modules is responsible for generating the occurrence and tunnel functionality loss corresponding to a specific type of event discussed in the previous section. A mainframe program was developed to combine all simulation modules to produce the overall time history of tunnel functionality for a particular time span specified by the user. The mainframe program also considers event overlapping from individual module simulation to avoid conflict (e.g., tunnel maintenance activity is unlikely to happen at the same time when there is a fire event in the tunnel).

Individual simulation modules are designed to generate samples of disruptive events and calculate their impact on tunnel functionality Q. The modules were all intended to produce a uniform data structure containing simulated information about the random (or planned) event stored in a structure array in MATLAB (shown in Figure 3.6). This data structure has values that describe an event, including event type, severity, tunnel closure condition and duration, and the calculated functionality (Q) loss during the event duration.

Once individual events were simulated within the modules, a history of events was combined in the main simulation framework to generate the time history of Q for the entire tunnel. The critical user input parameter for this step is the desired time range for simulation and the number of samples needed.
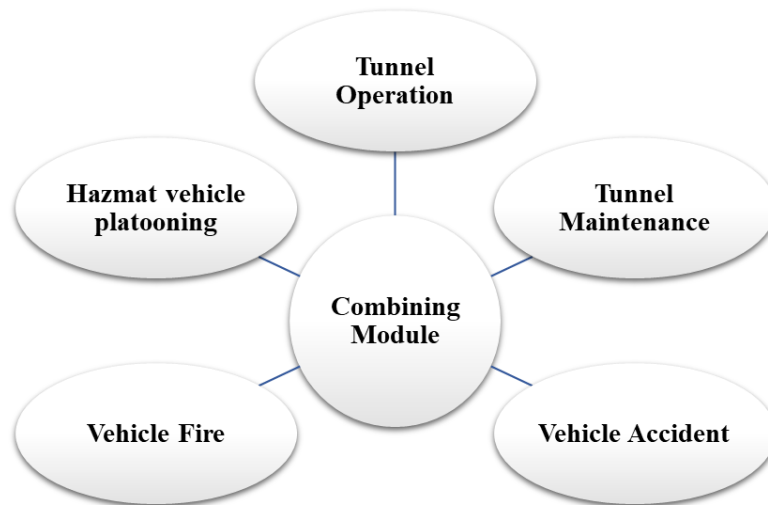
Figure 3.5. Modules stochastic event simulation model.
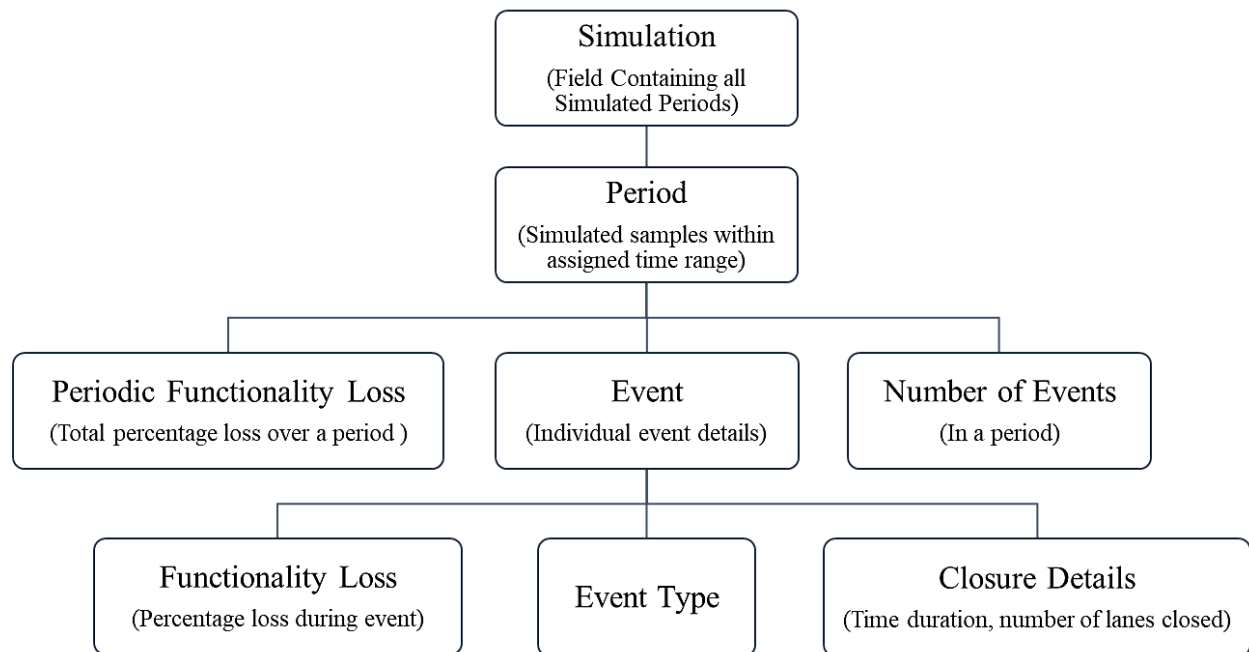
Figure 3.6. Simulation result structure.

While there are 6 major factors affecting tunnel functionality, the implementation details on some of them are similar. For example, since the simulation approaches for traffic accidents and fire are identical with only the difference in random event generator parameters and fragilities, they can be implemented with the same code. Figure 3.7 shows the details of both modules in one diagram. Each entity in Figure 3.7 maps to a function coded in MATLAB, providing needed output data for subsequent functions. Table 3.6 shows the source of input data used to estimate the probability of accident and fire events.
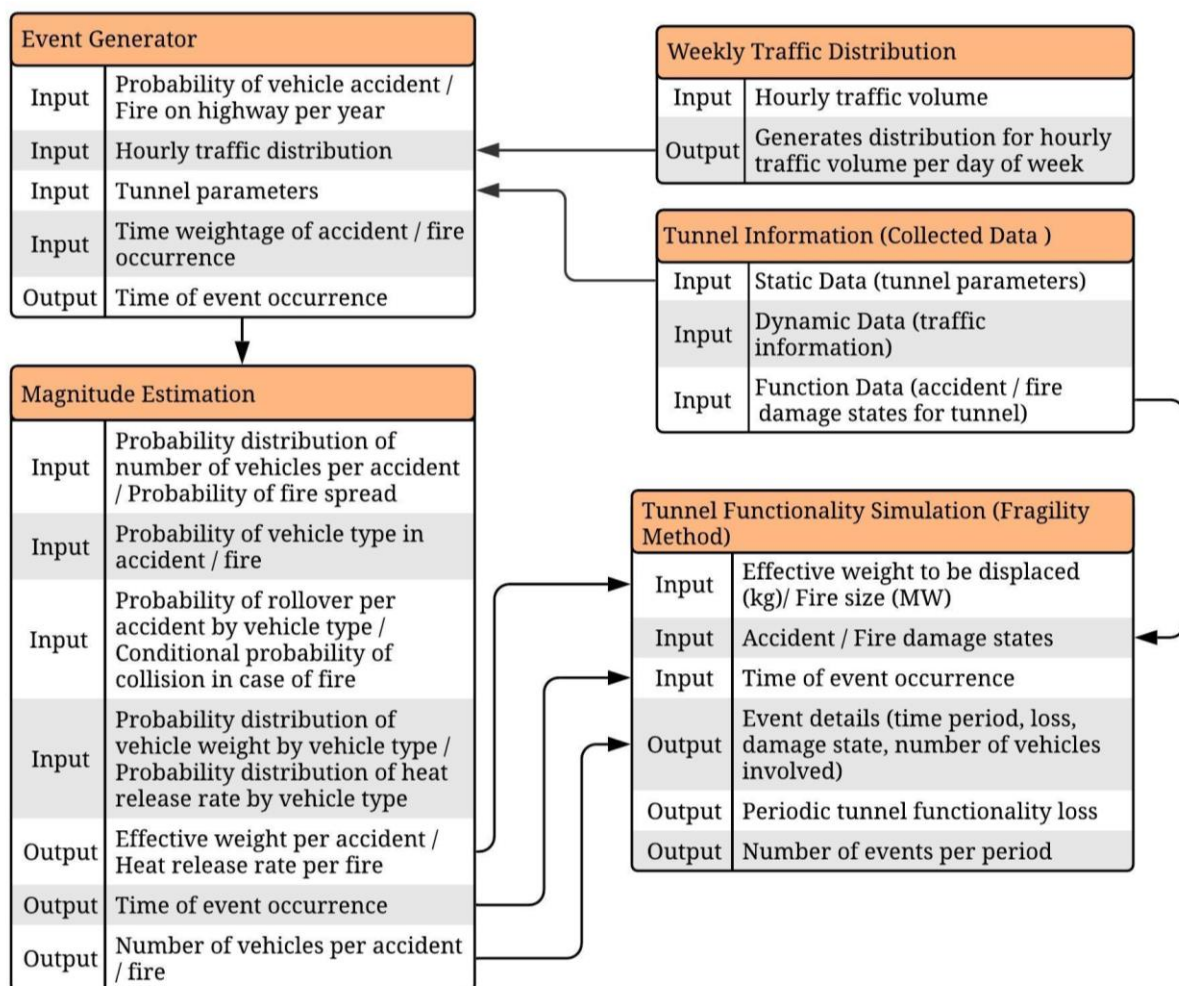
Figure 3.7. Schematic diagram of accident and fire modules.

Table 3.6. Input parameters for determining the probability of accident and fire events.

Input Parameter (Symbol)	Module	Source
Vehicle miles traveled (VMT)	Accident / Fire	Bureau of Transportation Statistics (BTS) (Highway Statics Series, 2019)

Average vehicle speed (AVS)	Accident / Fire	National Traffic Speeds Survey (NTSS) (Huey et al., 2012a; Huey et al., 2012b; De Leonardis et al., 2018)
Number of highway accidents (A_H)	Accident	National Highway Traffic Safety Administration (NHTSA)
Total Highway Fire Events (F_H)	Fire	National Fire Protection Association (NFPA) (Ahrens M, 2017)
Probability for accidents occurrence by month on the corresponding highway (M_p)	Accident	Highway Operation Data
Probability for accidents occurrence by hour on the corresponding highway (Hr_p)	Accident	Highway Operation Data
Monthly, day of the week and hourly fire occurrence probability on the highway (M_{pf}; Dow_{pf}; Hr_{pf})	Fire	United States Fire Administration (USFA) (Highway Vehicle Fires, 2018)
Tunnel length (*TL*)	Accident / Fire	Tunnel Data
Speed limit in tunnel (*SLT*)	Accident / Fire	Tunnel Data
Speed limit on the associated highway (*SLH*)	Accident / Fire	Tunnel Data
Number of tunnel bores (*NB*)	Accident / Fire	Tunnel Data
Hourly traffic volume (*TV*)	Accident / Fire	Tunnel Data

As presented in the modeling section, the interruption of tunnel traffic due to hazmat platooning is quite different from a simple random event. The simulation should consider the condition of the alternative route, the management strategy for truck platooning, and the unexpected arrival of Hazmat trucks. Some tunnels may not have this particular issue, such as when hazmat passing is completely banned, or the tunnel is too small to have onsite management for platooning. However, this is a significant contributor to tunnel functionality loss for large mountain tunnels (including the example tunnel used in this study). A dedicated simulation module was developed in this study to simulate hazmat platooning events. Figure 3.8 shows the alternate route closure and hazmat platooning event generation functions in the module.
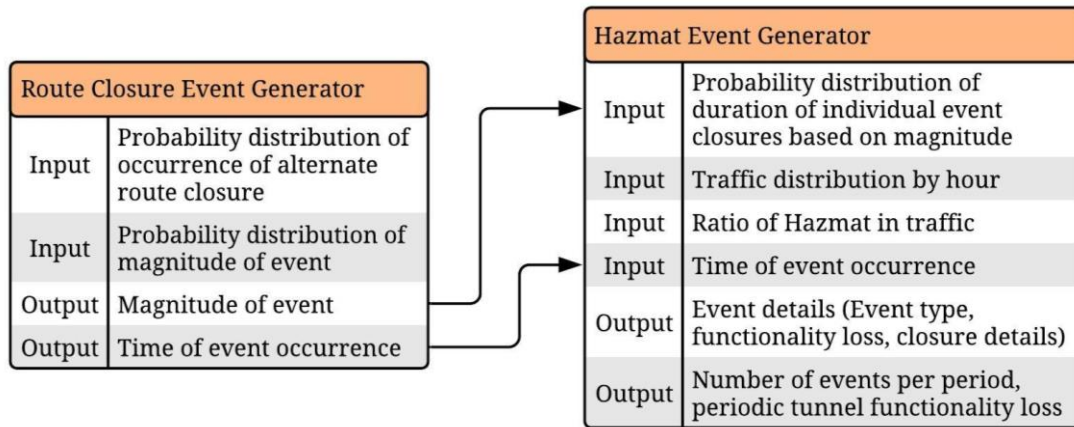
Figure 3.8. Schematic diagram of the hazmat module.

Maintenance activities in a tunnel are driven by the need to replace or repair deteriorated tunnel equipment or component when they reach an unsafe state or failure. In Figure 3.9, both maintenance category modules are combined to represent the input parameters required to generate functionality loss events. Each module contains two functions. One generating events for individual component/equipment types, and the other function compiles these results for all component/equipment. The parameters used are tunnel specific as each tunnel has a unique design. The input interface sheets allow the operator to specify and list the components and equipment, with their details, in the tunnel.
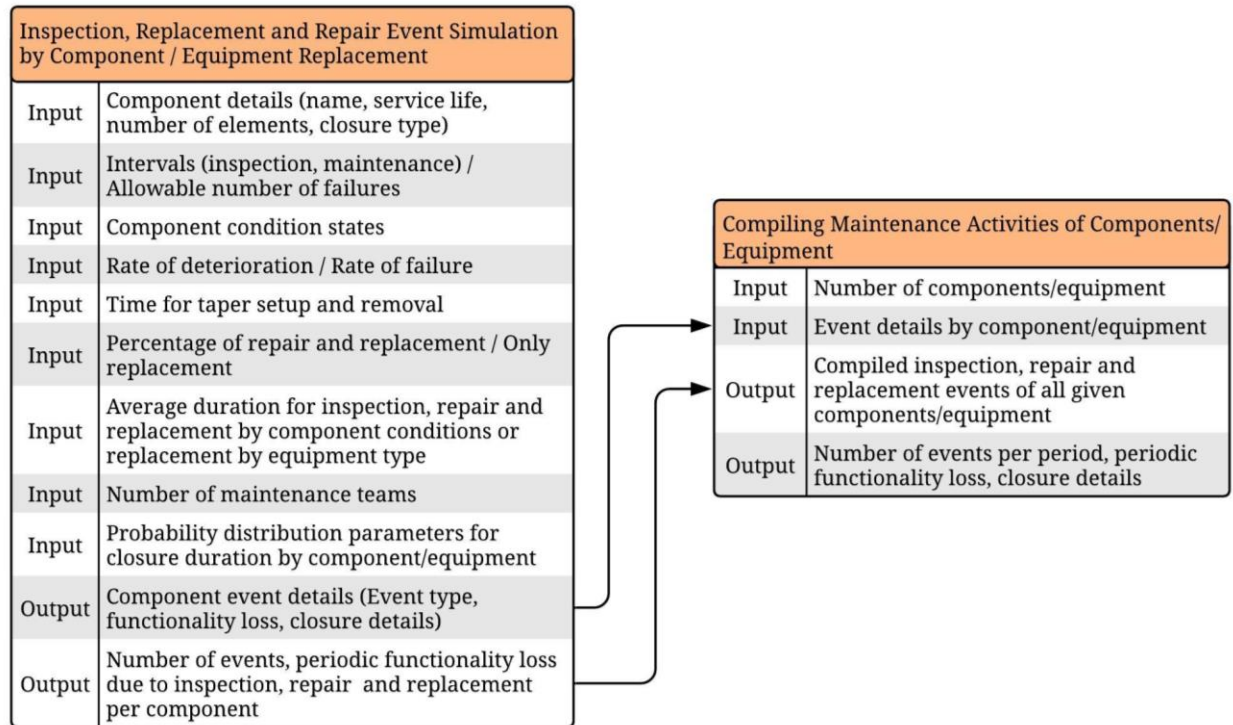
Figure 3.9. Schematic diagram of the maintenance module.

Operation activities are mostly driven by tunnel management. Most of these activities have a significant impact on tunnel functionality but can be planned to avoid high traffic demands. Because of the nature of planning, the input parameters of activities can be defined by the tunnel operator in the input interface sheet. Figure 3.10 presents the module parameters required to generate operation events. The module constitutes of two functions. The first creates an event for each activity, and the second compiles these events for all operation activities taking place in the tunnel. Operation events are scheduled according to seasons to avoid seasonal disruptive events (like, weather activities) and high traffic density (also seasonal). A season is usually considered three months. Since activity season is predefined, the activity occurs randomly within this time span.

Operation Event Simulation by Activity	
Input	Operation activity details (name, interval, unit work, number of units, closure type)
Input	Time for taper setup and removal
Input	Number of operation teams
Input	Probability distribution parameters for closure duration by operation activity
Output	Event details (Event type, functionality loss, closure details)
Output	Periodic details(number of events, periodic functionality loss due to activity)

Compiling Operation Activities	
Input	Number of operations
Input	Event details by operation
Output	Compilation of all operation activities
Output	Number of events per period, periodic functionality loss, individual event closure details

Figure 3.10.Schematic diagram of the operation module.

3.6   Simulation example and preliminary validation

While a probabilistic simulation model cannot be validated on an individual event basis, validation of the modeling outcome can be performed by comparing the simulated random event distribution with realistic tunnel operation data and observing the trend on event distribution. Because tunnel operation resilience has not been studied widely, the amount of data suitable for overall operation simulation validation is minimal. In a previous study (Khetwal et al., 2020), realistic tunnel functionality data of Eisenhower-Johnson Memorial Tunnel (EJMT), Colorado, over five years was gathered and processed. This provided an excellent opportunity to compare simulation results with real data to demonstrate the accuracy of the proposed model. The modeling process and results from the simulation for EJMT were discussed in this section.

EJMT is a twin-bore tunnel, and each tunnel consists of two traffic lanes operated by the Colorado Department of Transportation (CDOT). The tunnel is on interstate highway I-70, crossing the continental divide at approximately 3375 m above sea level. The length of each bore is about 2730 m. The width of the two-lane roadway inside the tunnel is 7.9 m, and the height clearance for traffic is 4.2 meters. The tunnel consists of a transverse ventilation system with exhaust and intake air ducts over the tunnel roadway. The air ducts are separated from the roadway by concrete and steel ceiling panels supported on steel ceiling girders and steel hangers. The tunnel was retrofitted with a deluge fire suppression system in 2015 and a fiber optic linear heat detection system and an upgraded drainage system.

CDOT records operation data in tunnel logs, manually typed in excel sheets, and in Colorado Traffic Management System (CTMS), a web-based traffic data collection and management system launched in 2013. It is cumbersome to extract data from manual logs. Still, one year of data from May 2017 – April 2018 provided by CDOT was extracted. The major drawback of the CTMS data is that it is newly implemented and lacks uniformity in recording events. Therefore, this study five years of data from 2015-2019 was extracted since it has a relatively more detailed record of events

than previous years. In the future, as the recording of events becomes more standardized, then the data could be more descriptive and quantitative than currently.

3.6.1   Example simulation input parameters

Since the frequency of event occurrence for accident and fire event is low, a more extensive statistical base is required to estimate the probability of event occurrence. Table 3.6 shows the sources of the parameters necessary to do so, and Table 3.7 shows the values of the parameters used. The traffic volume data is one-year hourly traffic volume data from the tunnel. Hourly traffic distributions are generated by day of the week and then combined with monthly and hourly event variations based on sources given in Table 3.6.

For the number of vehicles involved in an accident, the gamma distribution parameters ($\alpha = 6.31$ and $\theta = 0.29$) are estimated using the data from Fatality and Injury Reporting System Tool (FIRST) by NHTSA. From the same source, data was extracted to calculate the weighted probability of the vehicle type involved in the accident and the probability of rollover for each vehicle type, as shown in Table 3.1. To estimate the effective weight, vehicle weights were calculated based on the distributions developed for each vehicle class, as described by the Federal Highway Administration (FHWA). Figure 3.11 shows the correlation between the effective weight of vehicle and highway closure using the data from CTMS for a 12-mile segment of I-70 highway corresponding to the tunnel.

Table 3.7. Input parameter values for estimating probabilities of accident and fire event.

Input parameter	Symbol	Parameter type	Parameters	
Vehicle miles travelled per year (miles)	VMT	Mean	$\mu = 3.03 \times 10^{12}$	
Average vehicle speed on highways (mph)	AVS	Mean	$\mu = 5.78 \times 10$	
Annual probability vehicle fire on the highways	P_H (Fire)	Gamma distribution	$\alpha = 4.52 \times 10$	$\theta = 7.66 \times 10^{-4}$
Annual probability vehicle fire on the highways	P_H (Accident)	Inverse Gaussian distribution	$\mu = 3.47 \times 10^{-1}$	$\lambda = 1.66 \times 10^{1}$
Tunnel length (meter)	TL	Value	2730.00	
Speed limit in tunnel (kmph)	SLT	Value	80.00	
Speed limit on associated highway (kmph)	SLH	Value	100.00	
Number of tunnel bores	NB	Value	2.00	
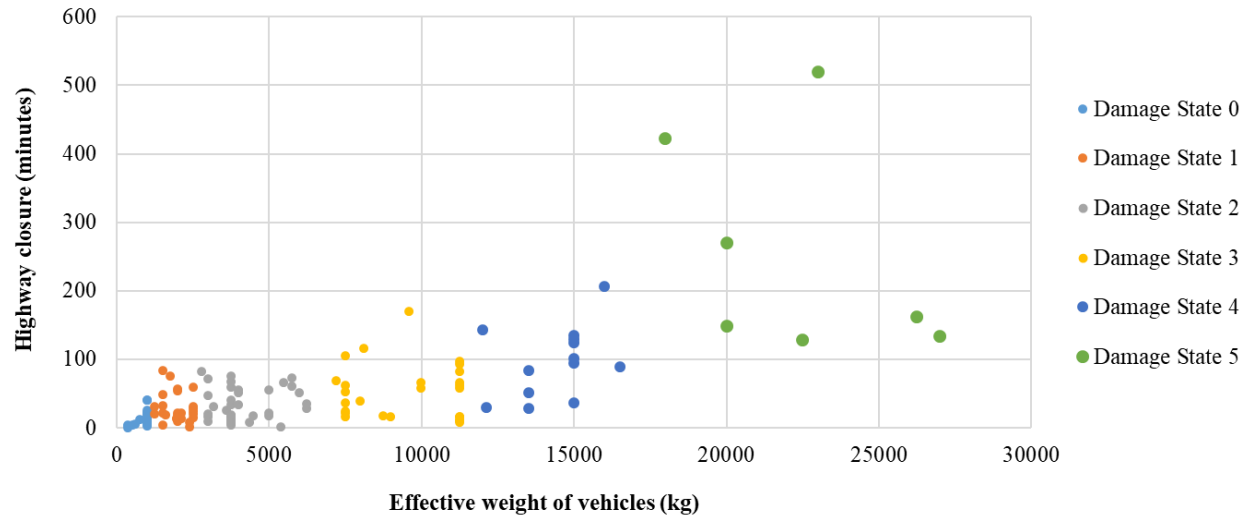
Figure 3.11.Effective weight vs. tunnel closure for a 12-mile segment of the I-70.

To calculate the number of vehicles involved in the fire probability of fire spread is used as given by Carvel et al. (2005). The type of vehicles catching fire is chosen based on vehicle miles traveled data (Highway statistics series, 2019). Each vehicle is associated with a heat release rate in case of fire. The heat release rate is estimated by the probability distributions for each vehicle type, shown in Table 3.3 (Design Fire Characteristics for Road Tunnels, 2017; Maevski, 2011).

The hazmat platooning event in case of EJMT triggered closures at Loveland pass (US 6), Colorado due to snowfall. Ten years of historical snowfall data at Loveland pass is collected based on which probability distribution parameters for the number of monthly snow days and depth of snow are estimated, as shown in Table 3.8. For calculating the number of Hazmat vehicles arriving at the tunnel, a ratio of 4.81×10^{-3} (National Transportation Statistics, 2018) of the number of vehicles arriving at the tunnel is taken.

Table 3.8. Distribution parameters for snow at Loveland Pass.

Month	Number of snow days		Snow depth (inch)	
	Gamma distribution parameters		Gamma distribution parameters	
	α	θ	α	θ
October	1.9	2.5	1.80	2.50
November	8.2	1.5	1.44	2.75
December	31.7	0.6	1.50	2.59
January	21.0	0.8	1.40	3.20
February	30.0	0.6	1.60	2.14
March	18.6	0.8	1.45	3.06
April	33.0	0.5	1.42	3.19
May	1.1	2.0	1.13	5.44

For maintenance events, the main input parameters for components/ equipment are the service life, inspection and maintenance intervals, total number of elements, initial condition state of the elements, and closure type. The service life of equipment/component was either provided by the tunnel operator (CDOT in this case) or taken from the 'Recommendations to determine lifecycle costs of road tunnels' (2018). Similarly, some of the inspection and maintenance intervals were provided by the tunnel operator. The rest were taken from runnel operations, maintenance, inspection, and evaluation (TOMIE) manual, 2015. The data for the number of equipment and initial condition state of the equipment/ component was extracted from the National Tunnel Inventory (NTI) database. This database is based on SNTI (2015) specifications. Other input parameters are the time of inspection and repair/ replacement per element, which is dependent on the condition state, rate of deterioration, and seasonality of the activity. The rate of deterioration is approximated as an inverse of service life. The tunnel operator provided the seasonality of the activities. The data for time per element for inspection or maintenance was approximated based on logical assumptions.

The input parameters for tunnel operation activities are the recurrence interval, number of units of work, average time taken per unit, number of teams, seasonality of activity, and average duration of continuous tunnel closure (lane restriction). Since the operational activities are tunnel specific, the data must be provided by the operator. Some input data is fixed, like the number of units of work and season of activity occurrence. Time taken to complete an activity is dependent on the available equipment at the tunnel and skills of the workers. For the current simulation, the data was provided by the tunnel operator.

3.6.2 Validation data

Once the model was set up for EJMT, a series of simulations was performed for a 5-year time frame to generate disruptive events and calculate functionality loss. Five years of time span was used in this study because the realistic operation functionality data set from EJMT was gathered during 2015-2019. Although EJMT has an extensive collection of paper-based operation logs from which additional data can be extracted, it is a highly labor-intensive process. The interested readers can refer to Khetwal et al. (2019), and Khetwal et al. (2020) for more information on the EJMT data. The validation data includes five years (2015-2019) of CTMS data, one year of tunnel log, and one year of tunnel operation planning sheets was collected from CDOT. Five years of CTMS data was used for validating accident and fire event simulation. Hazmat platooning event data was validated using one year of tunnel logs. Since the simulations were performed for a five-year interval, the Hazmat data was extrapolated for five years. A comprehensive one-year operation and maintenance data was compiled using operation planning sheets and comparing it with CTMS data. This was done as the CTMS data lacked a proper description of activities. Similar to hazmat, this data was extrapolated for the number of events over five years. The duration of individual events was validated based on five years of data from CTMS.

3.6.3 Comparison result: random event occurrence and their impact

Fifty samples for five years to match the duration of available data were simulated. The resilience of the tunnel is measured as the product of time (in minutes) and functionality (Q) over the period,

and its unit is Q in mins, where Q is a unitless quantity. A total of 51 to 54 accidents occurred at the tunnel from 2015 to 2019. The data for three events were not exact, hence the range. Figure 3.12 shows the histogram of the number of simulated accident events and the cumulative resilience loss due to events for five years. Figure 3.13 compares the empirical cumulative distribution function (*ecdf*) of the resilience loss due to individual simulated accident events and real accident events.

Figure 3.12. Histogram of simulated accident events (five-year period).
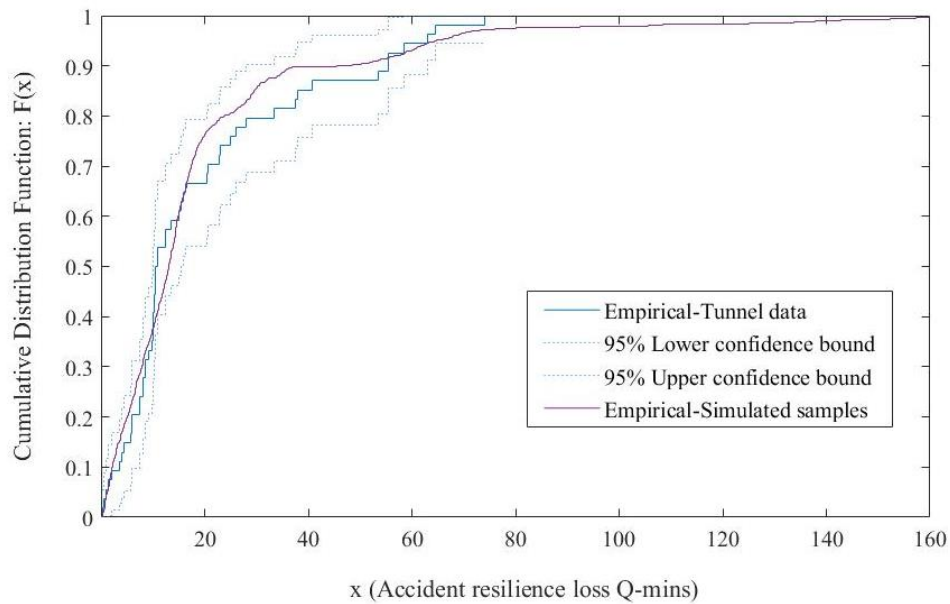
Figure 3.13. Accident event resilience loss empirical CDF simulated vs. historical data.

For fire events, the maximum value for tunnel resilience loss is an outlier that was generated due to a major fire event in one of the simulated samples. Six to nine fire events happened at EJMT

from 2015 to 2019. The range of events is due to the uncertainty of the location of the event, as some could be at the tunnel portal. In the tunnel resilience loss chart of Figure 3.14, the lower horizontal axis is not linear. As shown in Figure 3.15, the simulation considers the effects of fixed fire suppression system (*FFSS*). The peak heat release rate (*HRR*) of the fire is reduced by 40% if the *HRR* of fire is below 30 MW, and the reduction is considered by 20% for all fires above 30 MW (Road tunnels: An assessment of fixed firefighting systems, 2008). The reduction of fire magnitude due to *FFSS* is apparent in the data as the *ecdf* of the simulated sample considering *FFSS* is a better match than one without, as shown in Figure 3.16.
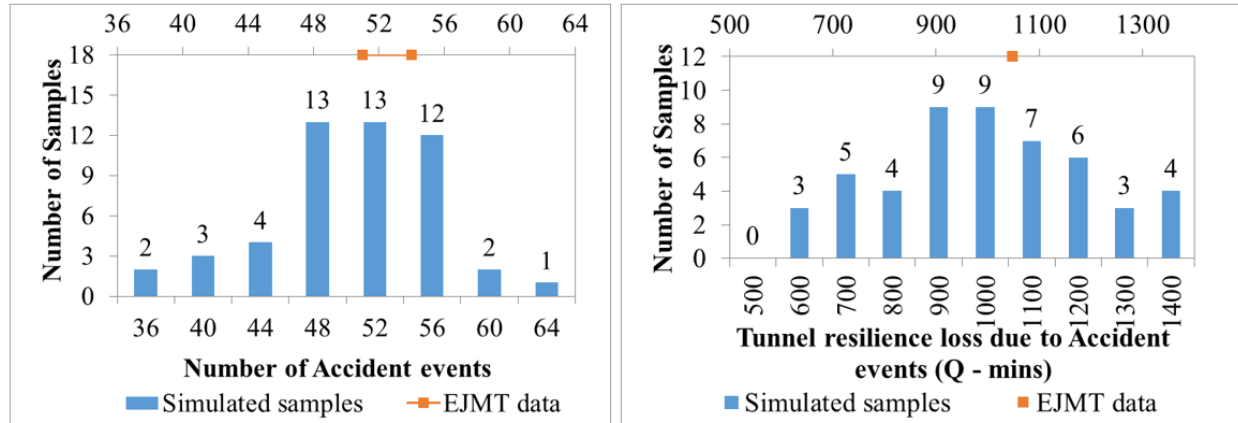

Figure 3.14. Histogram of simulated fire events over a five-year period.
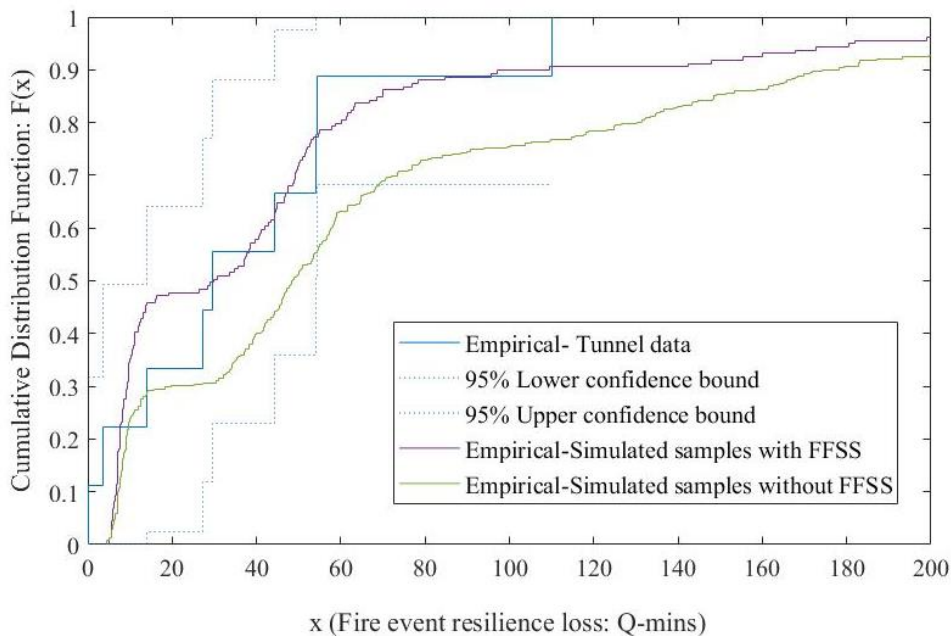
Figure 3.15. Fire event resilience loss empirical CDF simulated vs. historical data.

The hazmat platooning event data was only available for one year, but the data had to be extrapolated due to the duration of data available for other events. A total of 428 events occurred from May 2017 to April 2018, with 218 events in westbound and 210 events in the eastbound tunnel. Thus a range of 2100 to 2180 events is considered. Since only one tunnel bore is shut down during the event, the functionality at that moment is 50%. Figure 3.17 shows the comparison of the *ecdf* of the resilience loss during each event for real and simulated samples.
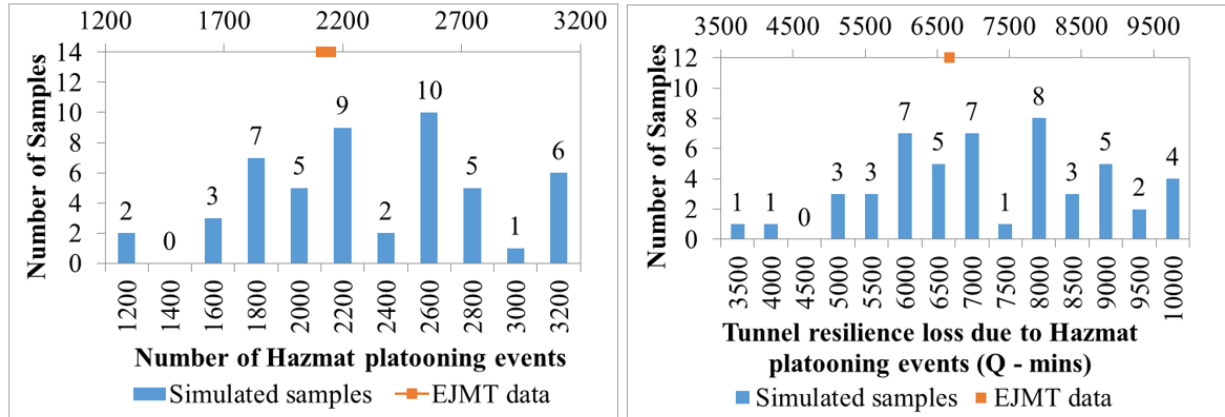
Figure 3.16.Histogram of simulated hazmat platooning events over a five-year period.
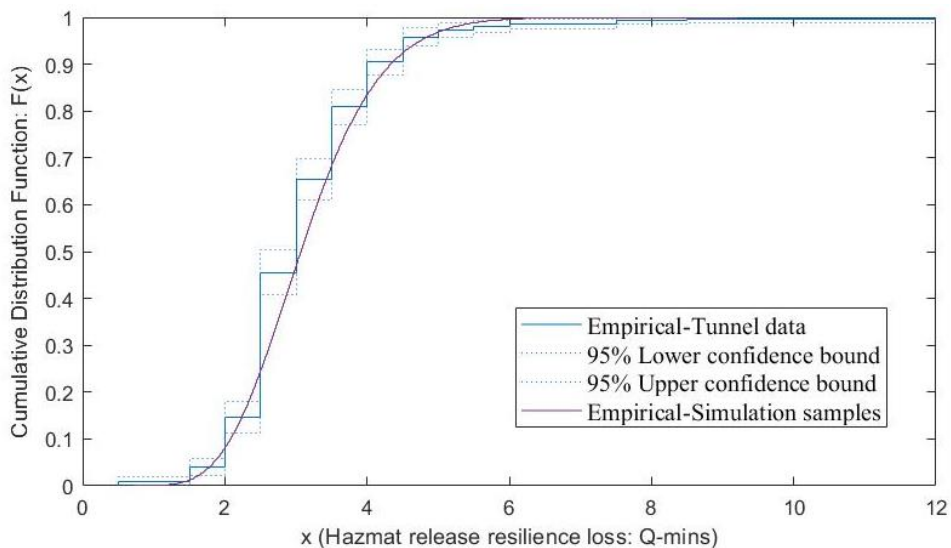
Figure 3.17.Empirical CDF of hazmat release event resilience loss simulated vs. historical data.

The mean of 50 simulated samples for five years was 2287 random events. In contrast, the historical data shows a range of 2167 to 2213 random events in 5 years due to uncertainty over event location and data recording inaccuracies. The range of the simulated sample and historical data is shown as a histogram in Figure 3.18. For random events, the tunnel resilience loss for the

five-year data was 8059.8 *Q-mins*. In contrast, the mean of tunnel resilience loss of simulated samples is 8934 Q-mins. Table 3.9 gives the details of the number of events and resilience loss for all random events.

Figure 3.18.Histogram of simulated random events over a five-year period.

Table 3.9. Simulated samples vs. historic data for random events.

	Historic Data		Simulated Samples	
	Number of events	Tunnel resilience loss (Q-mins)	Average number of events	Average tunnel resilience loss (Q-mins)
Random Events	2167 - 2213	8059.9	2287	8934
Accident	51 - 54	1047.5	49	947
Fire	6 - 9	337.4	8	959
Hazmat Release	2110 - 2150	6675	2231	7027

3.6.4   Comparison result: planned event occurrence and their impact

Observing the figures below shows the comparison between simulated samples and real data for planned events. The deviation of the number of events and resilience loss for planned events is comparatively less than random events. This can be attributed to the little deviation in the intervals for inspection, repair, and operations.

The one year of available data showed 140 operation events in 2019. Since the operation events were simulated for five years, this was extrapolated to 700 events. Similar extrapolation was performed for cumulative resilience loss due to operation events. The empirical *cdf* in Figure 3.20 shows the comparison of resilience loss due to these events to the simulated samples.
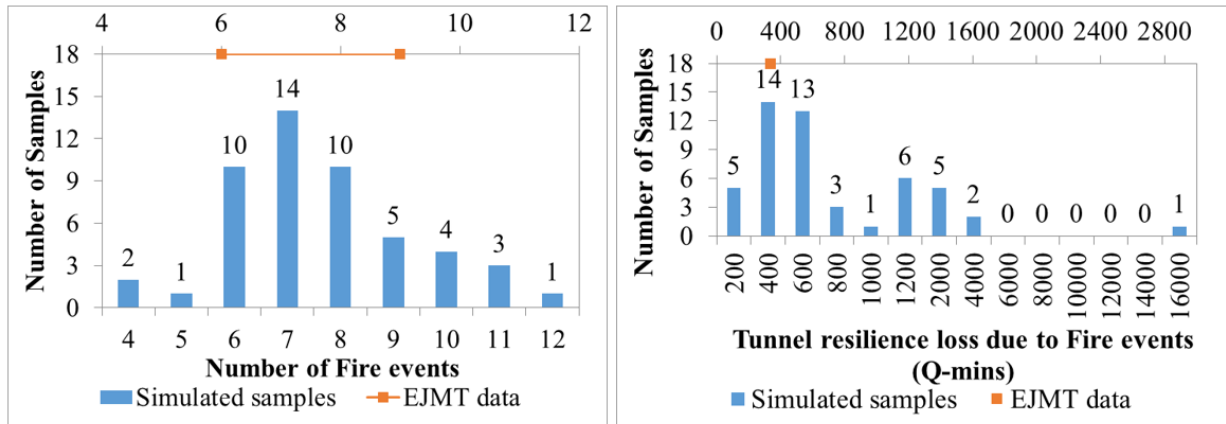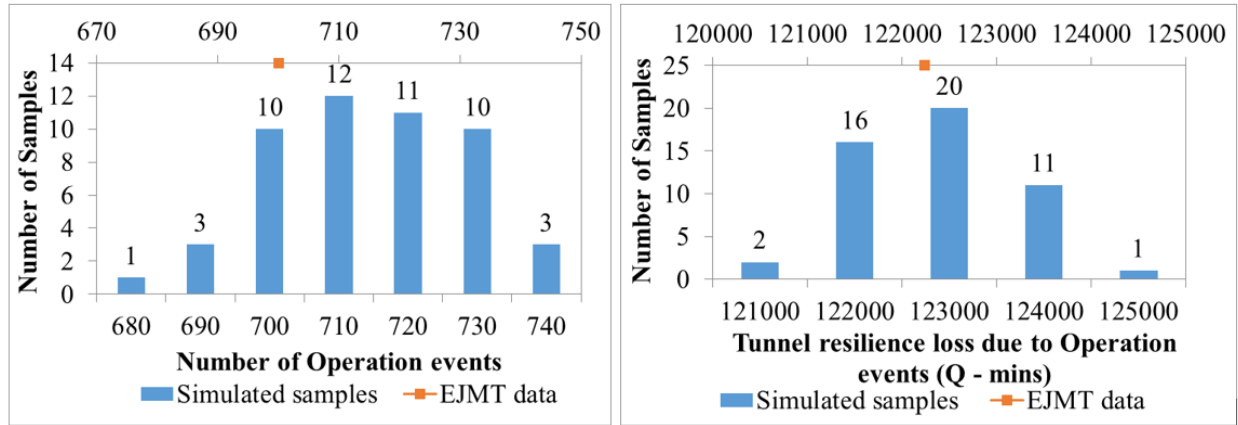
Figure 3.19. Histogram of simulated operation events over a five-year period.
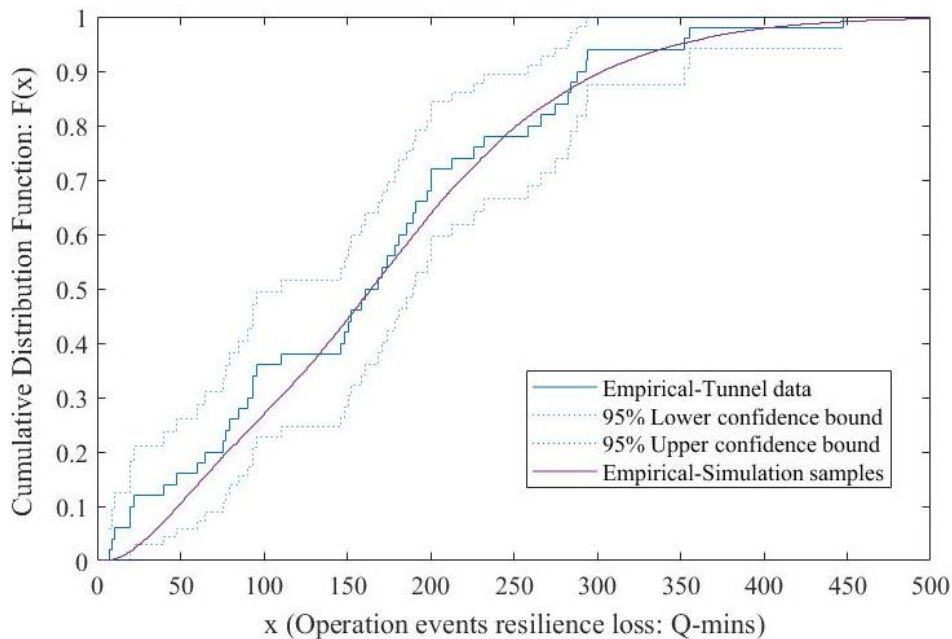
Figure 3.20. Operation events resilience loss empirical CDF simulated vs. historical data.

A total of 76 maintenance events occurred in 2019. Figure 3.21 shows the histogram of simulated samples for five years. The available data was extrapolated to 380 maintenance events in 5 years. Figure 3.22 shows the comparison of resilience loss due to real maintenance events versus simulated samples.
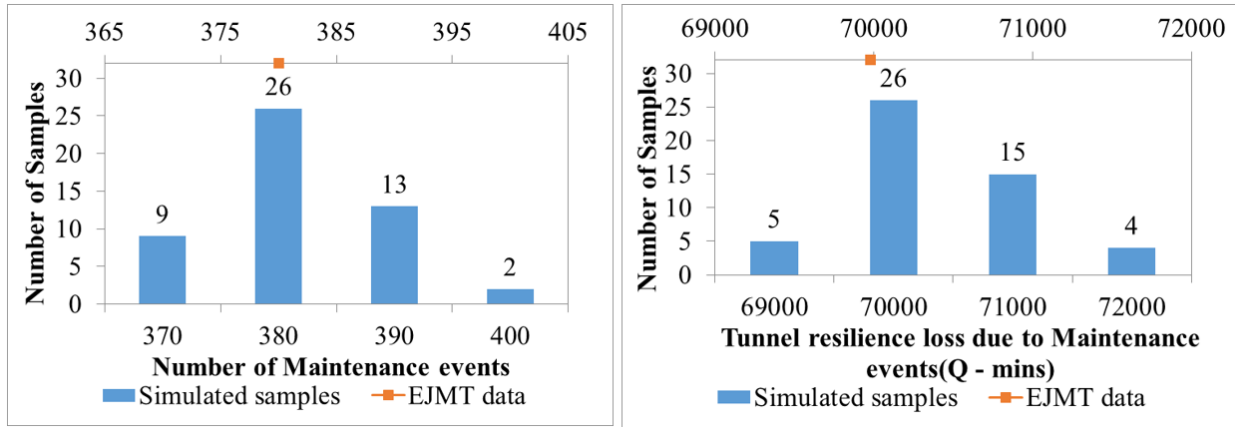
Figure 3.21.Histogram of simulated maintenance events over a five-year period.
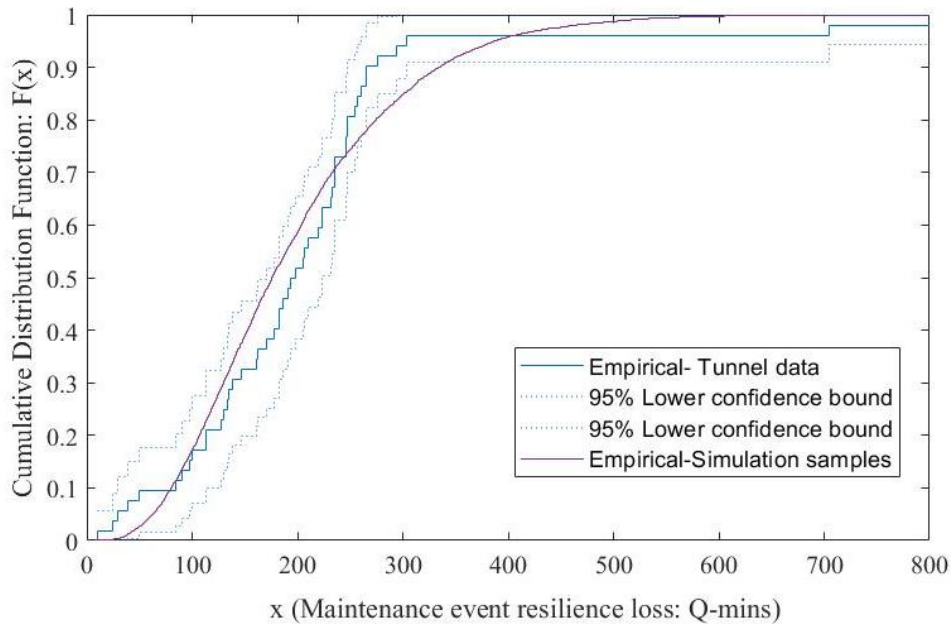
Figure 3.22.Maintenance events resilience loss empirical CDF simulated vs. historical data.

The histogram of the combination of all planned events is shown in Figure 3.23. Table 3.10. Simulated samples vs. historic data for planned events. Table 3.10 shows the details of the number of events and resilience loss for all planned events. Figure 3.24 shows the comparison between the pie charts for the average number of real and simulated events over a five-year period. Similarly, Figure 3.25 shows the comparison between the pie charts for actual and simulated cumulative resilience loss due to all events over five years.
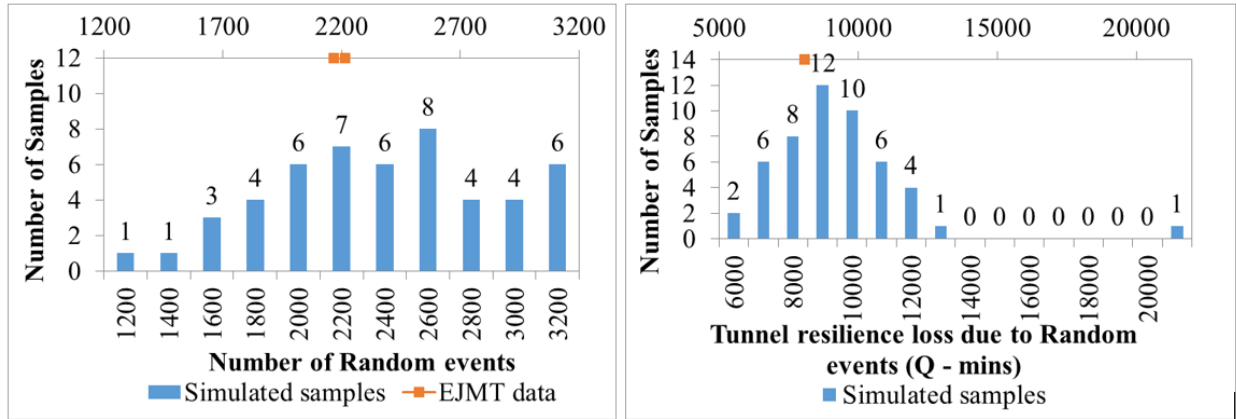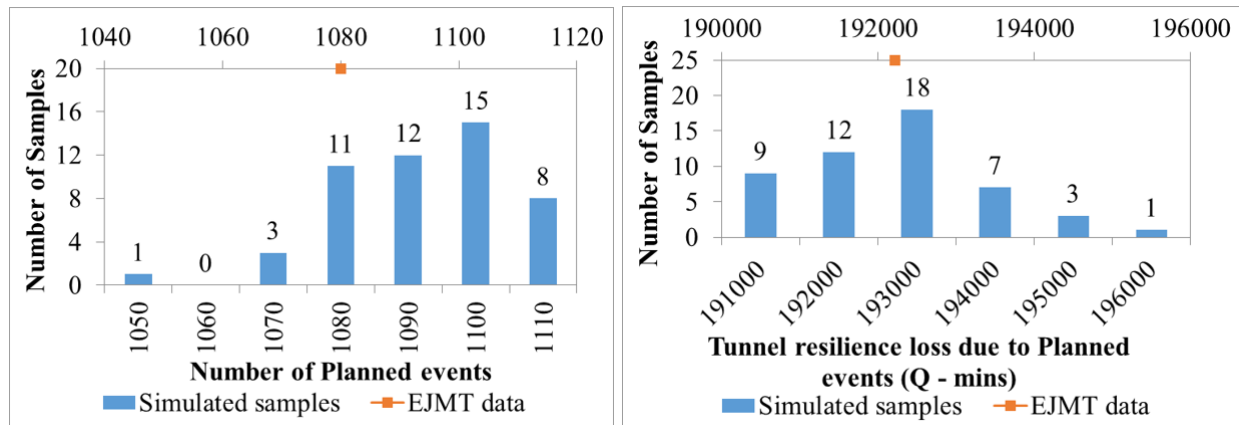
Figure 3.23.Histogram of simulated planned events over a five-year period.

Table 3.10.   Simulated samples vs. historic data for planned events.

	Historic Data		Simulated Samples	
	Number of events	Tunnel resilience (Q-mins)	Average number of events	Average tunnel resilience (Q-mins)
Planned Events	1080	192223	1087	192153
Operation	700	122243	710	122307
Maintenance	380	69980	377	69846
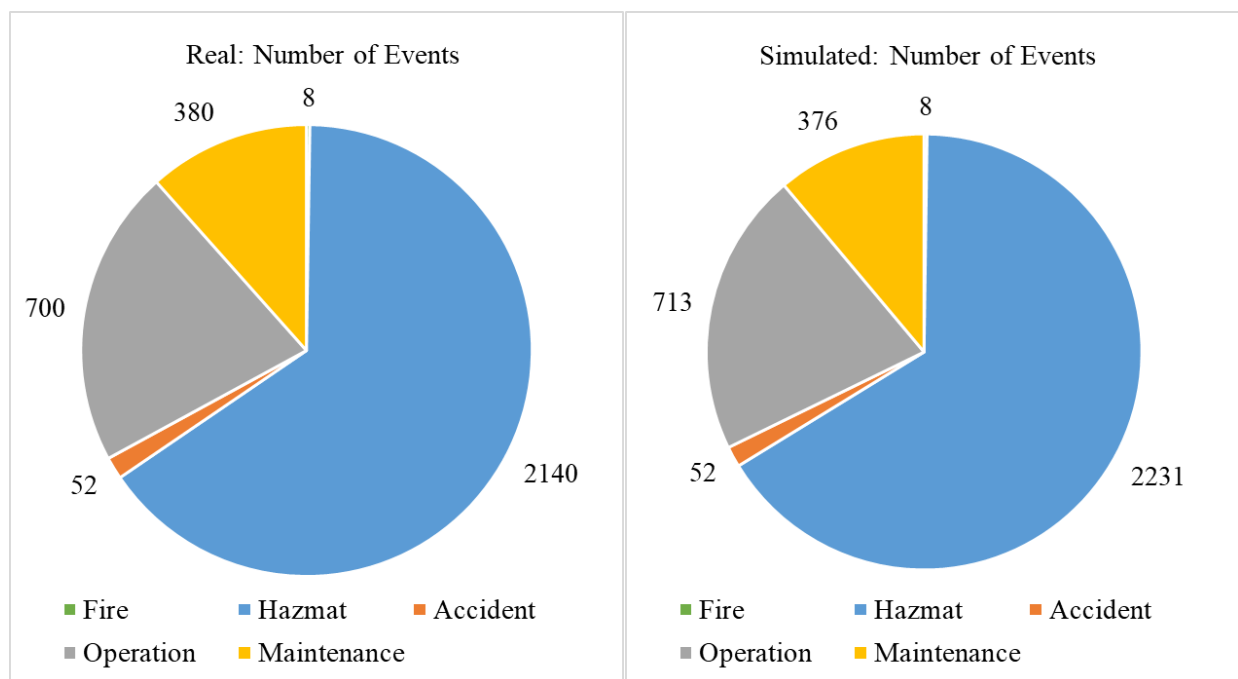
Figure 3.24. Pie chart of the average real and simulated number of events over a five-year period.
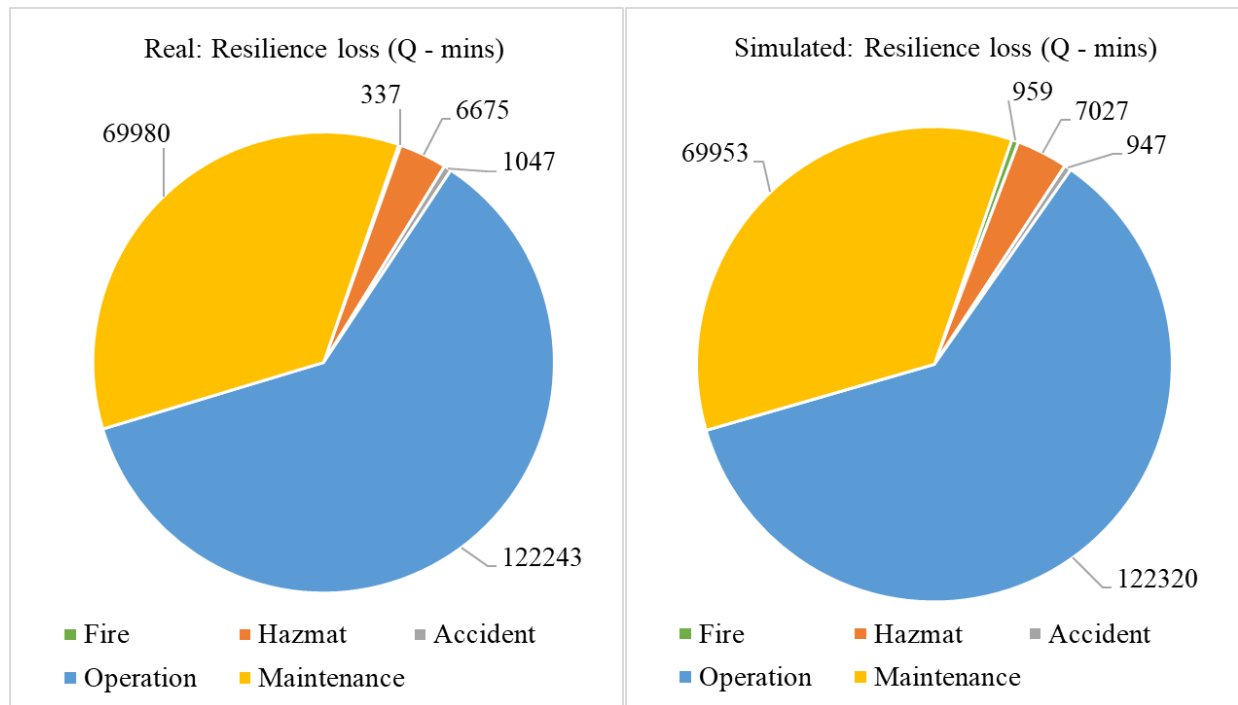
Figure 3.25.Pie chart of real and simulated cumulative resilience due to events over a five-year period.

3.7   Conclusion

To evaluate tunnel functionality loss and resilience quantitatively, a tunnel functionality metric was defined by its ability to accommodate through traffic. In this study, a probabilistic simulation framework was established to simulate tunnel functionality over time by considering several key influential factors and random disruptive events. Within the proposed framework, the occurrence and severity of disruptive events were simulated using underline probabilistic models (model parameters estimated from various data sources). Their impact on tunnel functionality was generated using fragility curves.

The proposed framework was implemented using the Monte Carlo simulation with MATLAB in this study. The program was used to generate disruptive events and functionality loss for the Eisenhower Johnson Memorial tunnel located in Colorado, USA, for five years. These simulated performance samples were then compared to the historic tunnel data collected by the Colorado Department of Transportation. By comparing this limited amount of data, it was concluded that the proposed simulation method could generate tunnel functionality loss and resilience data that falls within a reasonable range of actual tunnel operations. The five-year data from EJMT, although very limited, provided preliminary validation of the model proposed. Further validation of the model needs to be conducted with other types of tunnels under different environmental and traffic conditions. The sensitivity of tunnel resilience to various external circumstances and internal design decisions need to be investigated further in future studies.

3.8   Acknowledgement

3.9   References

Ahrens, M. (2017) *Trends and patterns of US fire loss*. Quincy, MA: National Fire Protection Association (NFPA).

Amundsen, F.H., & Ranes, G. (2000). Studies on traffic accidents in Norwegian road tunnels. *Tunnelling and Underground Space Technology*, 15 (1), 3–11.

Caliendo, C., & De Guglielmo, M.L. (2012). Accident rates in road tunnels and social costs evaluation. SIIV – 5th International Congress – Sustainability of Road Infrastructures. In: *Procedia-Social and Behavioral Sciences*, 53, 166–177.

Caliendo, C., De Guglielmo, M.L., & Guida, M. (2013). A crash-prediction model for road tunnels. *Accident Analysis and Prevention*, 55, 107–115.

Carvel, R. O., Beard, A. N., & Jowitt, P. W. (2005). Fire spread between vehicles in tunnels: Effects of tunnel size, longitudinal ventilation and vehicle spacing. *Fire Technology*, 41(4), pp 271–304.

Casey, N. (2020). Fire incident data for Australian road tunnels. *Fire safety journal*, volume 111, pp 1-11. https://doi.org/10.1016/j.firesaf.2019.102909

De Leonardis, D., Huey, R., & Green, J. (2018, March). *National Traffic Speeds Survey III: 2015* (Report No. DOT HS 812 485). Washington, DC: National Highway Traffic Safety Administration.

Fatality and Injury Reporting System Tool (FIRST), version 2.0.1 (2020) (https://cdan.dot.gov/query). Accessed March 15, 2020.

FHWA (Federal Highway Administration). (2015). *Specifications for the national tunnel inventory (SNTI)*. (Publication no. FHWA-HIF-15-006). Washington DC: FHWA.

FHWA (Federal Highway Administration). (2015). *Tunnel operations, maintenance, inspection, and evaluation (TOMIE) manual*. (Publication No. FHWA-HIF-15-005). Washington DC: FHWA.

German Tunnelling Committee (ITA-AITES) (2018). *Recommendations for the determination of lifecycle costs of road tunnels*. Cologne, Germany: DAUB.

Henke, A., & Galiardi, M. (2004). The 2001 Gotthard Road Tunnel Fire. *Tunnel Management International*, 7(1), pp 33-39.

Highway statistics series. Federal Highway Administration. (2019). Retrieved from https://www.fhwa.dot.gov/policyinformation/statistics.cfm

Highway Vehicle Fires (2014-2016) (2018). Topical Fire Report Series, 19(2), USFA.

Huey, R., De Leonardis, D., & Freedman, M. (2012, July). National travel speeds survey II: 2009. (Report No. DOT HS 811 638). Washington, DC: National Highway Traffic Safety Administration.

Huey, R., De Leonardis, D., & Freedman, M. (2012, August). National traffic speeds survey I: 2007. (Report No. DOT HS 811 663). Washington, DC: National Highway Traffic Safety Administration

Ingason, H. (2003). Fire development in catastrophic tunnel fires (CTF). In: *Proceedings of the International Symposium on Catastrophic Tunnel Fires*, Borås, Sweden, 31–48.

Khetwal, S.S., Pei, S., & Gutierrez, M. (2019). Operational resilience of traffic tunnels: An example case study. In: Proceedings of the *WTC 2019 ITA-AITES World Tunnel Congress*, Naples, Italy, May 3-9 (2019).

Khetwal, S.S., Pei, S., & Gutierrez, M. (2020). *A Unified Data Collection Framework for Quantitative Resilience Assessment of Road Tunnels*. Manuscript submitted for publication.

Kohl, B., Forster, C., & Wiesholzer, S. (2014). Upgrading of the Austrian tunnel risk model TuRisMo –methodical and practical aspect. In *7th International Conference 'Tunnel Safety and Ventilation'*, Graz, pp. 170–179.

Maevski, I. Y. (2011). NCHRP Synthesis 415: Design Fires in Road Tunnels. *Transportation Research Board*, Washington, DC, USA. https://doi.org/10.17226/14562.

Mashimo, H., & Ishimura, T. (2006). State of the art and future prospect of maintenance and operation of road tunnel. In: *23rd International Symposium on Automation and Robotics in Construction (ISARC)*, 299–302.

Montero, R, Victores, J.G., Martínez, S., Jardón, A., & Balaguer, C. (2015). Past, present and future of robotic tunnel inspection. Automation in Construction 59:99–112

Nævestad, T.O., & Meyer S. (2014). A survey of vehicle fires in Norwegian road tunnels 2008–2011. *Tunnelling and Underground Space Technology*, 41(1), pp 104–112.

Nelisse, RML, & Vrouwenvelder, ACWM (2016). Probability of a large fire in a road tunnel Bayesian Inference. *In 14th International Probabilistic Workshop (Caspeele R., Taerwe L., Proske D. eds)*. Springer, Cham, Switzerland.

NFPA 502: Standard for Road Tunnels, Bridges, and Other Limited Access Highways (2017). National Fire Protection Association, Quincy, MA, USA.

PIARC Committee on Road Tunnel Operation (C5). (2005). *Good practice for the operation and maintenance of road tunnels*. France: World Road Association (PIARC).

PIARC Technical Committee C3.3 Road tunnel operations. (2008). *Road tunnels: An assessment of fixed firefighting systems*. France: World Road Association (PIARC).

Rattei, G., Lentz, A., & Kohl, B. (2014). How frequent are fire in tunnels - analysis from Austrian tunnel incident statistics. In: *7th International Conference on Tunnel Safety and Ventilation*, Graz, Austria, pp. 5–11.

Ren, R., H. Zhou, Z. Hu, S. He, & Wanga, X. (2018). Statistical analysis of fire accidents in Chinese highway tunnels 2000–2016. *Tunnelling and Underground Space Technology*, 83, pp 452–460.

Richards, J.A. (1998). Inspection, maintenance and repair of tunnels: international lessons and practice. *Tunnelling and underground space technology*, volume 13, no.4, pp 369-375.

Sprung, M.J., Nguyen, L.X., Riley, D., Zhou, & S., Lawson, A. (2018). *National Transportation Statistics*. Bur. Transp. Stat. US Dep. Transp., Washington, DC.

Technical Committee 3.3 Road Tunnel Operations (2017). *Design Fire Characteristics for Road Tunnels*. France: World Road Association (PIARC). **ISBN:** 978-2-84060-471-6.

CHAPTER 4 SENSITIVITY STUDY ON ROAD TUNNEL RESILIENCE THROUGH STOCHASTIC SIMULATION

4.1 Abstract

A probabilistic resilience model for tunnel exposed to disruptive events is important to understand and estimate the functionality loss and its recovery time due to these events. Performing sensitivity analysis will help in identifying the critical parameters contributing to the tunnel resilience. Present analysis aims at identifying the sensitivity of tunnel resilience for parameters like traffic volume, presence of fire suppression system, changes in maintenance and operation parameters using simulation model that estimates overall tunnel resilience for a given period. Overall compatibility of the simulation model is checked for twenty-two tunnels using information from National tunnel inventory and resilience correlation is established. The results show that resilience loss due fire and accidents are directly correlated with traffic volume and significant reduction in the loss due to fire can be seen due to installation of fire suppression system. Increasing the service life of equipment and frequency of inspection and repair contributes to increase in the resilience index of tunnels. Resilience correlation study for the twenty-two tunnels showed that an average resilience index for these tunnels is 96.65%. Linear relation between the loss due to fire and operations can be made with tunnel length while accidents and fire events are with average traffic in the tunnel. Tunnel speed limit, age, number of lanes and bores do not show considerable effect on the disruptive events. Overall, the study shows that the proposed simulation model has the capability to encompass various disruptive events to estimate resilience of the tunnel.

4.2 Introduction

The road tunnels are susceptible to disruptive events, which can be caused by a random event like vehicle accident or can be planned by the tunnel crew in order to maintain the infrastructure. The only way one can quantitatively evaluate the disruption from disruptive events is to accurately track the functionality loss and its recovery of the tunnel during these events. While such data can be collected during tunnel operation, the existing data collection practice for tunnels lacks uniformity and consistence to generate such detailed data at large scale (paper 1 ref). Even such data collection effort can be implemented, it is not possible to evaluate hypothetical design and management choices on tunnel resilience. In order to better understand tunnel functionality loss to disruptive events, a stochastic event simulation model/tool was developed to quantitatively predict road tunnel downtime and resilience given tunnel parameter inputs (ref paper 2). The simulation model focuses on 5 main types of disruptive events for tunnels. These events include vehicle fire, vehicular accident, hazardous material platooning, tunnel components and equipment maintenance, and tunnel operation activities.

In the simulation model, each event type was represented with tunnel and external parameters which are believed to have a strong influence on the tunnel resilience. Some parameters change with time due to external factors like the traffic volume tend to increase with the increase in economic activity. Others change due to the decisions taken by the tunnel operator based on the financial constraints and experience like inspection interval of components. Therefore, a sensitivity analysis was conducted in this study to help understanding the impact of these parameters on the tunnel resilience. Key parameters such as traffic volume change and improvement to firefighting

equipment were investigated. Furthermore, this study showcased the potential of integration of the simulation tool and an existing national tunnel database. Even with very limited existing data provided in National Tunnel Inventory (NTI), the resilience of major tunnels in the United States was evaluated with reasonable outcome. The future direction of tunnel resilience study and implementation was also proposed at the end.

4.3 Literature Review

4.3.1 Tunnel resilience

Road tunnels play a very important role in reducing the distance between two locations and are mostly part of the critical path in case of accessibility of different locations. FHWA published that just by using Eisenhower tunnel in Colorado, public saved 90.7 million miles of travel per year. Hence, any disruption in their operation causes significant downtimes and traffic congestion. Attempts are made to reduce the tunnel closure time by keeping records of inventory, maintaining readily available maintenance crew, installing continuous tunnel monitoring system like SCADA among others. However, all these attempts are not assessed collectively to optimize the tunnel operation and therefore resilience of the tunnel need to be estimated to make an informed decision in case of emergency.

Resilience in general terms is defined as the measure of the ability of a system to recover from disturbances that interrupts their regular operation. Its quantification comprises of two aspects namely functionality loss at the time of disruption and time and resource needed for their recovery to return to fully functional system (Bocchini et al., 2014). While the concept is widely used for civil infrastructures like buildings, its usage for tunnels are still at preliminary stage. Bruneau et al. (2003) defined seismic resilience as a measure Q(t) which defines the quality of infrastructure. The resilience for tunnel was first defined by Rinaudo et al. (2016) as the capacity of tunnels to withstand fires with minimum loses and to recuperate a specific tunnel service level as fast as possible. Probabilistic approach for assessing resilience was proposed by Chang and Shinozuka (2004) using performance loss and recovery time. Quantification of tunnel resilience was done by Huang and Zhang (2016) and Huang et al. (2017) which was limited to tunnel lining. Khetwal et al. (2019) proposed a functionality loss metrics and a preliminary data collection framework. The paper emphasized on the requirement for data collection for calculating tunnel resilience. Fire event simulations were performed by Khetwal et al. (2020a) for Eisenhower Johnson Memorial tunnel (EJMT) using preliminary simulation model developed for fire events only. Functionality loss during the duration of fire events was estimated using the metric proposed earlier. Further, an elaborate tunnel data collection framework is proposed by Khetwal et al. (2020b) and tunnel resilience loss and resilience index are calculated for real data collected for EJMT. This collected data will contribute in evaluating tunnel resilience for events by a data driven approach. This data will also be used in calibrating the tunnel event simulation model parameters proposed by Khetwal et al. (2020c). The present study aims at using this proposed data framework to assess its applicability for other tunnels in variable circumstances.

4.3.2 Stochastic event simulation and sensitivity analysis

The uncertainty related to tunnel operation can be assessed using stochastic simulation wherein the events can be associated with their probability of occurrence. With enough iterations, MC

method models most combinations of input parameters providing a statistical distribution of the outcome (Sari et al, 2010). The stochastic simulation model to predict the structural response of tunnel in a maintenance strategy framework was developed by Baji et al. (2017) that equipped the tunnel operators and asset managers to develop a risk cost optimized maintenance strategy under their management. The risk assessment method using stochastic approach to enhance the underground road tunnel fire safety was proposed by Ntzeremes and Kirytopoulos (2018) with further implementation of real time notification to the tunnel operator of traffic and environmental conditions was presented by Ntzeremes et al. (2020). For railway tunnels exposed to risks like derailment, collision, impact with obstacles and fire, risk assessment methodology using stochastic simulation was suggested by Vanorio and Mera (2012). A study to control the Dangerous Good Vehicles and Abnormal Load Vehicles into the road tunnels using traffic simulations to improve the travel time and traffic queues for Dartford crossing tunnel was performed by Bhargava et al. (2020) wherein these vehicles were implemented with autonomous driving systems and tunnel was equipped with intelligent communication technologies. Influence of traffic flow due to deceleration behavior in response to sun glare in urban tunnels was analyzed using stochastic approach by Hu et al. (2019) and the results show that traffic volume decreases and critical density of congestion traffic increases as the illuminance of sunlight increases and change in the flow pattern can be observed. The available literature as discussed above are focused on the individual events or component and do not account for the overall tunnel performance. Khetwal et al. (2020c) presents a MC based simulation that generates events like fire, accident, operation and maintenance over a defined time period and combines their magnitude and duration of functionality loss to compute tunnel resilience over the given period. The model calculates an overall performance of tunnel due to disruptive events statistically.

Sensitivity analysis holds a significant position in a variety of computational engineering problems and quantifies the difference in the output due to small changes in the system parameters. The analysis is performed for various tunnel construction processes where the sensitivities to output parameters become more distinct as the replications are increased to certain extent. Khetwal et al. (2020) performed 50 replications to assess the sensitivity of various tunneling activities performed during construction using discrete event simulation as after this threshold, the number of repetitions did not add much to the precision or sensitivity of the models. However, to the author's knowledge, sensitivity analysis has not been used for tunnel operations studies considering the various tunnel downtimes or disruptive events. In this study, sensitivity analysis is performed to understand the response of simulation model with respect to change in parameters like equipment maintenance, tunnel operations and others for EJMT tunnel with 50 replications to encompass the uncertainty in the input parameters and worst-case scenarios.

4.4   Simulation methodology

A probabilistic simulation model was developed to generate disruptive events. The simulation model is based on Monte Carlo method. Five main types of disruptive events were shortlisted and incorporated, including vehicle fire, traffic accident, hazmat platooning, maintenance activities, and tunnel operations. The four major characteristics of a disruptive event are frequency of occurrence, magnitude, functionality loss (respective tunnel lane/s closure and reduction in speed limit) and duration.

The disruptive events are divided into two categories, namely random and planned events. Vehicle accident, vehicle fire and hazmat event platooning are considered as random events because their frequency and magnitude can only be statistically estimated. Tunnel maintenance events like inspection, repair and replacement of equipment/components and routine operation events like tunnel wash, sweeping, drain cleaning, etc., are planned events as their frequency can be adjusted by the management. However, the magnitude of planned event is a random parameter related to the rate of deterioration of tunnel components/equipment. Each type of event was simulated using a separate module implemented with Matlab. Finally, the results of each module are combined in a single tunnel functionality time history for the period of simulation, which can then be used to calculate functionality loss and resilience.

The methodology to simulate accident and fire events were similar and detailed in Chapter 3. Since the frequency of these events is relatively low a larger statistical base (data from all highways in the United States) was used to estimate the probability of event occurrence. Assuming that the frequency of events on any segment of the highway (including tunnels) is uniform. The magnitude of the event defined by the number and type of vehicles involved in the event. The parameter for accident was effective weight of involved vehicles and for fire was the heat release rate of involved vehicles. To estimate the functionality loss and its duration due to the event fragility-based method was used.

In most of the major tunnels restrictions are imposed on the transportation of hazardous material carrying vehicle (Hazmat) through the tunnel. In some tunnel like EJMT Hazmat are allowed to cross the tunnel when the alternate route (detour) is shut down due to weather of other reasons. In such case trucks are queued outside the tunnel and the tunnel is shut down for regular traffic to pass platoon of Hazmat in intervals. Probabilistic forecasting is used to generate alternate route closure event and estimating its magnitude. The number and duration of tunnel closures generated every hour depend on the traffic volume and the number of hazmat queued outside the tunnel. Complete bore closure is considered for every hazmat platooning event.

Tunnel maintenance is a planned activity and is divided into inspection, repair and replacement events. All these events occur in a predefined interval with slight variations on duration, which is related to the number of elements of component/equipment to be maintained and their rate of deterioration. The tunnel maintenance module is divided into two categories namely, repairable components and irreparable (to be replaced only) equipment. Four condition states of repairable components are defined as per Specification for the national tunnel inventory (SNTI), 2015. Number of repairs or replacement of these components to trigger a maintenance operation (which will cause tunnel functionality loss) is a decision to be made by the tunnel management, often related to the percentage of elements that can break or in worst condition states (i.e. Condition state 3 and 4) before public safety is of concern. The condition states of elements will be updated following maintenance operation. During maintenance/repair operation, the number of lane closures is predefined for each type of component/equipment as a procedural requirement, therefore defining the functionality of the tunnel during the event.

Tunnel operations are the routine maintenance activities like tunnel wash, sweeping, cleaning drains, etc. These activities are also planned but can vary in case a random event happens that require such activities. But the dates generally vary within a season, making these events

predictable for an effectively managed tunnel. Operation events occur at fixed time interval. The amount of time required to complete the activity is roughly proportional to the tunnel dimensions and the number of elements that need to be worked on (e.g. Cleaned or washed). Sometimes the activity is spread over a number of days. The amount of time required each day is constrained by the low traffic hours, mostly night hours. Number of lane closures and consequently tunnel functionality depends on the type of activity.

4.5   Scope of the sensitivity analysis

In order to improve the knowledge on how different factors will affect tunnel's functionality loss and recovery from disruptions several key factors were selected in this study as the focus of sensitivity analysis. Intuitively the parameters that might impact the tunnel resilience the most should be size of the tunnel, traffic volume, its age, number of lanes, presence of safety systems like ventilation, fire suppression, etc. as well as the maintenance and operation decisions taken by the operator. These parameters can be incorporated as part of the simulation model in various event modules. While it is relatively easy to predict the relationship between the change in these parameters and tunnel resilience, the quantitative impact from these factors is difficult to evaluate without simulation. For example, it is reasonable to speculate that increased traffic volume can increase the chance of tunnel functionality loss, while installing advance fire suppression system can help with tunnel resilience against fire. But it is difficult to put quantitative metric on their impact, thus making it difficult to compare these factors. How much increase in traffic volume would warrant an upgrade in the fire suppression system? Questions like this provided the motivation for a quantitative sensitivity analysis.

In this study, a base case was first established based on a realistic tunnel in Colorado. Then the key parameters that are believed to have significant impact to tunnel functionality were varied in the sensitivity analysis to evaluate their influence.

4.5.1   Base Case

The Eisenhower Johnson Memorial tunnel (EJMT) in Colorado was selected as the base case for performing the sensitivity analysis. As it was detailed in Chapter 3, EJMT tunnel operation during a 5-year time period was simulated because the performance can be validated to a reasonable extent using collected data. The basic parameters of the tunnel, according to the data framework, for compiling the data for the analysis are given in Table 4.1. The functionality loss (Table 4.2) related to tunnel lane and bore closures are calculated based on the functionality metric given in Khetwal et al. (2020b). A total of 50 replications (i.e. samples) were simulated to capture the stochastic characteristics of the performance. The model showed the capability to generate functionality loss and closure duration data with reasonable accuracy for various disruptive planned and random events. The detailed parameters of the simulation model are given in Khetwal et al. (2020c). The sensitivity analysis was conducted by varying key influential parameters of this model and observe their impacts on tunnel resilience.

Table 4.1. Input parameters for the framework preparation of EJMT tunnel.

Item No.	Basic Parameters		
1	Tunnel Name		Eisenhower
2	Location		Colorado
3	Built Year		1979
4	Highway (NHS) or Road ID		I-70
5	Length	m	2728
6	Finished Diameter (Width)	m	8.7
7	No. of Bores		2
8	No. of Lanes per Bore		2
9	Vertical Clearance	m	4.1
10	Roadway Width	m	7.9
11	Sidewalk Width	Right Side	0.5
12		Left Side	0
13	Fire Suppression	FSS	Y
14	Average Daily Traffic	ADTT	32000
15	Detour Length	km	144

16	Highway Speed Limit	km/hr	100
17	Tunnel Speed Limit	km/hr	80
18	Hazardous Material Restriction	Hazmat	Y
19	Hazmat Restriction Reason		Snow
20	Rehabilitation		N
21	Rehabilitation Year		0

Table 4.2. Functionality loss for various types of tunnel closures of EJMT tunnel.

	Specification	Tunnel open	Single Lane Closure	Single Bore Closure	Full tunnel closure (all bores)
1	Allowable Speed (km/hr)	80	64	80	0
2	Number of open lanes	4	3	2	0
3	Q (Functionality) (%)	100.0%	70.0%	50.0%	0.0%
4	Functionality loss (%)	0.0%	30.0%	50.0%	100.0%

4.5.2   Sensitivity parameters selection

The applicability of the framework and the interdependencies of various components were assessed by performing sensitivity analysis. The sensitivity of the simulation model was observed by examining the changes in accident, fire, maintenance and operation events versus 5 sensitivity cases as given in Table 4.3. The parameters were varied by changing the values in the ranges shown also in Table 4.3. The parameters selected to assess the effect of variation were traffic

volume, presence of fire suppression system, frequency of tunnel maintenance, service life of equipment, change in the maximum number of allowable failures, and change in the efficiency of the tunnel operations teams. Each of these parameters affect specific event modules of the simulation model, as it is shown in the table. These parameters are chosen for this study because they are expected to have notable impact on tunnel functionality. Some of them can be managed and controlled either through design, upgrade, and planning.

Table 4.3. Sensitivity Analysis parameters.

Event	Case	Parameter	Variation	Reason
All	1	Baseline	5 years 100 iterations	5 years 100 iterations
Fire/ Accident	2	Traffic Volume	-10%	Traffic will eventually increase
			+20%	
			+50%	
Fire	3	Fire suppression system	With (Base case)	Effect of FSS
			Without	
Maintenance	4a	Frequency of inspection and repair of lining and ceiling	24 months (Base case)	Effect of maintenance interval on prominent component
			36 months	
			48 months	
	4b	Service life of equipment (lights)	15 years (Base case)	Impact of changes in parameter of the equipment with most elements
			20 years	
			25 years	
	4c	Change of equipment (lights) Maximum number of allowable failures	3.5% (200 lights) (Base case)	
			7% (400 lights)	
			10% (600 lights)	
Operation	5	Efficiency of operation activities	1.0 (Base case)	Impact of improvement in operation efficiency
			1.1	
			1.2	

4.6   Sensitivity Analysis

Because the simulation sample size is relatively small, in order to eliminate the impact of randomness in other modules, cases where the impact on a specific type of event was apparent were simulated using only that affected module. For example, in the case of lights replacement, only the equipment replacement category of maintenance module was run. Each replication of the simulation is done for a 5-year period.

Traffic volume is a time varying parameter. It generally increases with time and economy growth. On Interstate I-70 at EJMT, the traffic volume is found to increase by 2% annually based on history data. The change in traffic volume will certainly affect fire and accident events in tunnels. Figure 4.1 and Figure 4.3 shows the resilience loss due to fire and accident events respectively and the variations with the change in traffic volume. Figure 4.2 and Figure 4.4 shows the number of fire

and accident events. The number of fire and accident events tend to increase linearly with the increase in traffic volume (which is expected). In Figure 4.1 an outlier event with resilience loss of around 16000 Q-mins, for traffic volume 150%, was removed from the plot in order to show a clear spread for all cases which was otherwise not visible. The resilience loss for fire events increases nonlinearly whereas for accident events the increase is linear with traffic volume.
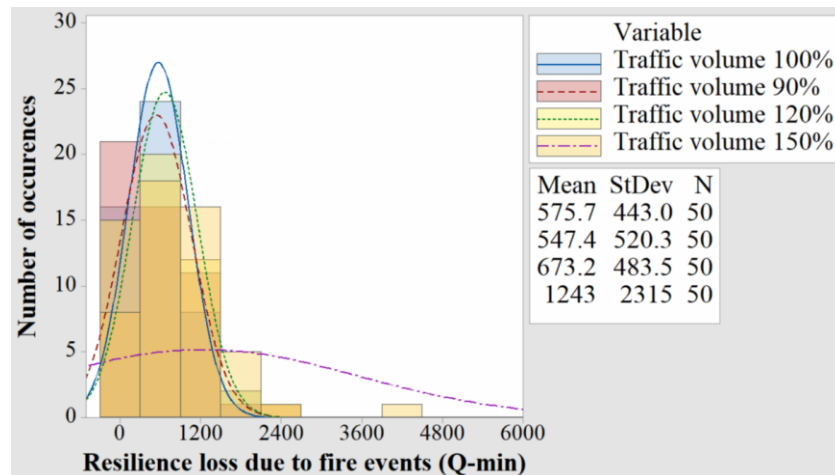
Figure 4.1. Case 2 - Fire resilience loss due to change in traffic volume.
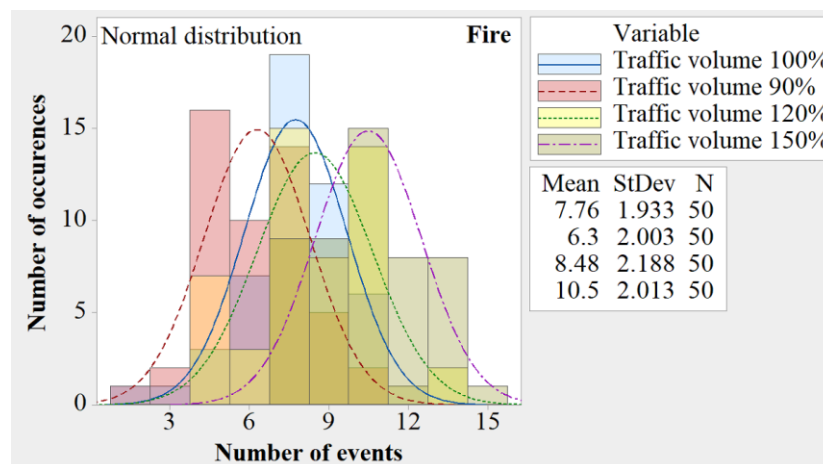
Figure 4.2. Case 2 - Variation in number of fire events due to change in traffic volume.
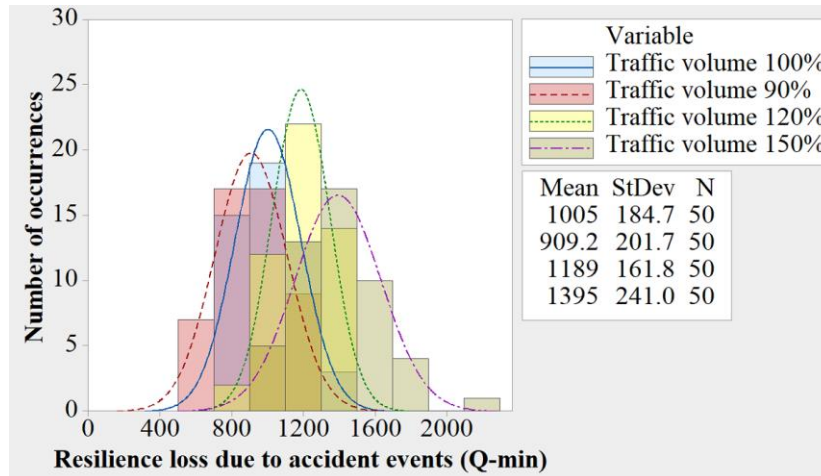
Figure 4.3. Case 2 - Accident resilience loss due to change in traffic volume.
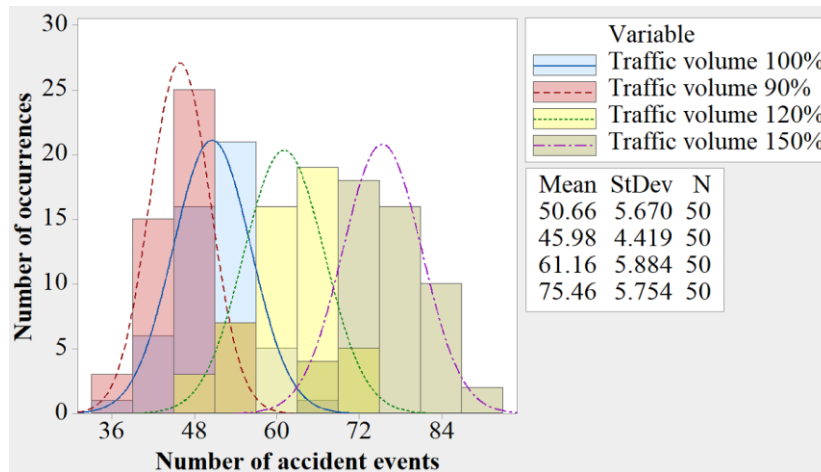
Figure 4.4. Case 2 - Variation in number of accident events due to change in traffic volume.

Figure 4.5 shows the distribution of functionality loss for EJMT with and without fire suppression system (FSS). Again, one replication is not shown in Figure 4.5 as it was an outlier in without FSS distribution with value 13772 Q-mins. The average number of events in both cases are approximately 7 for a 5-year period. This clearly demonstrates that the magnitude of the fire events is more in case the FSS has not been installed and that the model is sensitive to the installation of FSS. A two sample T-test was performed for the sample sets. However, the test does not reject the null hypothesis with 5% significance level, the low p-value, 0.0841, makes the validity of the null hypothesis uncertain. The null hypothesis will be rejected if the significance level is 10%.
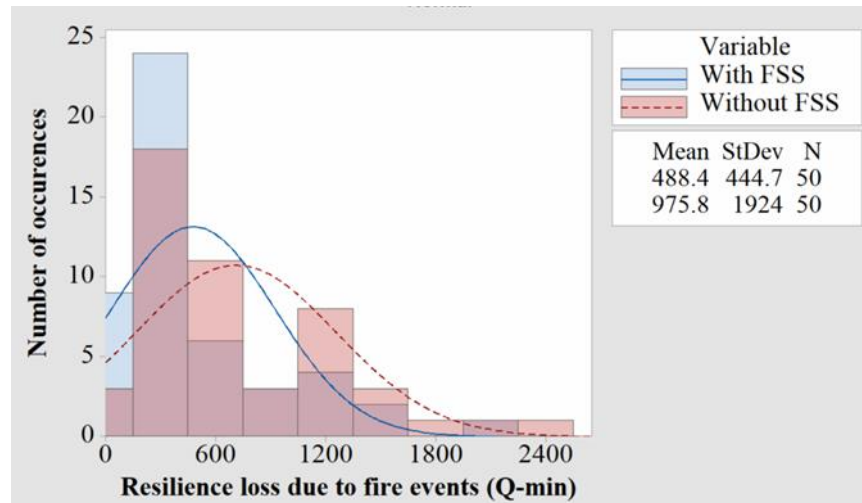
Figure 4.5. Case 3 - Resilience loss due to fire event with and without fire suppression system.
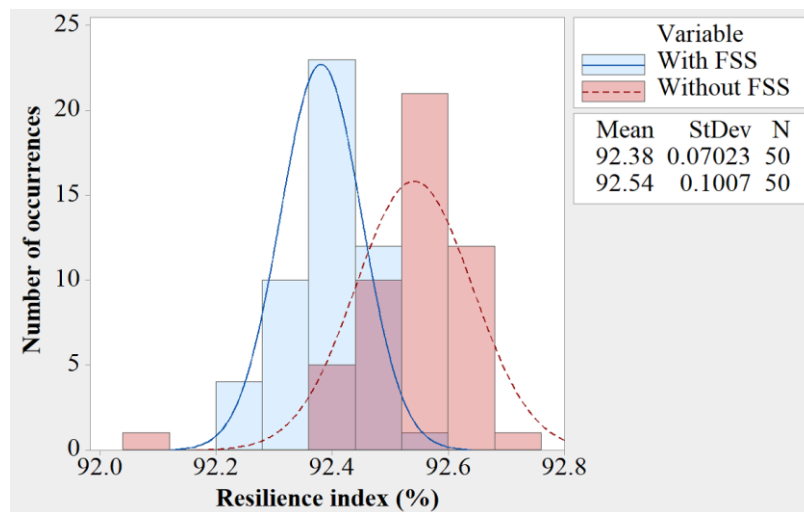
Figure 4.6. Case 3 - Tunnel resilience index with and without fire suppression system.

When looking at overall tunnel functionality loss (i.e. resilience), the resilience index comparison in Figure 4.6 shows that the resilience index of the tunnel is greater when the FSS is not installed. This is counter-intuitive but the reason behind this simulation result is the increased maintenance disruption for additional equipment and components brought in by the fire suppression system (sprinklers, heat and smoke sensors, etc.). The operation events also increase due to the scheduled testing events of the FSS. Since these additional events are planned and can be performed during hours when the traffic is less, their impact can be mitigated. But based on the simply defined functionality metrics used in this study, the functionality loss was not calculated with the time of the interruption in mind. Further, the cost of a major fire event could be significant in terms of fatalities and financial loss. Cost analysis for fire and accident events can be performed using the

model but not included in the scope of this study. Since the costs corresponding to the magnitude of event have not been calibrated accurately that part of the analysis is not presented here. Nonetheless, this observation indicated that resilience of the tunnel can be a complicated problem that will be affected by multiple factors. Installing FSS for any tunnel will not automatically guarantee a resilience improvement.

For case 4a the simulation was focused on component maintenance module which simulate inspection, repair and replacement of the elements of the component. Four different inspection and repair intervals were investigated, namely every 2 years (current practice), 3 years, 4 years, and 1 year. Since the least common multiplier of all cases is 12 years, the simulation duration was selected to be 12 years, with each case simulated with 20 samples.
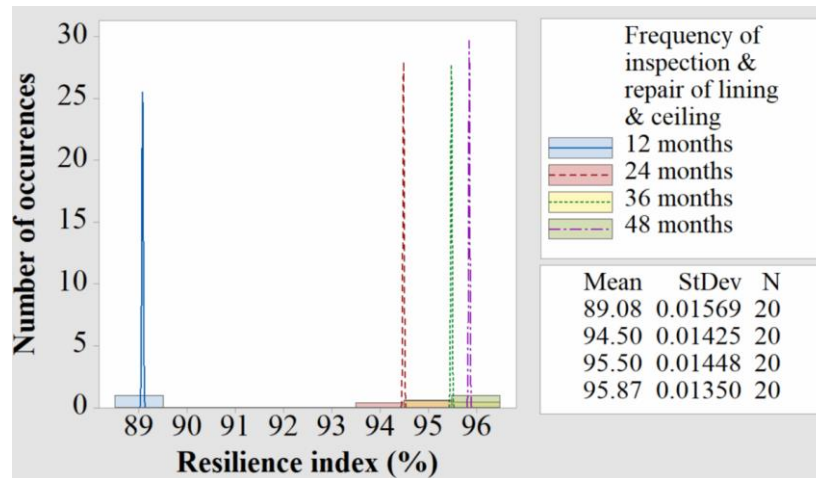
Figure 4.7. Case 4a - Tunnel resilience index with variation in the frequency of inspection and repair.

Lining and ceiling components were chosen for the variation in the interval as they have significantly greater number of elements than other components whose maintenance interval is kept constant, like sprinklers and hydrants. The results in Figure 4.7 show that the resilience index improves as the maintenance (inspection and repair/replacement) interval increases from 24 months to 48 months by more than 1%(equivalent to 3500 hours of partial bore closure over 12-year period) . The module consists of inspection and repair/replacement process. In the scenario of longer maintenance interval, the repair events will be of longer duration as the number of elements to be repaired will increase. However, this increase in the duration is countered by the inspection durations as all elements (considerably more than repair/replacement elements) have to go through inspection lesser number of times for longer inspection intervals. For example, in case of 48-month interval inspection will be held thrice but for 24-month interval it will happen six times. Also, a simulation duration of only 12 years is not long enough to capture long term deterioration of components and hidden deterioration that cannot be identified in a routine inspection. It is important to highlight the importance of regular inspection in order to reduce the probability of catastrophic events (e.g. lining collapse), but at the same time, the current simulation model did illustrate the trade-off of having interruption to traffic with more frequent inspections.
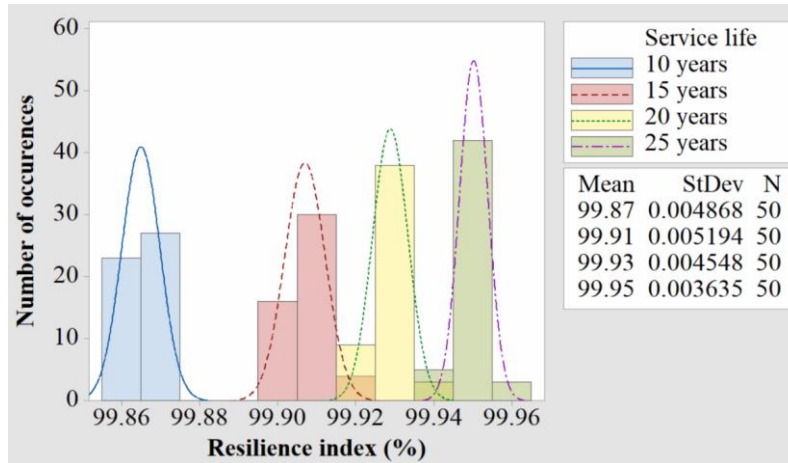
Figure 4.8. Case 4b - Tunnel resilience index with variation in the service life of equipment.

Using more reliable equipment or component will likely improve the resilience of the tunnel, at the cost of higher initial investment. For case 4b only the quality of lights in the tunnel are considered because their quantity is much more than any other equipment like camera or traffic signals. Service life of the lights was varied from base case of 10 years to 25 years. The overall resilience index of the tunnel improves by 0.08 %, as shown in Figure 4.8, this is equivalent to approx. 110 hours of partial bore closure at EJMT over 5-year period. Similarly, method was used for case 4c. The threshold number of light failures which will trigger maintenance event for changing of lights was varied. 200 lights are approximately equal to 3.5 % of lights in EJMT, which is the current practice in the tunnel. The variation ranges from 3.5% to approx. 10% of the light failure, representing a more tolerant style of maintenance management. The resilience index of tunnel with respect to the equipment replacement category of tunnel improves by 0.02%, as shown in Figure 4.9. A two sample T-test was conducted for resilience index samples for 200 and 600 lights failure and replacement. The test rejects the null hypothesis at 5% significance level. However, this simulation did not take into account on the potential drawback of having more lights out during operation, which may increase the rate of traffic accident. This is a clear limitation of current sensitivity analysis, but due to lack of information on how the lighting condition and accident rate interact, such simulation was not included within the scope of this study.
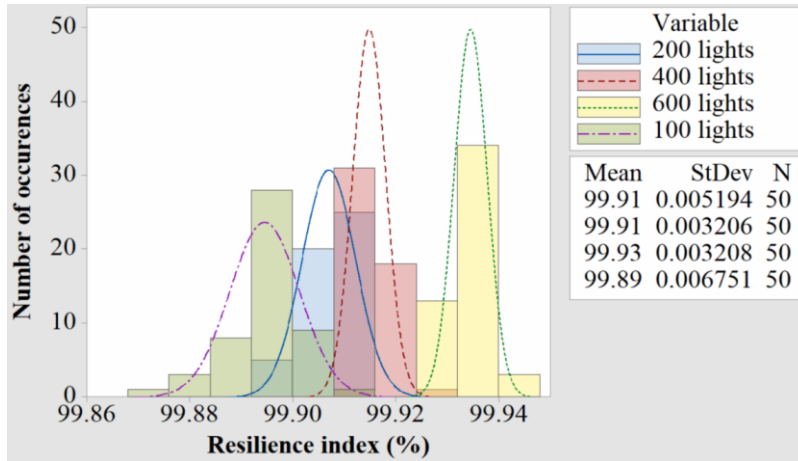
Figure 4.9. Case 4c - Tunnel resilience index with variation in the minimum number of elements to be replaced.

Tunnel operations have the least level of dispersion in their resulted functionality loss, because they are planned events. However, due to their high frequency, they contribute to a significant part of the functionality loss, approx. equal to 60 % of the total loss. In sensitivity study case 5, the simulation was performed for the operation module of the model based on efficiency of the operation work. In real life, the duration for a given operation activity is related to the number of staff on the task and their experience level. The quality and quantity of the equipment available to the staff to complete the task also can play a role. Improvement in any of these will lead to increase in efficiency of the operation activity. In case 5, as shown in Figure 4.10, efficiency of operation activity is varied by using a factor which changes from 0.9 to 1.0 (base case) and to 1.2. A significant improvement in tunnel resilience index is observed. The change of 0.65% of resilience index is equal to approx. 900 hours of single lane closure for one tunnel bore at EJMT. Reduction of 0.47% is seen when the efficiency is changed from 1.0 to 0.9.
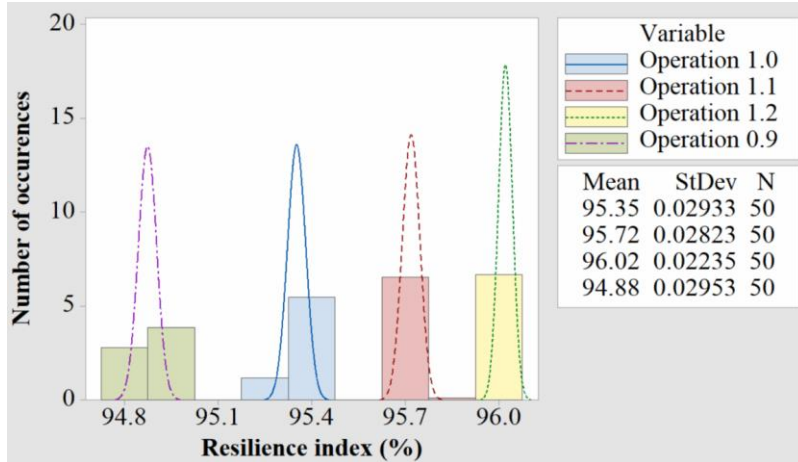
Figure 4.10.Case 5 - Tunnel resilience index with variation in the efficiency of the operation activities.

Based on all the sensitivity analysis conducted here, although it is a highly simplified and hypothetical analysis, some interesting conclusions can be drawn. Overall, the sensitiviy analysis showed that the simulation model proposed was able to generate rational simulation outcomes. More specifically, we can use the generated data to compare impact of different design and operation parameters. Among the parameters investigated in this study, frequency of inspection and repair of lining and ceiling is the most influential. Some interesting management decisions can also be made. For example, if EJMT traffic volume is increased to 150% in the next 10 years, it seems reasonable to use a 1.2% increase on personal or equipment improvement (efficiency) to offset the impact on tunnel resilience.

4.7   Resilience correlation study using NTI tunnel data

Since every tunnel is unique in terms of its design, construction, location, elevation, etc., the sensitivity analysis will provide results according to the tunnel parameters. In the previous section, sensitivity analysis was performed for EJMT as the data on tunnel parameters was comprehnsive as compared to other tunnel data. It is likely that for a different base case, some of the parameters and events will show different impact. So this gives motivation to conduct another study on the impact of a design parameters on tunnel resilience. This was done in this study by conducting a regression analysis using tunnels of different configurations and designs. In order to do this, best case is that one have gathered real tunnel performance data over a long period of time from a large number of tunnels. However, as it was indicated in early chapter, such a comprehensive uniformed data base is not available. So the simulation tool was used in this study to generate such data. The simulation is not extremely comprehensive at this stage because of the limited information available from target tunnels. But this is the first time to the author's knowledge that this type of analysis has been conducted with the hope to provide some insight on tunnel resilience at a grand scale.

4.7.1   Data collection methodology

The tragic collapse of Interstate 90 Connector tunnel in Boston, Massachusetts served as a strong message towards the requirement for tunnel inspections. Eventually, National Tunnel Inspection Standards and guidelines were formed wherein emphasis was given on maintaining a proper inventory and assessing of the condition of tunnel elements. The National Tunnel Inventory (NTI) was prepared so that a timely report regarding the number and condition of tunnels to the Congress can be made. The database include the information like name, age and service, classification, geometry, structure type, various systems like structural, civil, mechanical, electrical and lighting, fire safety and security, signs and protective systems.

Table 4.4. Criteria for tunnel selection for resilience correlation study.

Sr. No.	Criteria	Detail
1	Average daily tunnel traffic	>10000
2	Functional classification of tunnel -	Tunnels on interstate, principal arterial
3	Length of tunnel	>1 km
4	Complexity of tunnels	Containing electro-mechanical equipment

The database obtained from NTI uses many specific codes that were described in detail in Specifications for the national tunnel inventory (SNTI, 2015) report. While the format and details on the NTI data are not as comprehensive as the data collection framework proposed in this study (Chapter 2), the data in NTI can be used to create compatible input parameters with the simulation model. This process will require some subjective assumptions related to input parameters not included in the data base, such as operation activities, detailed equipment installed like cameras and presence of fire suppression systems and their components like sprinklers and hydrants. The assumptions made on these unknown input parameters are explained in the next section.

Based on NTI data and rational assumptions, input dataset for 22 tunnels from the database were established for the simulation analysis. The resilience index was calculated for these tunnels over a 5-year period. The tunnels were selected on the criteria as given in Table 4.4. The regression analysis was performed for several design and environmental parameters including location, tunnel length, fire suppression system inclusion, average daily traffic (ADT), speed limit, age, number of bores and total number of lanes. For simulation, the Hazmat module which simulate hazmat platooning was not considered because it is not clear from NTI data whether hazmat vehicles are allowed under certain conditions. The details of the tunnels are given in Table 4.5. The simulation generated 50 samples for each tunnel.

Table 4.5. Tunnels considered for resilience correlation study.

Sr. No.	Tunnel Name	Length (m)	Built Year	No. of Bores	No. of Lanes per Bore	Total Lanes	Fire Suppression	Average Daily Traffic	Tunnel Speed Limit (kmph)
1	Hugh Carey Tunnel	2785	1950	2	2	4	Y	55768	65
2	Eisenhower Johnson Tunnel	2728	1973	2	2	4	N	32000	80
3	Holland Tunnel	2608	1927	2	2	4	N	85318	65
4	Lincoln Tunnel	2504	1937	3	2	6	N	102964	50
5	Baltimore Harbor Tunnel	2332	1958	2	2	4	N	77235	80
6	Hampton Road Tunnel	2255	1957	2	2	4	N	89000	90
7	Fort McHenry Tunnel	2197	1985	4	2	8	Y	122820	90
8	Harano Tunnel	1931	1994	2	2	4	Y	47400	90
9	Queens Midtown Tunnel	1912	1940	2	2	4	Y	79526	65
10	East River Mountain Tunnel	1725	1974	2	2	4	N	30000	90
11	Sumner Tunnel	1724	1934	1	2	2	Y	28970	65
12	Callahan Tunnel	1545	1961	1	2	2	N	27535	65
13	Monitor Merrimac Memorial Bridge Tunnel	1481	1992	2	2	4	Y	61000	90
14	Devil's Slide Tunnel	1302	2013	2	1	2	Y	14500	70
15	Big Walker Mountain Tunnel	1289	1972	2	2	4	N	30000	90
16	Hanging Lake Tunnel	1216	1992	2	2	4	Y	14000	80
17	Port of Miami Tunnel	1213	2014	2	2	4	Y	28869	60
18	Caldecott Tunnel Bore 1	1102	1937	1	2	2	N	38750	80
19	Caldecott Tunnel Bore 2	1100	1937	1	2	2	N	38750	80
20	Caldecott Tunnel Bore 4	1036	2013	1	2	2	Y	38750	80
21	Caldecott Tunnel Bore 3	1027	1965	1	2	2	N	38750	80
22	Alaskan Way Tunnel	3267	2018	1	4	4	Y	45100	72

4.7.2 Input parameters for all tunnels from NTI

For the case of accident and fire, the basic parameters of each tunnel changes like length, traffic volume, speed limits as given in Table 4.5.While for maintenance and operation, tunnel components and equipment are set as input specific to the tunnel. For example, some tunnels have ceiling slab while others do not, these details are incorporated in the simulation model. Considering the variability in the equipment and components, following assumptions were considered:

- Only the equipment / component inside the tunnel are considered.
- Author had detailed knowledge of EJMT. However, for this study for consistency EJMT data was extracted from NTI same as other tunnels with the same assumptions made for other tunnels.
- The tunnels built after 1990 or tunnel that are refurbished recently are assumed to have fire suppression system in them.
- For maintenance, basic tunnel components are considered as they are most influential due to their quantities and other components, like girder and hangers, are considered part of these components. They are tunnel lining, ceiling panels, roadway (asphalt / concrete).
- For operation, basic activities considered are tunnel wash, street sweeping, washing lights/signs, drain cleaning and sand removal. These activities are defined in Tunnel operations, maintenance, inspection, and evaluation (TOMIE, 2015) manual.
- The types of equipment are chosen depending on the information available in NTI database and considering that these are inside the tunnel, like lights and signs, such that their replacement caused functionality loss.

4.7.3 Results

The average resilience index of the 22 tunnels is 96.65%, as shown in Figure 4.11. This means on average loss of functionality for tunnels investigated. The lowest 94.41 % is for the EJMT while the best resilience index is 98.06% is for Monitor Merrimac Memorial Bridge Tunnel (MMMBT) in Virginia. This is due to a combination of reasons. For example, the smaller length of the tunnel which means less components/equipment and lesser duration for operation activities. The length of tunnel is also a factor in number of accidents and fire inside tunnel, as it will be shown in the next section. The MMMBT is less than 30 years old which translates into the components being in better condition states also.
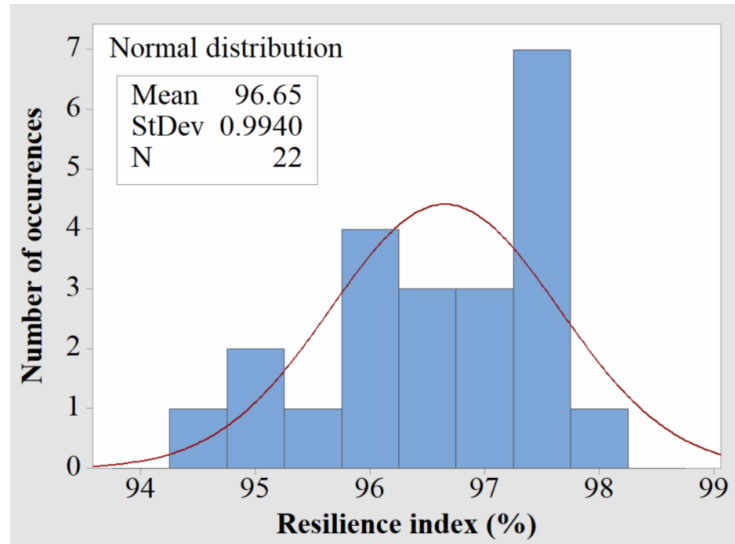
Figure 4.11. Mean resilience index for 22 tunnels.
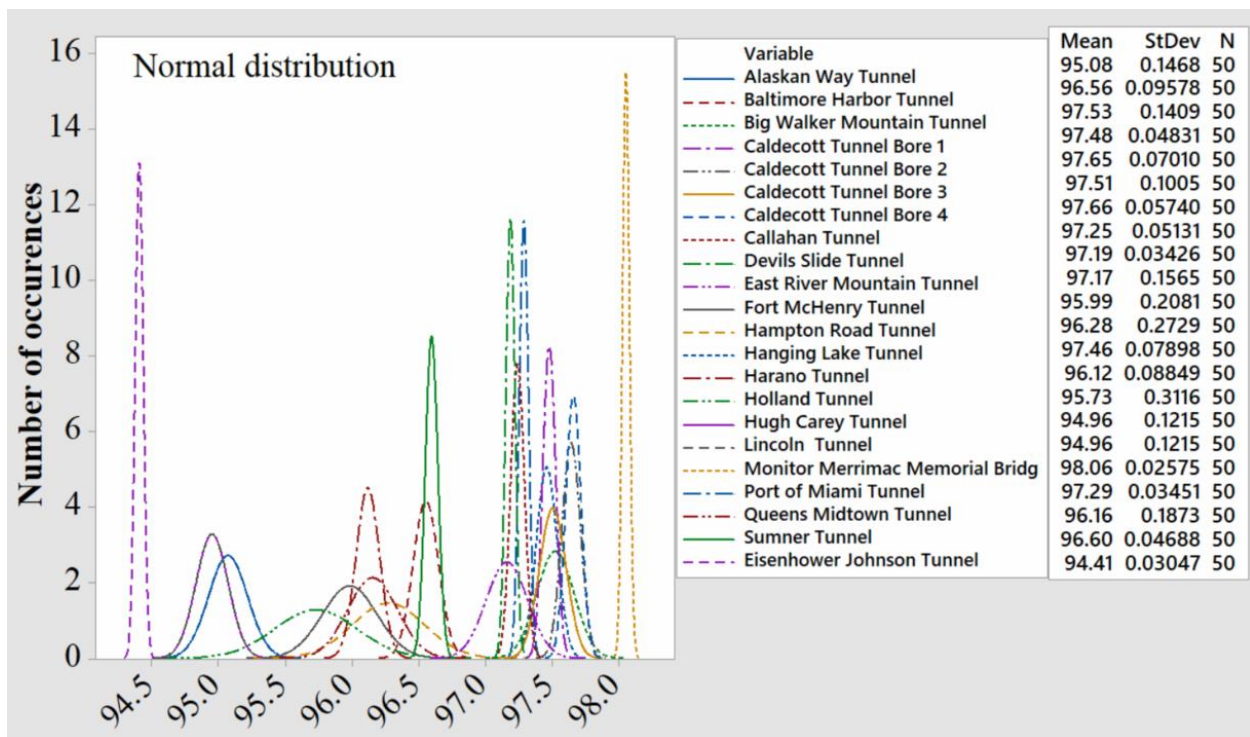
Figure 4.12. Stochastic distribution of resilience index for 22 tunnels generated using 50 samples.

Road tunnels can be divided into 2 main categories namely urban and rural. Urban road tunnels are important part of the city infrastructure as they create space for development and reduce the travel time across the city. Tunnels are built in rural areas to overcome an obstruction on a highway

like a mountain range or a river, reducing travel time and environmental impact. Figure 4.13 shows the fitted (lognormal distribution) and empirical CDF of the resilience loss for these two categories of tunnels. T-tests were conducted to identify the statistical significance of the difference. It turned out that under 5% significance level, random events like fire and accident have low p-values, 0.2031 and 0.1128 respectively and p-value for overall random events is 0.1379. While for planned events like tunnel maintenance and operation, the p-value is relatively high as 0.2772 and 0.4693 respectively and p-value for overall planned events is 0.8445. When, two sample T-test was conducted for total resilience loss for urban and mountain tunnels, a p-value of 0.9934 was obtained which strongly validates the null hypothesis that normal distributions have equal means, assuming equal but unknown variance.

The overall resilience index does not show any trend to the presence and absence of FSS, although the tunnels without FSS show greater resilience loss, as shown in Figure 4.14. The average resilience loss due to fire events for tunnels with FSS is 1216 Q-mins having average length of 1900 m whereas, its almost twice for tunnels without fire suppression system is 3028 Q-mins having average length of 1749 m. Although, two sample T-test does not reject the null hypothesis at 5% significance level, the p-value is 0.1072 which is small and makes the validity of null hypothesis doubtful.

Aside from the inspection between tunnel groups with different characters (discrete category comparison), the correlation between tunnel functionality loss to continuously varying parameters (such as length, age, etc.) was examined through regression analysis.
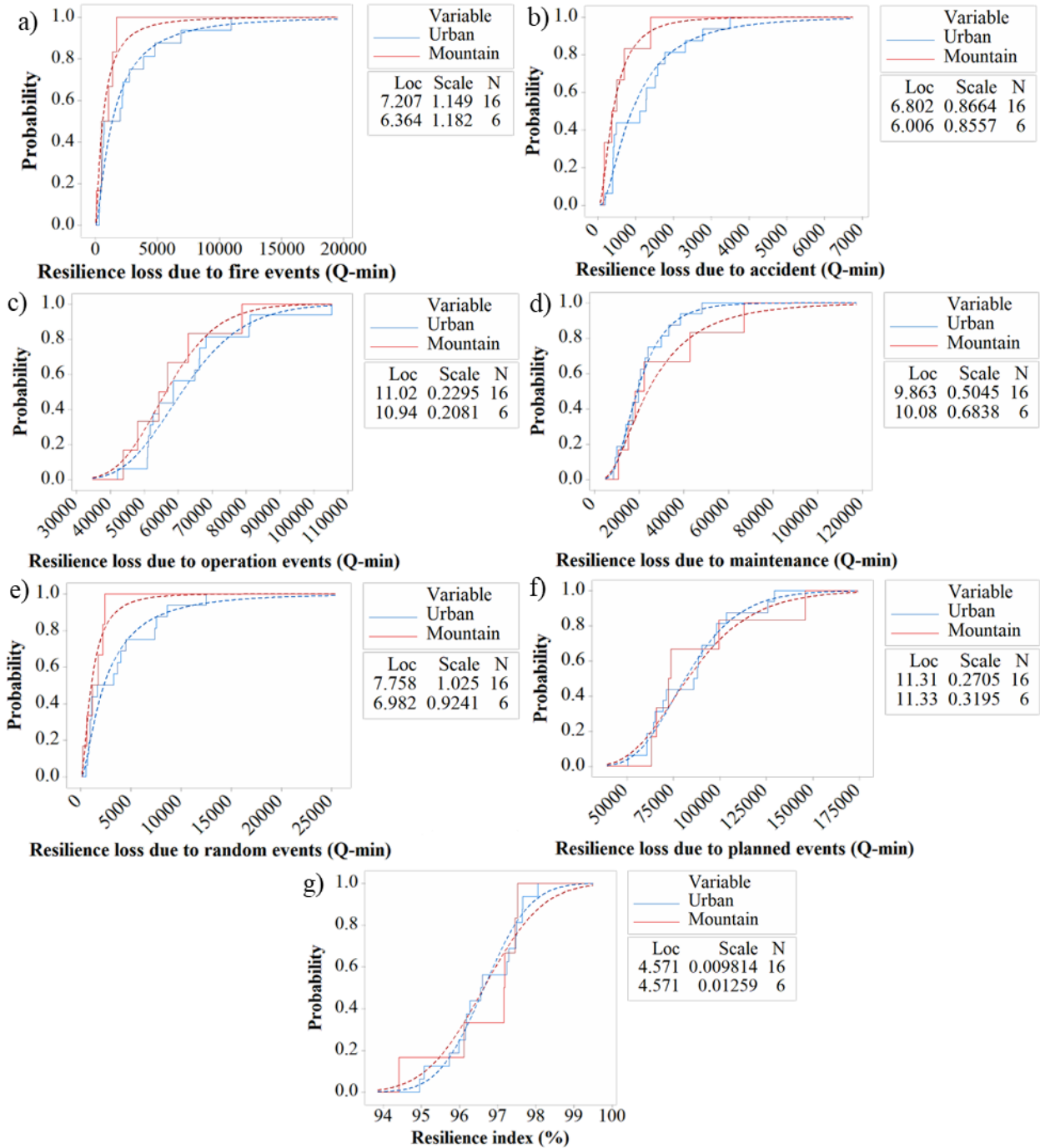
Figure 4.13.Empirical CDF and lognormal fit (dashed) for all events with respect to tunnel category.
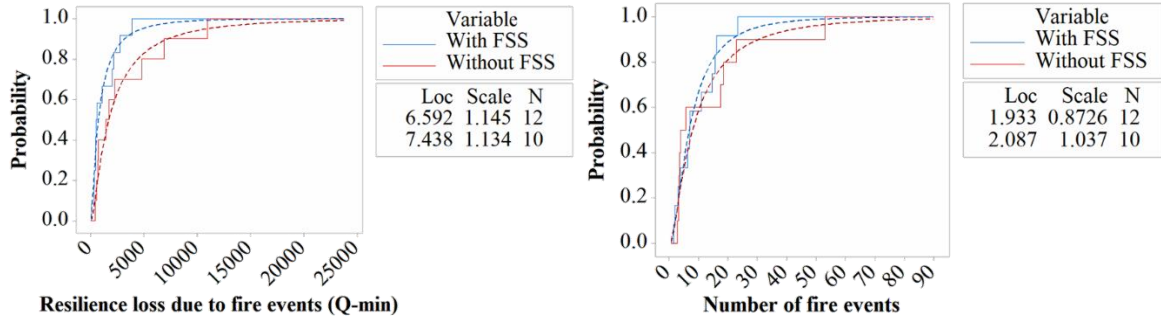
Figure 4.14.Empirical CDF and lognormal fit (dashed) due to fire events with respect to the presence of fire suppression systems.

Regression analysis was conducted for two main performance parameters (Y-axis), the first is the average resilience loss, the second is the overall tunnel resilience. Those parameters are the output of the simulation that signifies the performance of the tunnel. They are influenced by a wide range of input parameters. The regression analysis specifically focuses on the following: tunnel length, tunnel age, tunnel speed limit, avergae daily traffic in tunnel, number of lanes and number of bores. Sometimes a particular input parameter may only affect a specific module, thus the correlation with the overall tunnel resilience may not show up to be strong. When the functionality loss of a specific cause was separated, stronger correlation may be found.

Comparing different modules with resepct to tunnel length as given in Figure 4.15 shows that resilience index are linearly related to tunnel length with R-square of 0.86. For operation events and planned events, linear relationship can be seen. However, for other modules like fire, accident, random events and maintenance, poor relationship is observed and therefore no inference about the influence of tunnel length on them can be made.
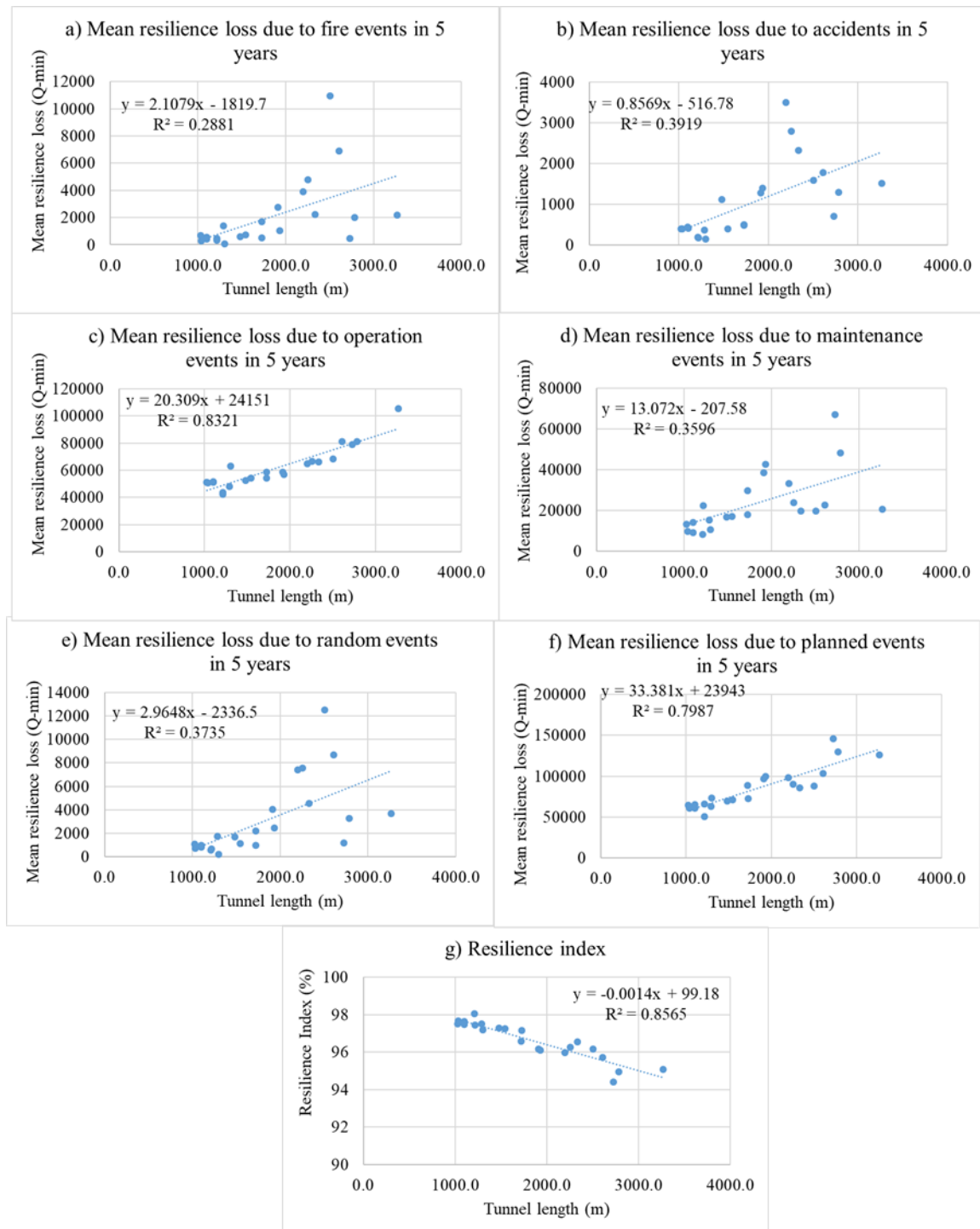
Figure 4.15. Variation of parameters with respect to tunnel length.
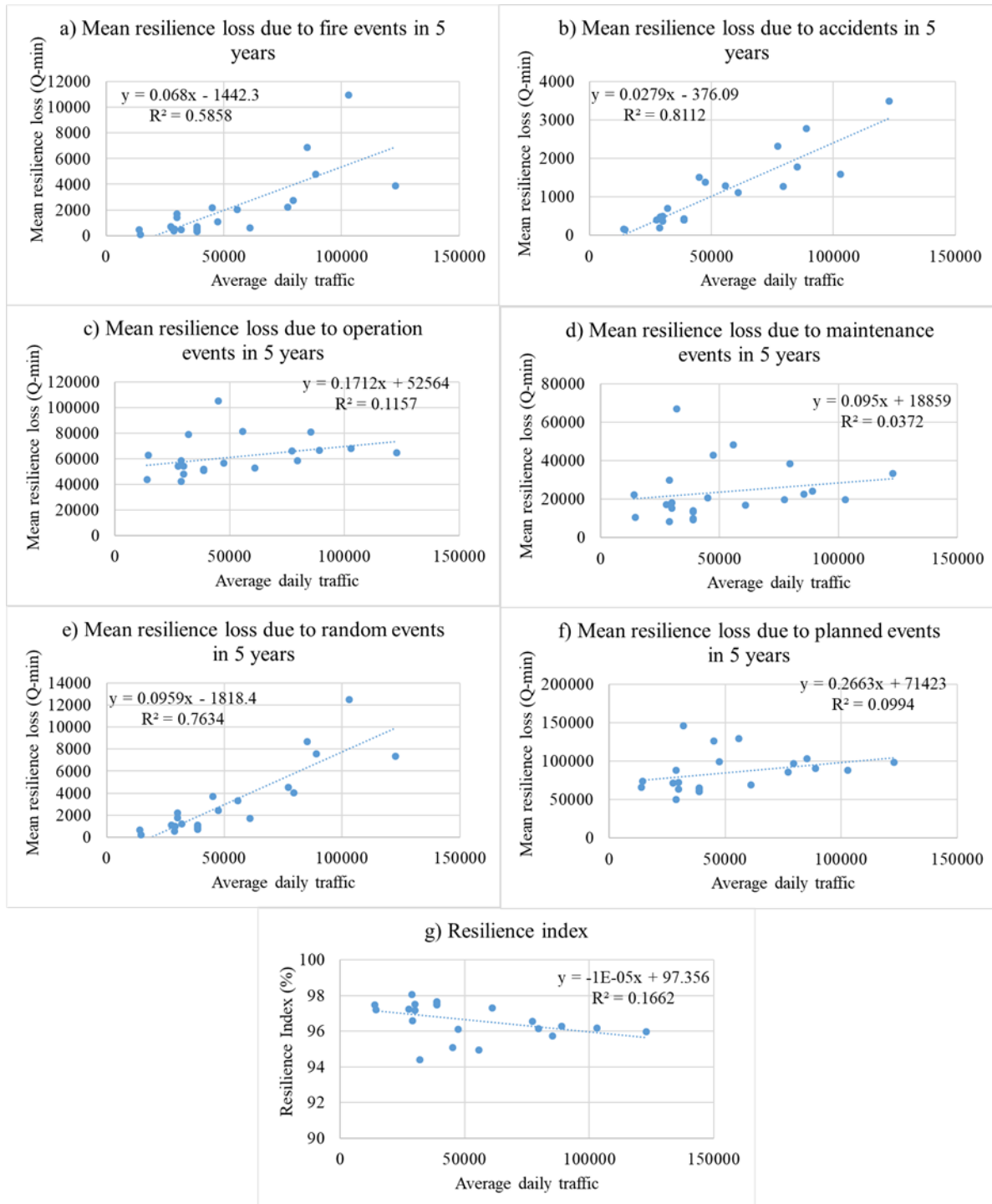
Figure 4.16. Variation of parameters with respect to average daily traffic.

Comparing the modules with average daily tunnel traffic, accidents and random events show linear relationship with R-square of 0.81 and 0.76 respectively. However, for operation and maintenance, no relationship can be seen. This seems to be reasonable as the deterioration of tunnel components

considered in this study is not related to traffic volume (road and pavement are not considered here). No significant correlation of resilience index with average daily traffic can be seen because resilience index is affected greatly by operation and maintenance activities.

Comparing the resilience loss with tunnel speed limit, age, number of lanes and number of bores, no particular trend can be established (Figure 4.17, Figure 4.18, Figure 4.19 and Figure 4.20). Therefore, their direct effect cannot be determined.

Combining the parameters could be a way to find a correlation. For example, Queens Midtown Tunnel (QMT) and Harano Tunnel are similar in length and both have 2 bores of 2 lanes each. The major difference is the traffic volume which shows correlation with fire and accident events and not with planned events (maintenance and operation). Both tunnels show almost same resilience loss value for planned events. Therefore, a combination of factors could lead to better correlations. Another reason for the lack of correlation could be the absence of detailed information about the tunnels.
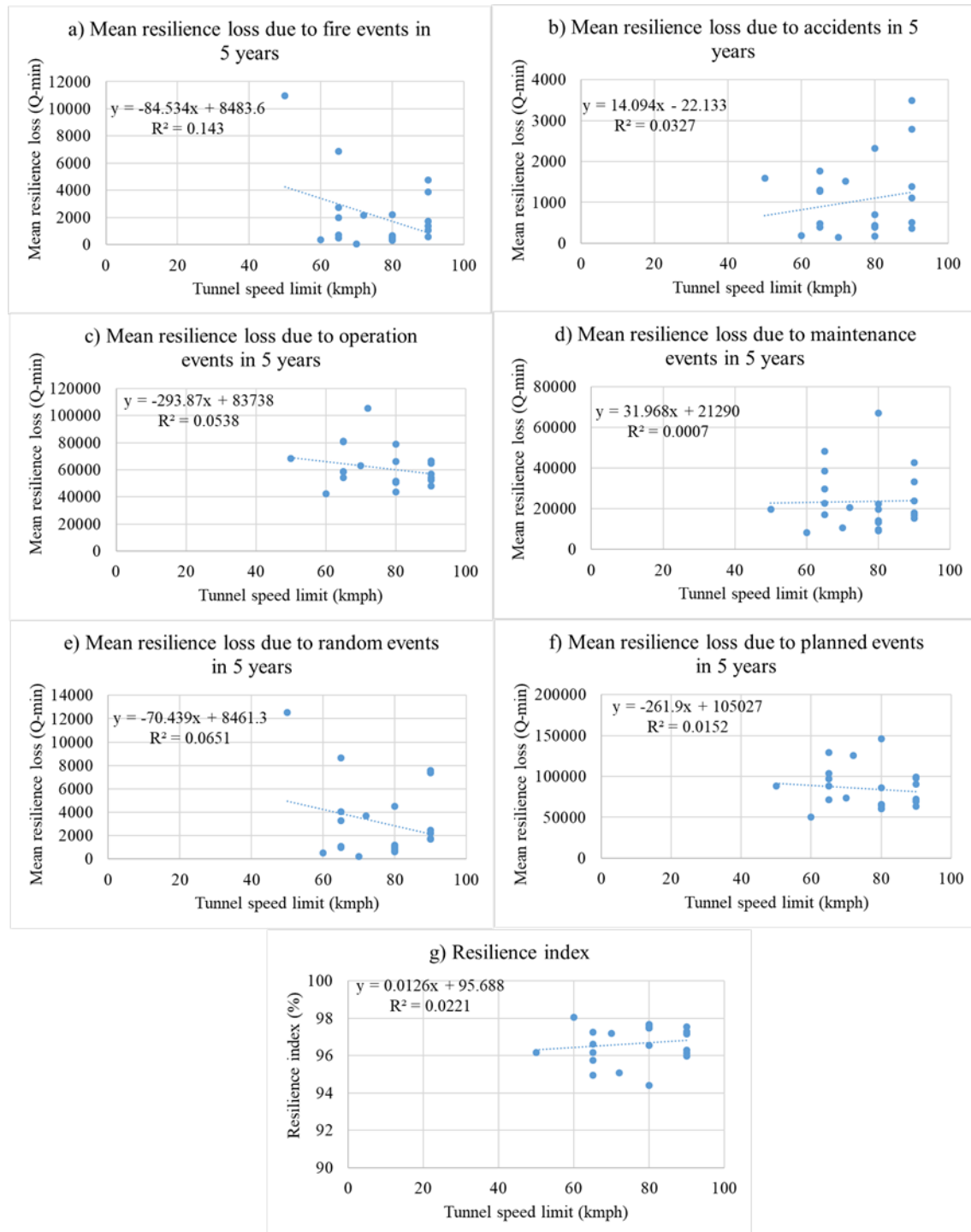
Figure 4.17. Variation of parameters with respect to tunnel speed limit.
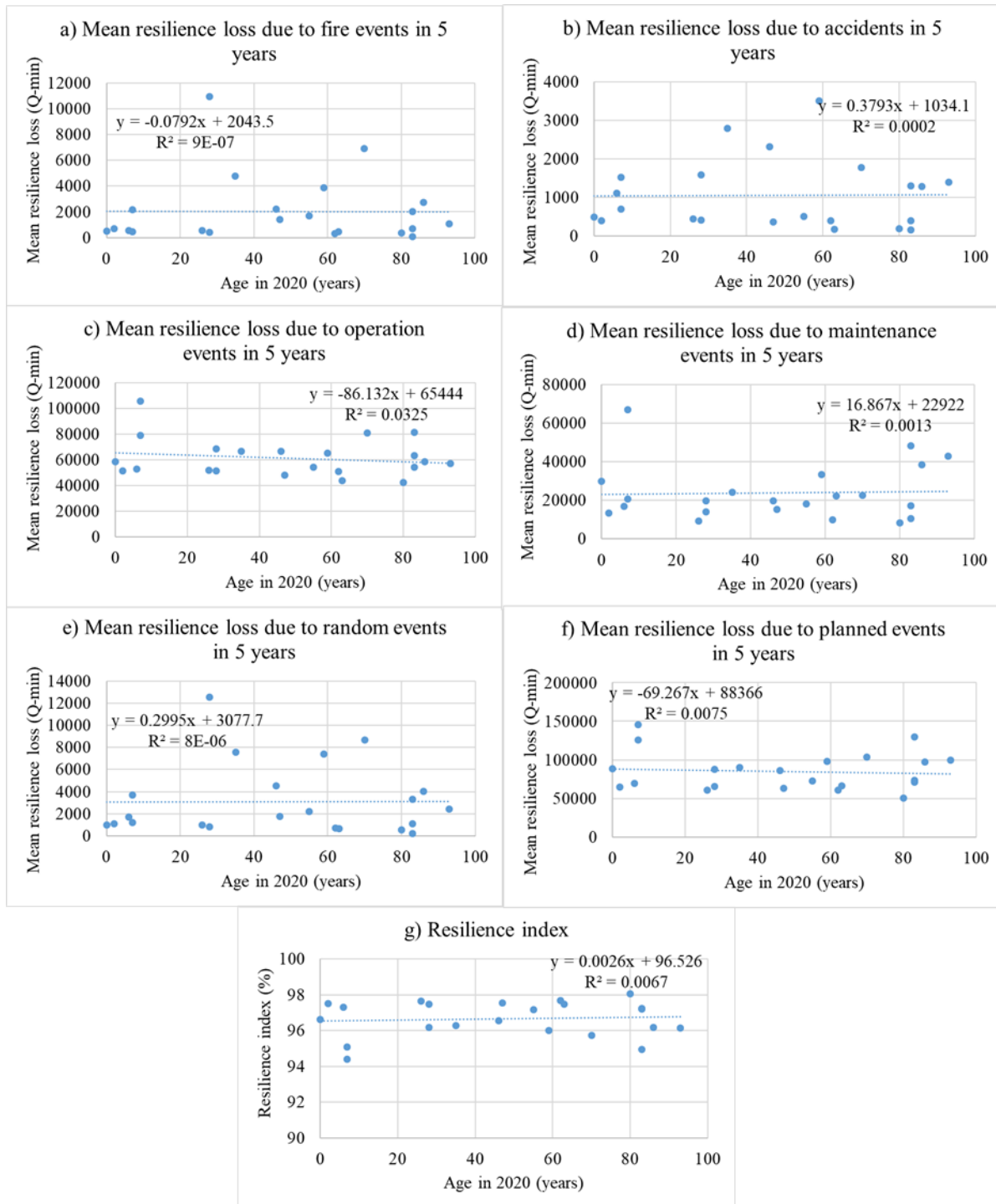
Figure 4.18. Variation of parameters with respect to age of tunnels.
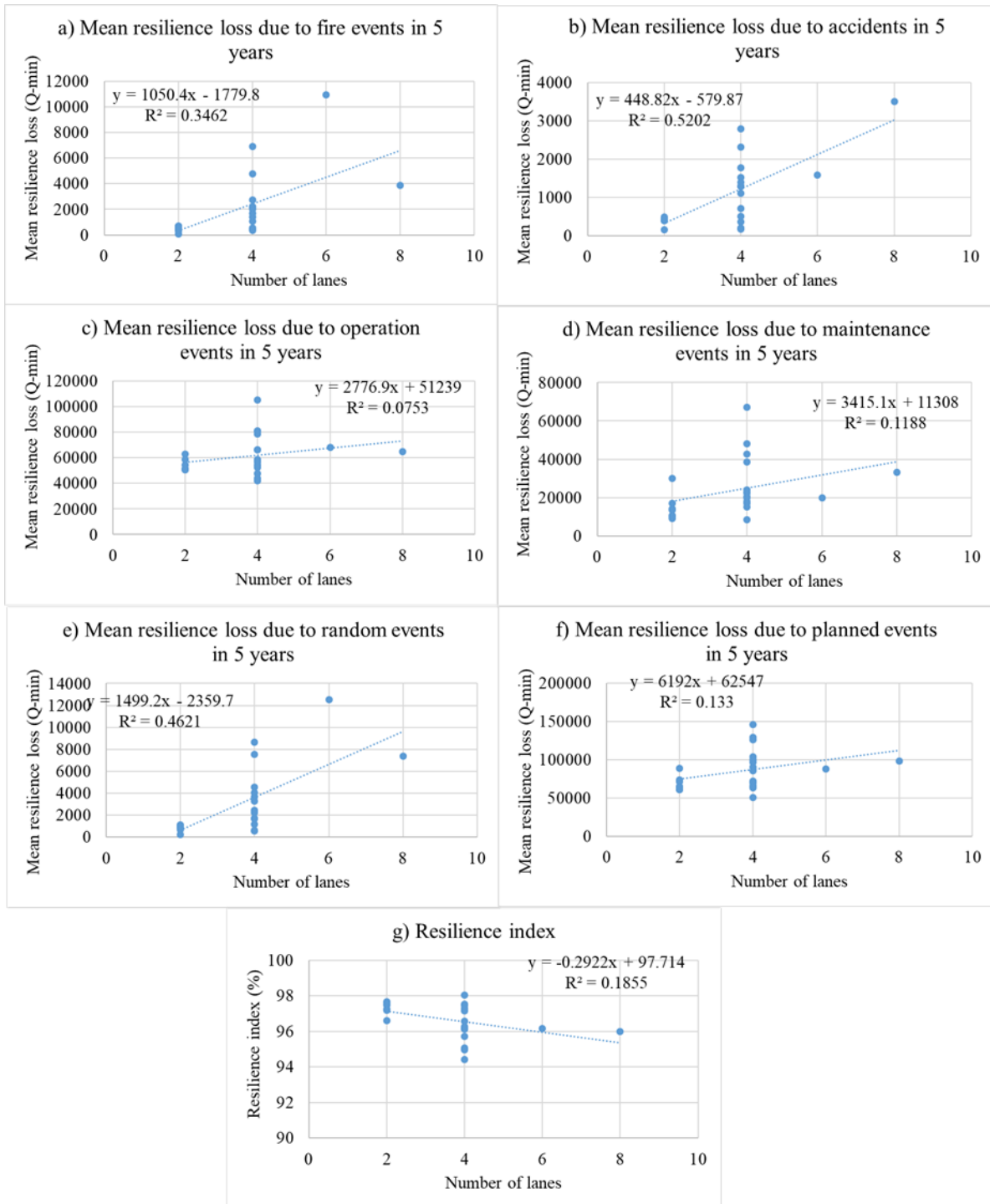
Figure 4.19. Variation of parameters with respect to total number of lanes.
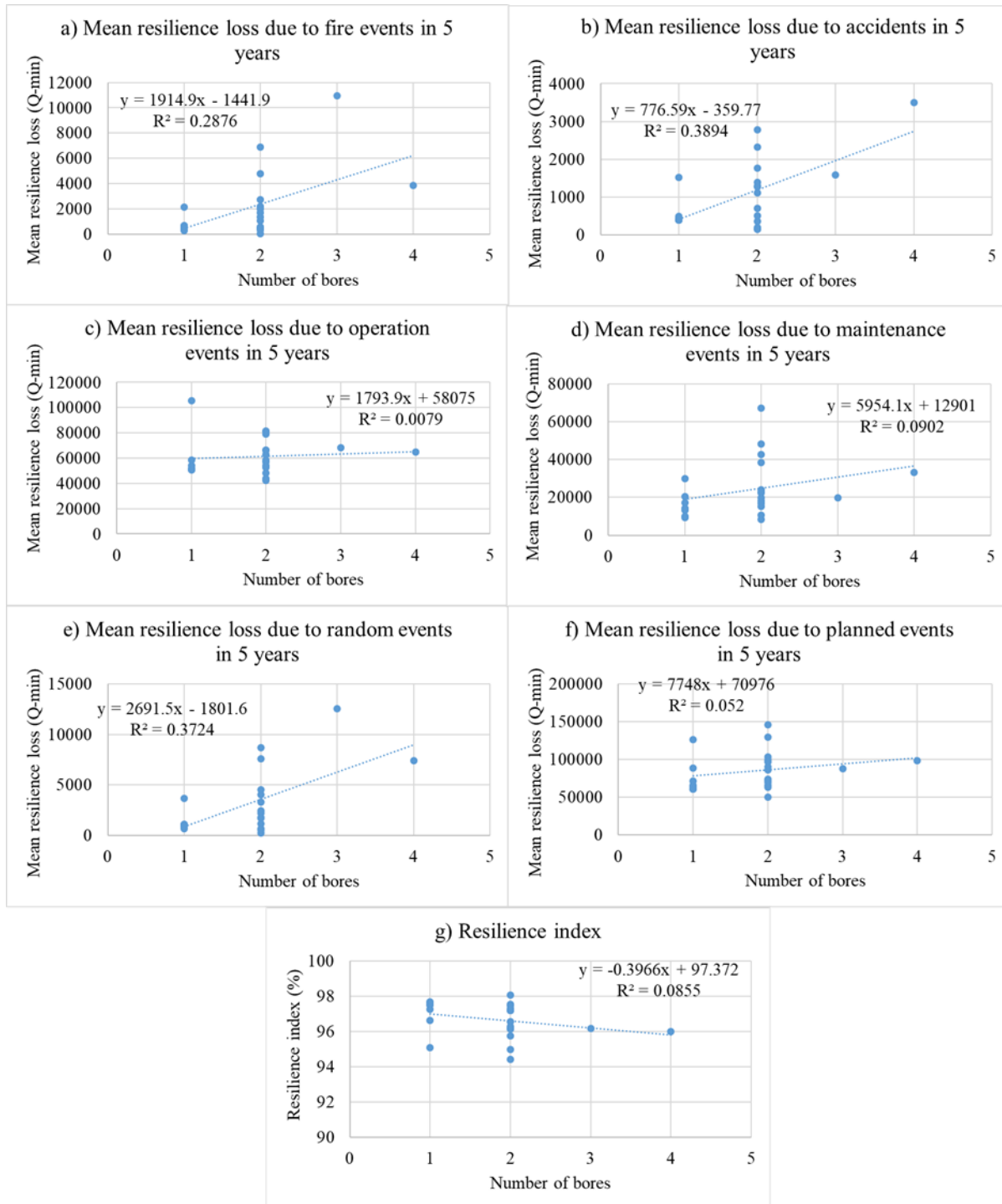
Figure 4.20. Variation of parameters with respect to number of bores.

Table 4.6. Significant parameters as per regression analysis.

| Dependent variable	Independent variable	a	b	R^2
Resilience loss due to operation	Tunnel length	20.309	24151	0.83
Resilience loss due to planned events	Tunnel length	33.381	23943	0.80
Resilience index	Tunnel length	-0.0014	99.18	0.86
Resilience loss due to accident	Average daily tunnel traffic	0.0279	-376.09	0.81
Resilience loss due to randon events	Average daily tunnel traffic	0.0959	-1818.4	0.76
Resilience loss due to accident	Total number of lanes	448.82	-579.87	0.52

From Table 4.6, it can be seen that tunnel operation activities and planned activities show a strong correlation to tunnel length. Since, planned events have the largest impact on tunnel resilience the tunnel resilience index seems to follow planned event resilience loss in correlation with tunnel length. Resilience loss due to accident and random events is somewhat correlated to average daily traffic. Resilience loss due to accidents is somehow influenced by total number of lanes.

Resilience Index proposed in this study is suitable to be used for various tunnels with very limited disruptive event information. The current RI values could not be used directly unless one knows the through capacity of the tunnel because it is a normalized value. When a tunnel was simulated to yield a 95% RI, it simply means about 5% of time the tunnel's through capacity is blocked due to disruptive events. The overall tunnel RI in this particular study cannot be used for decision making directly because the calculation of RI does not take into account the time of this interruption. This Index was calculated as an aggregated value for general comparison purposes in the sensitivity study. However, the simulation tool does yield the entire functionality loss time history over the simulated time. So very precise prediction of event consequences can be obtained when the simulated time history on tunnel functionality availability is applied to other analysis such as financial loss, user experience, or management demands.

Because of this reason, while improving RI is always a good thing, there is no "target" RI for all tunnels. Activities and improvement to tunnel for RI improvement always have a cost associated with them, thus the decision to improve RI should be done on a case-by-case basis and will additional cost-benefit analysis beyond just looking at a single aggregated RI number.

4.8   Conclusion

The current study was focused on assessing the extent to which simulation model proposed in Khetwal et al. (2020c) can be used and understanding the criticality of various disruptive events

on resilience of tunnel. While most of the conclusions and observations conform to common knowledge and qualitative estimation of tunnel functionality, this study was the first of its kind to apply comprehensive functionality modeling and simulation to quantitatively assess tunnel resilience. Simple integration of NTI data into stochastic simulation illustrated the proposed approach as a promising method to analyze the functionality of tunnel as various disruptive events at large scale. Implementation of data for 22 tunnels showed the universal characteristic of the model while sensitivity analysis proved its capability to encompass worst-case scenarios and future probable tunnel functionality related issues.

Sensitivity analysis shows the impact of the selected parameters on the tunnel resilience. Resilience loss due to fire and accident show sensitivity to traffic volume. Overall tunnel resilience shows sensitivity to FSS, this can be used as an example for other upgrades which will likely take place in older road tunnels. Maintenance module shows sensitivity towards change in inspection interval, equipment with better service life and operational procedure for replacing equipment. Improving the efficiency of the operation activities can significantly improve the resilience index.

Compatibility of the model for the 22 tunnels showed that while accident and fire do show apparent sensitivity, operation and maintenance have negligible effect due to variation in the parameters like daily traffic volume, speed limit, number of lanes, number of bores and age of tunnels. The interrelation between these parameters are overshadowing the effect of one parameter on another thereby showing lower sensitivity. However, all these conclusions are related to a relatively short operation period (i.e. 5 years) without considering intricate interactions among different influential factors.

Overall, the study showed that even a very simple simulation model has the capability to consider various external and internal parameters of a tunnel to determine the tunnel functionality loss and resilience quantitatively. The method provides a powerful tool that can be improved for making design and operation related decisions that are often not considered together beforehand. Additional efforts can be made to expand the simulation model to various other factors like disabled vehicles inside tunnel and natural events.

4.9   Acknowledgement

4.10   References

AbouRizk, S.M., Halpin, D.W. (1992). Statistical properties of construction duration data. Journal of Construction Engineering and Management, volume 118, no. 3, pp 525-544. ISSN 0733-9364/92/0003-0525

AbouRizk, S. and Mohamed, Y. (2000). Simphony-an integrated environment for construction simulation. Proceedings of the 2000 winter simulation conference, pp 1907-1915

Bhargava, K., Choy, K.W., Jennings, P.A., Birrell, S.A., Higgins, M.D. (2020). Traffic simulation of connected and autonomous freight vehicles (CAV-F) usinf a data-driven traffic model of a real-world road tunnel. Transportation engineering, volume 2. 100011. https://doi.org/10.1016/j.treng.2020.100011

Bocchini, P., Frangopol, D. M., Ummenhofer, T., Zinke, T. (2014). Resilience and Sustainability of Civil Infrastructure: Toward a Unified Approach. Journal of Infrastructure Systems, volume 20, issue no.2, pp 1–16

Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O'Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A., Von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. Earthquake Spectra, volume 19, issue no. 4, pp 733–752

Chang, S. E., Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. Earthquake Spectra 20(3), 739–755.

FHWA (Federal Highway Administration). (2015). *Specifications for the national tunnel inventory (SNTI)*. (Publication no. FHWA-HIF-15-006). Washington DC: FHWA.

FHWA (Federal Highway Administration). (2015). *Tunnel operations, maintenance, inspection, and evaluation (TOMIE) manual*. (Publication No. FHWA-HIF-15-005). Washington D.C.: FHWA

Huang, H. and Zhang, D. (2016a). Resilience analysis of shield tunnel lining under extreme surcharge: characterization and field application. Tunnelling and underground space technology, volume 51, pp 301-312

Huang, H. and Zhang, D. (2016b). Resilience of operated tunnels under extreme surcharge: field study. Japanese geotechnical society special publication. The 15th Asian regional conference on soil mechanics and geotechnical engineering, pp 1492-1496. http://doi.org/10.3208/jgssp.ATC6-06

Hu, X., Zhang, F., Lu, J., Liu, M., Ma, Y. and Wan, Q. (2019). Research on influence of sun glare in urban tunnels based on cellular automation model in the framework of Kerner's three-phase traffic theory. Physica A, volume 527, 121176. https://doi.org/10.1016/j.physa.2019.121176

Khetwal, A., Rostami, J., Nelson, P.P. (2020). Investigating the impact of TBM downtimes on utilization factor based on sensitivity analysis. Tunnelling and underground space technology, volume 106, pp 1-10. https://doi.org/10.1016/j.tust.2020.103586

Khetwal, S.S., Pei, S., Gutierrez, M. (2019). Operational resilience of traffic tunnels: an example case study. Tunnels and underground cities: engineering and innovation meet archaeology,

architecture and art-Peila, Viggiani and Celestino (Eds). Taylor and Francis group, London, ISBN 978-1-138-38865-9

Khetwal, S.S., Pei, S., Gutierrez, M. (2020a). A data-driven approach for direct assessment and analysis of traffic tunnel resilience. Springer Nature Switzerland AG 2020, A. G. Correia et al. (Eds.): ICITG 2019, Springer Series in Geomechanics and Geoengineering, pp. 168–177, 2020. https://doi.org/10.1007/978-3-030-32029-4_15

Khetwal, S.S., Pei, S., & Gutierrez, M. (2020b). A Unified Data Collection Framework for Quantitative Resilience Assessment of Road Tunnels. Manuscript submitted for publication.

Khetwal, S.S., Pei, S., Gutierrez, M. (2020c). Stochastic event simulation model for quantitative prediction of road tunnel downtime. Manuscript submitted for publication.

Ntzeremes,P. and Kirtopoulos, K. (2018). Applying a stochastic-based approach for developing a quantitative risk assessment method on the fire safety of underground road tunnels. Tunnelling and underground space technology, volume 81, pp 619-631

Ntzeremes,P., Kirtopoulos, K., Leopoulos, V. (2020). Development of a risk-based method for predicting the severity of potential fire accidents in road tunnels based on real-time data. Environmental research, volume 189, 109895. https://doi.org/10.1016/j.envres.2020.109895

Rinaudo, P., Paya-Zaforteza, I. and Calderon, P.A. (2016). Improving tunnel resilience against fires: a new methodology based on temperature monitoring. Tunneling and underground space technology, volume 52, pp 71-84.

Sari, M., Karpuz, C., Ayday, C. (2010). Estimating rock mass properties using Monte Carlo simulation: Ankara andesites. Computers & Geosciences., volume 36, pp 959-969.

Vanorio, G. and Mera, J.M. (2012). Methodology for risk analysis in railway tunnels using Monte Carlo simulation. Computers in railways XIII, WIT transactions in the built environment, volume 127, pp 673-683. doi:10.2495/CR120571

CHAPTER 5 CONCLUSION

1.1   Conclusion

There are more than 500 road tunnels in the United States with their lengths varying from few meters to about 4 km. An average of 4 road tunnels are being built annually in the last 20 years. Therefore, it is important to quantify the functionality of this critical infrastructure. The functionality and resilience of the tunnel is found to be impacted by disruptive events. Disruptive events are categorized as random events like vehicle fire and accidents or as planned events like maintenance and operation activities.

As it is important to collect tunnel data in order to evaluate the impact of disruptive events, a literature review was conducted for existing tunnel data collection frameworks, reports and recommendations. A lack of structured data collection was identified. Therefore, a tunnel data collection framework was proposed to collect and store tunnel data as it will assist in evaluating tunnel resilience. In the review it was also realized that there is no method or metric to quantify tunnel resilience specific to road tunnels. Consequently, a tunnel functionality metric was proposed which is applied in quantification of tunnel resilience.

The tunnel data collection framework has 3 main categories, static data, dynamic data and functionality data. Static data consist of general information and as built details. Dynamic data consist of tunnel operation and maintenance details. Functionality data consist of event and corresponding functionality loss details. Tunnel data was collected from the EJMT from various sources in order to quantify the resilience of the tunnel. The data was found to be inadequate mostly regarding functionality data. As the data duration was limited to 5 years, fire sample data was limited. Operation logs often did not match with CTMS data. A combination of data from all sources facilitated in providing the adequate data as needed in the framework.

To estimate the functionality of the tunnel and resilience loss quantitatively a simulation model of the physical processes and operational procedures during and after disruptive events was developed. The probabilistic simulation model simulates the tunnel functionality over time by considering several key influential factors and the parametric information collected based on the tunnel data collection framework. Random samples of functionality loss parameters will be generated for various events. The distributions of these generated samples will be compared to the collected functionality loss data to validate the simulation model.

The model is built on MATLAB as the programming platform and it is implemented using the Monte Carlo simulations. The model consists of five modules estimating resilience loss separately due to accident, vehicle fire, hazmat platooning events, tunnel maintenance and operation activities. The model was used to generate disruptive events, their magnitude and corresponding resilience loss for EJMT. Fifty samples for five year were generated and were compared to the historic collected data by CDOT. Although limited, the five year collected data provides a preliminary validation for the model.

The last objective of the study was to assess the sensitivity and versatility of the developed stochastic event simulation model. Sensitivity study is focused on understanding the impact of the parameters on tunnel resilience with respect to disruptive events. Whereas the versatility of the model is determined by using the model for road tunnels in different geographical and social settings. Sensitivity analysis was performed on EJMT. For resilience correlation study data of 22 road tunnels from National tunnel inventory was utilized to generate their resilience to disruptive events.

For the selected parameters, resilience loss due to fire and accident show sensitivity to traffic volume. Presence of fire suppression system impacted the fire, maintenance and operation events due to decrease in magnitude of fire events contrarily additional equipment and system testing activities. Inspection and maintenance interval, equipment service life and varying amount of equipment replaced impact resilience loss due to maintenance events. Change in operation activity efficiency significantly improves the overall resilience index. The analysis demonstrates the sensitivity of the model to various tunnel parameters and that it can be used to predict tunnel resilience in case of changes to the parameters.

The use of NTI database to enable the simulation model for the 22 road tunnels shows the potential to apply the proposed simulation method to a large number of tunnels using standard database. The tunnels have variation in the parameters like daily traffic volume, speed limit, number of lanes, number of bores and age of tunnels. A regression analysis was performed for resilience loss due to disruptive events with respect to these parameters. Although some patterns do emerge, the sensitivity analysis conducted in this study was limited both in its scope and by the availability of accurate input data. It is expected that if a more comprehensive database on the scale of NTI data can be established using the proposed data collection framework, a more comprehensive understanding of tunnel performance and resilience can be obtained through the proposed method.

Based on 5-year duration simulated in the correlation study, it is evident that tunnel planned activities show a strong correlation to tunnel length, specially operation activities. The tunnel resilience index seems to be correlated with tunnel length, similar to planned events. Resilience loss due to accident and random events is apparently correlated to average daily traffic. Total number of lanes impact resilience loss due to accidents.

1.2   Future work

While it will take significant level of resources and coordination, it is extremely beneficial to implement the uniform data collection framework to all tunnels in order to support further model validation or even data-driven analysis. This is a need for more efficient tunnel infrastructure management that goes beyond the scope of a single study. If we would one day hope to improve our analysis and decision making on tunnels from a case-specific model to a more generalized format, such a diagram shift in data collection and management practice must happen in a coordinated fashion. If additional data can be collected, further validation and improvement of the proposed simulation model needs to be conducted. More realistic and intricate interaction of different factors within the simulation can be added to the model, such as the correlation between maintenance and component service life. The sensitivity of tunnel resilience to various external

circumstances and internal design decisions need to be investigated further in future studies, with more detailed consideration of user experience and costs. The tunnel resilience and functionality model can be incorporated into a higher-level model focused on transportation network resilience.

The functionality metric defined in the study is a simple performance-based metric that has many limitations. For example, it only depends on the speed limit in the tunnel set by the tunnel operator and number of open lanes and is a relative percentage to the full capacity (i.e. a normalized metric). This configuration is designed to focus on using the resilience estimation methodology developed in this study as a component (or node) in a full transportation network simulation. This functionality metric by itself did not consider the actual traffic volume or speed inside the tunnel, it did not consider the time of the day the interruption occurs either. Some of these limitations can be addressed when more information about the actual usage pattern of the tunnel is considered, such as the average hourly traffic volume from historical data (which is typically available from tunnel logs). Others will need to be addressed when the tunnel resilience model were applied to a transportation network simulation model. These are all very interesting future research directions that should be pursued later.

APPENDIX A – TECHNOLOGY TRANSFER ACTIVITIES

1. Accomplishments

1.1. What was done? What was learned?

- A simple and direct measurement metric, for tunnel functionality was proposed, for road tunnels.
- An ideal data collection framework for road tunnels was proposed, to support the calculation of tunnel functionality, as well as additional data-driven analysis.
- Existing tunnel operational data collection practice in Eisenhower tunnel, in Colorado was summarized.
- Due to insufficient and incomplete tunnel data to perform a completely data-driven analysis, a stochastic simulation model to predict tunnel resilience over time was developed.
- The model was a combination of modules representing five disruptive event, accident, vehicle fire, hazmat platooning, maintenance and operations.
- A preliminary validation of model was performed using real Eisenhower tunnel data.
- A parametric sensitivity analysis was performed, to identify the impact of tunnel parameters, associated with disruptive events, on the tunnel resilience loss
- Finally, a preliminary correlation assessment of tunnel key parameters using 22 major road tunnels in the United States was performed.

1.2. How have the results been disseminated?

- Conference Papers:

  Khetwal, S., Pei, S., Gutierrez, M. (2020). A Data-Driven Approach for Direct Assessment and Analysis of Traffic Tunnel Resilience. In: Correia A., Tinoco J., Cortez P., Lamas L. (eds) Information Technology in Geo-Engineering. ICITG 2019. Springer Series in Geomechanics and Geoengineering. Springer, Cham.

  Khetwal, S.S., Pei, S., Gutierrez, M. (2019). Operational resilience of traffic tunnels: An example case study. In: Proceedings of the WTC 2019 ITA-AITES World Tunnel Congress, Naples, Italy, 3–9 May (2019)

  Khetwal, S., Pei, S., Gutierrez, M., Harelson, S. (2020) Quantitative Simulation of Tunnel Functionality Loss due to Fire Events. Transportation Research Board, Washington, D.C., USA. (Poster presentation)

- Journal Papers:

  Khetwal, S.S., Pei, S., Gutierrez, M. (2020). A Unified Data Collection Framework for Quantitative Resilience Assessment of Road Tunnels. Structure and Infrastructure Engineering (Under Review)

Khetwal, S.S., Pei, S., Gutierrez, M. (2020). Stochastic Event Simulation Model for Quantitative Prediction of Road Tunnel Downtime. Tunnelling and Underground Space Technology (Under Review)

Khetwal, S.S., Pei, S., Gutierrez, M. (2020). Sensitivity Study on Road Tunnel Resilience through Stochastic Simulation (To be submitted)

- Poster Presentation

  Resilience Assessment of Transportation Tunnels

  Transportation Resilience Innovations Summit and Exchange (RISE), Denver, Colorado, October 9-10, 2018.

  The results were also presented at UTC-UTI workshops

2. Participants and Collaborating Organizations

Colorado Department of Transportation

3. Outputs

Journal publications

Conference publications

Khetwal, S., Pei, S., Gutierrez, M. (2020). A Data-Driven Approach for Direct Assessment and Analysis of Traffic Tunnel Resilience. In: Correia A., Tinoco J., Cortez P., Lamas L. (eds) Information Technology in Geo-Engineering. ICITG 2019. Springer Series in Geomechanics and Geoengineering. Springer, Cham.

Khetwal, S.S., Pei, S., Gutierrez, M. (2019). Operational resilience of traffic tunnels: An example case study. In: Proceedings of the WTC 2019 ITA-AITES World Tunnel Congress, Naples, Italy, 3–9 May (2019)

Presentations

Khetwal, S., Pei, S., Gutierrez, M., Harelson, S. (2020) Quantitative Simulation of Tunnel Functionality Loss due to Fire Events. Transportation Research Board, Washington, D.C., USA. (Poster presentation)

Resilience Assessment of Transportation Tunnels, Transportation Resilience Innovations Summit and Exchange (RISE), Denver, Colorado, October 9-10, 2018. (Poster presentation)

Software

Develop a stochastic event simulation model/tool in MATLAB to quantitatively predict road tunnel downtime and resilience given tunnel parameter inputs.

4. Outcomes

- A tunnel functionality metric is defined to quantify tunnel resilience. Currently, data must be collected from different sources. So, a tunnel data collection framework was developed, which in combination with functionality metric can be used to estimate tunnel resilience. It was identified that the data from different sources for Eisenhower tunnel does not match frequently. Therefore, it was ascertained that the framework provides a baseline for tunnel operators, to bring uniformity in the data collection. The Eisenhower tunnel data analyzed and 5 major event types were identified.
- A probabilistic simulation model with the objective to simulate tunnel functionality over time is developed. The model generates events and estimates their magnitude, functionality loss and duration. The five events covered in this model are accident, fire, hazmat platooning, maintenance and operations. Functionality loss samples were generated for Eisenhower tunnel, for a period of 5-years. We get a preliminary validation of the simulation results with the real data from Eisenhower tunnel. Further validation is required for other road tunnels and larger data sets over longer durations.
- The results of the sensitivity analysis show fire & accident events increase with traffic volume. Without fire suppression system the tunnel resilience loss due to fire events doubles. Maintenance module is sensitive to change in inspection interval, equipment service life and equipment replacing criteria. Improving efficiency of operations shows significant improvement in resilience index. Overall difference in resilience index for urban and mountain tunnel is insignificant. Resilience loss due to accident and operation have strong correlation with daily traffic and tunnel length respectively.

5. Impacts

There are more than 500 road tunnels in the United States with their lengths varying from few meters to about 4 km. An average of 4 road tunnels are being built annually in the last 20 years. Therefore, it is important to quantify the resilience of this critical infrastructure. In this study a method to estimate the tunnel resilience for major events was developed. Now optimization of the tunnel design, maintenance and operation can take place by predicting the improvement in tunnel resilience using the stochastic event simulation model.

APPENDIX B - DATA FROM THE PROJECT

Table B1.Weighted probability of traffic for mountain and urban tunnels.

Hour	Tunnel Name	Mountain Tunnel	Urban Tunnel
0		0.005	0.010
1		0.004	0.004
2		0.003	0.002
3		0.003	0.002
4		0.004	0.004
5		0.010	0.018
6		0.022	0.054
7		0.050	0.067
8		0.065	0.065
9		0.072	0.062
10		0.072	0.050
11		0.071	0.047
12	Weekday	0.066	0.044
13		0.074	0.045
14		0.086	0.054
15		0.086	0.068
16		0.084	0.072
17		0.067	0.074
18		0.046	0.071
19		0.038	0.055
20		0.030	0.039
21		0.020	0.036
22		0.013	0.033
23		0.009	0.024
0		0.005	0.034
1		0.003	0.017
2		0.002	0.008
3		0.002	0.007
4		0.003	0.006
5	Weekend	0.006	0.008
6		0.033	0.016
7		0.052	0.023
8		0.054	0.030
9		0.064	0.039
10		0.079	0.048
11		0.080	0.056

12		0.078	0.062
13		0.077	0.066
14		0.081	0.066
15		0.083	0.065
16		0.075	0.065
17		0.065	0.065
18		0.052	0.064
19		0.043	0.062
20		0.032	0.055
21		0.018	0.051
22		0.009	0.049
23		0.005	0.038

Table B2. Number of vehicles per crash.

Gamma distribution parameters	
α(shape)	θ(scale)
6.31	0.29

Table B3. Weighted probability of vehicle types in accident.

Car	Pickup/ Utility / Van	Bus	Truck
0.506	0.336	0.002	0.156

Table B4 Probability of rollovers for vehicle type.

Car	Pickup/ Utility/ van	Bus	Truck
0.19	0.40	0.07	0.09

Table B5. Variation of accident rate by vehicle speed.

Vehicle speed		Accident rate ratio
mph	kmph	
25	40	0.17
30	48	0.25
35	56	0.34
40	64	0.44

Vehicle speed		Accident rate ratio
mph	kmph	
45	72	0.56
50	80	0.69
55	89	0.84
60	97	1.00
65	105	1.17
70	113	1.36

Table B6. Weighted probability month wise highway fire variation.

Month	Normal distribution parameters	
	μ	σ
Jan	0.080	0.002
Feb	0.075	0.004
Mar	0.082	0.001
Apr	0.083	0.001
May	0.087	0.001
Jun	0.089	0.001
Jul	0.095	0.003
Aug	0.091	0.002
Sep	0.083	0.001
Oct	0.082	0.000
Nov	0.076	0.001
Dec	0.076	0.002

Table B7. Weighted probability of day wise highway fire variation.

Day	Probability
Sunday	0.133
Monday	0.146
Tuesday	0.142
Wednesday	0.141
Thursday	0.141
Friday	0.152
Saturday	0.146

Table B8. Weighted probability of hourly highway fire variation.

Hour	Normal Distribution parameters	
	μ	σ
0	0.033	0.00079
1	0.031	0.00052
2	0.029	0.00113
3	0.027	0.00183
4	0.024	0.00156
5	0.024	0.00209
6	0.026	0.00139
7	0.031	0.00054
8	0.034	0.00027
9	0.036	0.00035
10	0.040	0.00001
11	0.045	0.00011
12	0.051	0.00014
13	0.054	0.00040
14	0.058	0.00103
15	0.063	0.00042
16	0.062	0.00205
17	0.062	0.00249
18	0.056	0.00207
19	0.050	0.00102
20	0.045	0.00068
21	0.043	0.00051
22	0.039	0.00043
23	0.036	0.00018

Table B9. Probabilities of impingement for a two-lane tunnel at 1 m/s wind speed.

S	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1–2MW	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2–4	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4–8	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8–16	1	1	1	1	0.41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16–32	1	1	1	1	1	1	0.95	0.02	0	0	0	0	0	0	0	0	0	0	0	0	0
32–64	1	1	1	1	1	1	1	1	1	0.7	0.3	0.01	0	0	0	0	0	0	0	0	0
64–128	1	1	1	1	1	1	1	1	1	0.99	0.5	0.3	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
128–256	1	1	1	1	1	1	1	1	1	0.99	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
256+	1	1	1	1	1	1	1	1	1	0.99	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5

Table B10. Number of occurrences of alternate route closure.

Gamma distribution parameters	
α(shape)	θ(scale)
13	2.4

Table B11. Duration of alternate route closure (magnitude of event) (hours).

Gamma distribution parameters	
α(shape)	θ(scale)
1	10.25

Table B12. Duration of individual closure event.

Gamma distribution parameters	
α(shape)	θ(scale)
12.5	0.5

Table B13. Snow days per month at Loveland pass.

Month	Gamma distribution parameters	
	α(shape)	θ(scale)
October	1.9	2.5
November	15.4	0.8
December	44.3	0.4
January	41.0	0.4
February	42.5	0.4
March	53.3	0.3
April	56.7	0.3
May	1.2	3.0

Table B14. Snow depth by month at Loveland pass.

Month	Gamma distribution parameters	
	α(shape)	θ(scale)
October	1.80	2.50
November	1.44	2.75
December	1.50	2.59
January	1.40	3.20
February	1.60	2.14

Month	Gamma distribution parameters	
	α(shape)	θ(scale)
March	1.45	3.06
April	1.42	3.19
May	1.13	5.44

Table B15. Loveland pass closure by snow depth.

Snow depth (inch)	Minimum stoppage (hours)	Maximum stoppage (hours)	Mean stoppage	Gamma distribution parameters	
	Loveland Pass Closure			α (shape)	θ (scale)
5	0	5	2.5	12.5	0.2
6	2	7	4.5	22.5	0.2
7	4	9	6.5	32.5	0.2
8	5	12	8.5	28.3	0.3
9	6	16	11.0	36.7	0.3
10	8	20	14.0	46.7	0.3
11	10	24	17.0	56.7	0.3
12	12	30	21.0	52.5	0.4
13	14	32	23.0	57.5	0.4
14	16	34	25.0	50.0	0.5
15	17	36	26.5	53.0	0.5

Table B16. Tunnel functionality for different possibilities.

Parameters	Single lane closure	Bore closure	Single Lane open	Complete closure	Tunnel open
Allowable Speed	64	80	64	0	80
No. of open lanes	3	2	1	0	4
Functionality (Q)	0.7	0.5	0.2	0	1
Functionality loss	0.3	0.5	0.8	1	0

Table B17. Eisenhower tunnel component parameters (continued).

#	Component Name	Service Life (years)	Inspection Interval (months)	Maintenance Interval (months)	Total Element #	Initial Element States				Inspection Time per Element (minutes)				Rate of Deterioration (per month)			% Repair			Replace % of CS4
						CS1	CS2	CS3	CS4	CS1	CS2	CS3	CS4	R1	R2	R3	CS2	CS3	CS4	
1	Attenuator	50	12	12	56	10	24	16	6	0.5	2	5	10	0.0002	0.0002	0.0003	0	10	40	60
2	Hydrants	50	12	12	56	10	24	16	6	0.5	2	5	10	0.0002	0.0002	0.0003	0	10	40	60
3	Sprinklers	25	12	12	2184	1800	330	44	10	0.5	2	5	10	0.0003	0.0004	0.0006	0	10	40	60
4	Lining	100	12	12	139171	127443	5469	6223	36	0.15	0.4	0.8	1.5	0.0002	0.0002	0.0003	0	10	100	0
5	Ceiling	50	12	12	56818	56752	56	9	1	0.15	0.4	0.8	1.5	0.0002	0.0002	0.0003	0	10	0	100
6	Roadway	15	12	12	47455	34148	0	13307	0	0.15	0.4	0.8	1.5	0.0005	0.0008	0.011	0	10	100	0

Table B17 Continued

#	Component Name	Time of repair per unit (minutes) (in case of CS4 removal and repair at shop)			Time of replacement m (minutes)	Gamma parameters		First Inspection, Time of year	First Maintenance, Time of year	Inspection Closure Type	Maintenance Closure Type	No. of Inspection Teams	No. of Repair Teams	Mean Closure Time minutes	Partial Closure Parameters		Mean Closure Time minutes	Full Closure Parameters	
		CS2	CS3	CS4		a	b	Season	Season	P / F	P / F				a	b		a	b
1	Attenuator	5	20	35	25	10	2.5	Spring	Fall	P	F	2	2	520	3	173.33	360	2	180
2	Hydrants	5	20	35	30	12	2.5	Summer	Fall	P	P	1	1	520	2	260	0	6	0
3	Sprinklers	5	20	35	10	5	2	Fall	Winter	F	P	2	2	520	2.5	208	360	6	60
4	Lining	10	35	80	0	0	0	Spring	Summer	P	P	2	2	600	10	60	0	6	0
5	Ceiling	10	35	90	90	22.5	4	Spring	Summer	P	F	2	2	600	5	120	360	6	60
6	Roadway	5	8	12	0	0	0	Spring	Fall	P	P	2	2	650	10	65	0	6	0

Table B18. Eisenhower tunnel equipment parameters.

Eqp #	Equipment	Service Life	Number of Equipment	Rate of Failure	Actionable	Time per replacement	m parameters		Planning Time	Closure Type	# of teams	Mean Closure	Partial Closure Parameters		Mean Closure	Full Closure Parameters	
		years		1 per hours		m (minutes)	Gamma a	Gamma b	days	P / F		minutes	a	b	minutes	a	b
1	Lights	15	5600	7.61 E-06	200	15	6	2.5	15	P	2	510	10	51	510	6	85
2	Traffic Lights	15	20	7.61 E-06	2	20	8	2.5	15	P	1	40	2.5	16	0	3	0
3	Camera	10	24	1.14 E-05	2	120	20	6	15	P	1	240	2	120	360	3	120
4	Guidance Signs	15	100	7.61 E-06	5	30	10	3	15	P	1	150	2.5	60	0	3	0
5	Fire Sensor	33	6	3.46 E-06	1	600	45	15	30	F	1	650	8	81	360	3.5	103

Table B19. Eisenhower tunnel operation activity parameters.

	Operation	Interval	Unit work	# of units	Time taken per team for Unit work	# of Teams	Closure Type	First Activity, Time of year	Mean Closure Time	Closure Parameters	
#	Name	(months)	description	n	minutes		P / F	*Season*	minutes	a	b
1	Tunnel Wash	6	wash 100 m	54.56	135	0.9	P	Spring	585	10	58.5
2	Street Sweeping	6	sweep 100 m	54.56	215	0.9	P	Spring	750	15	50
3	Washing Lights	6	lights	5600	0.25	0.9	P	Spring	270	2.5	108
4	Camera Cleaning	3	one camera	28	21	0.9	P	Winter	240	2.5	96
5	Snow Removal	12	per lane	4	310	0.9	P	Winter	370	2.5	148
6	Snow Removal	12	per lane	4	310	0.9	P	Spring	370	2.5	148
7	Drain Cleaning	12	per lane	4	960	0.9	P	Summer	590	2.5	236
8	Blow Down	12	double per lane	8	1700	0.9	P	Spring	1100	20	55.0
9	Sand Removal	12	double per lane	8	370	0.9	P	Spring	560	10	56
10	Ice Flow	12	ice zone	4	325	0.9	P	Spring	240	2.5	96
11	Ice Flow	12	ice zone	4	325	0.9	P	Winter	240	2.5	96
12	Fire Sensor Testing	12	zones	6	400	0.9	P	Summer	580	8	72.5
13	Fire Sensor Testing	12	zones	6	250	0.9	F	Summer	365	2.5	146