QUANTITATIVE RISK ANALYSIS FOR FIRE IN URBAN ROAD TUNNELS

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NATIONAL UNIVERISTY OF SINGAPORE

2012

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A THEIS SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHYLOSOPY

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING

NATIONAL UNIVERISTY OF SINGAPORE

2012

ACKNOWLEDGEMENT

My deepest gratitude first goes to my Ph.D supervisor, Associate Professor Meng Qiang, for his valuable supervision, assistance and suggestions throughout the duration of this research in National University of Singapore. This thesis is a result of three years of interesting research with him. His passion and enthusiasm in research has profoundly infected me and helped in shaping my interest in academic research. His guidance is inspirational; his encouragements and efforts are memorable.

I wish to express my sincere appreciation to the members of my oral Qualifying Examination Committee who monitored my work and gave me invaluable suggestions on my research topic: Associate Professor Chin Hoong Chor and Professor Michael Beer. Special thanks also go to Professor Fwa Tien Fang for his invaluable assistance and encouragements during my Ph.D study.

I would acknowledge my module lecturers and some other professors in Department of Civil and Environmental Engineering in National University of Singapore: Associate Professor Lee Der Horng, Associate Professor Chua Kim Huat, David, Associate Professor Chan Weng Tat, and Dr. Ong Ghim Ping, Raymond.

I am indebted to Mr. Kum Thong Yong, Mr. Shang Pang Lee, Ms Siew Chee Wong, Ms Yoke Heng Wong, and Ms Vivi Yuanita from the System Assurance and Integration Division of Land Transport Authority of Singapore. The monthly discussions with them provide me rich industrial knowledge which is essential for my Ph.D study.

Heartfelt thanks are also due to Liu Zhiyuan, Wang Xinchang, Wang Shuaian, Wang Tingsong, Weng Jinxian, Farhan Javed, H. R. Pasindu, Ju Fenghua, Yang Jiasheng, Chen Jianghang, and Zhang Lei in transportation group for their encouragement and discussions on relevant topics, and Mr. Goh Joon Kiat and Mr. Mohd Farouk in the Highway Laboratory, and Mr. Foo Chee Kiong, Madam Yap-Chong Wei Leng, Madam Theresa Yu-Ng Chin Hoe in the Traffic Laboratory of National University of Singapore for their generous helps and supports.

A special appreciation is expressed to my parents, wife Yang Ying for their precious devotion and understanding given to me when I was undertaking the Ph.D study in National University of Singapore.

Last but not least, I wish to express my appreciation for the research Scholarship and President's Graduate Fellowship offered by the university, which provide me with indispensable financial support for this work.

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SUMMARY

Road tunnels are important transport infrastructures, providing underground vehicular passageways for commuters and motorists, especially useful in densely populated cities such as Singapore. However, the safe operation of road tunnels is of the utmost concern, due to the heavy traffic that urban road tunnels carry. Accidents occurring in a road tunnel may lead to catastrophic consequences in terms of deaths, due to the enclosed nature of the tunnel structure. Accordingly, quantitative risk analysis (including risk assessment and control/management) has become an explicit requirement under the European Union Directive (2004/54/EC) and the Project Safety Review Manual in Singapore.

The tunnel characteristics (e.g. geometries, safety provisions, and traffic flow) for some urban road tunnels may vary from one section to another. These urban road tunnels with non-uniform tunnel parameters are referred to as non-homogeneous urban road tunnels in this study.

In this dissertation, we propose a risk assessment model (QRAM-I), whereby a non-homogeneous urban road tunnel can be segmented into a number of homogeneous sections. For each tunnel section, the frequency of fire is estimated using a fault tree technique incorporating a proposed Time to Collision (TTC)-based crash frequency estimation model (as detailed in Chapter 3); a fire simulation model and fractional effective dose (FED) methodology are applied to estimate the number of fatalities under different accident scenarios, by taking into account the different working statuses of tunnel safety provisions. Having obtained the frequency and consequences for various accident scenarios for all tunnel sections, an aggregated QRA model is built by combining the section-based QRA models (as detailed in Chapter 4). The model is further computerized as software, to facilitate tunnel operators' evaluation of risks in urban road tunnels (as detailed in Appendix C). The software has been applied by the Land Transport Authority of Singapore to assess the risks of urban road tunnels in the country.

In the QRAM-I model, a number of input parameters possess epistemic or aleatory uncertainty. Apparently, crisp values are not appropriate for representing these uncertain parameters. Therefore, we carry out a further study (QRAM-II) by taking into account the parameter uncertainty in the QRA modelling framework (as detailed in Chapter 6): aleatory uncertainty is formulated by probability distribution functions, and parameters with epistemic uncertainty are represented by fuzzy numbers. A hybrid Monte Carlo simulation-based approach is proposed to propagate the parameter uncertainty, by taking into account the dependencies among these uncertain parameters. Finally, percentile-based individual risk and α -cut based societal risk are proposed, to provide more information to tunnel operators with distinct risk attitudes.

Two studies concerning risk control/management are also conducted on the basis of the two risk assessment models. Based on the QRAM-I, a risk impact analysis methodology is proposed to examine the effects of traffic flows on risk control/ management (as detailed in Chapter 5). An excess risk index is defined to quantify the severities of unacceptable scenarios which place road tunnel operations above a predetermined safety target. A contour chart, based on the excess risk index, could be used to help tunnel operators implement suitable risk control/management solutions. Based on the QRAM-II, an optimization model is proposed to select optimal combinations of tunnel safety provisions (as detailed in Chapter 7). The objective function is aimed at minimizing the life cycle costs of tunnel safety provisions, subjects to the requirements for tunnel safety provisions and the safety targets. By taking advantage of the special structure of the optimization model, a Bi-Section Search and Bound Algorithm (BSSBA) is designed to efficiently solve the problem.

In this thesis, two risk assessment models (QRAM-I and QRAM-II) are developed to assess the risks of non-homogeneous urban road tunnels. On the basis of the two risk assessment models, two risk control/management strategies are proposed to assist tunnel operators in controlling/managing tunnel risks.

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LIST OF ABBREVIATIONS

AID	Automatic Incident Detectors
ARSON	Frequency of Fire Due to Arson
ASTM	American Society for Testing and Materials
AW	Annual Worth
BSSBA	Bi-Section Search and Bound Algorithm
CBD	Central Business District
CCPS	Centre for Chemical Process Safety
CCTV	Closed Circuit Television
CDF	Cumulative Distribution Function
CFD	Computational Fluid Dynamics
CLN	Frequency of Fire Due to an Act of Carelessness
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CTE II	Central Expressway Phase II Tunnel Project
CTE	Central Expressway
DRAC	The Deceleration Rate To Avoid The Crash
ERP	Electronic Road Pricing
ET	Event Tree
EU	European Union
EV	Expected Value of Number of Fatalities
F/N	Frequency / Number of fatalities
FBO	Frequency of Fire Due to Brake Overheating
FCL	Frequency of Vehicle Collision

FCS	Frequency of Chain Vehicle Collision
FDS	Fire Dynamics Simulator
FED	Fractional Effective Dose
FT	Fault Tree
GIA	General Insurance Association of Singapore
HCD	Historical Crash Damage Database
HFD	Hardware Failure Dominated
HGV	Heavy Goods Vehicles
IG	Inverse Gaussian Distribution
IR	Individual Risk
KPE	Kallang Paya Lebar Expressway
K-S	Kolmogorov-Smirnov
LCCA	Life Cycle Cost Analysis
LHD	Linear Heat Detectors
LTA	Land Transport Authority of Singapore
LVCF	Ignition Probability of Vehicles Involving in Collision
MARR	Minimum Attractive Rate of Return
MCE	Marina Costal Expressway
MCF	Motor Claims Framework
MLE	Maximum Likelihood Estimation
N.A.	Not Applicable
NIST	National Institute of Standards and Technology
O_2	Oxygen
OCC	Operational Control Centre
OECD	Organization for Economic Cooperation and Development

PET	The Post Encroachment Time
PI	Probability of Ignition When Vehicle Defects Take Place
PIARC	World Road Association
PSR	Project Safety Review of Singapore
QRAM-I	Quantitative Risk Analysis Model for Urban Road Tunnels with Deterministic Parameters
QRAM-II	Quantitative Risk Analysis Model for A Urban Road Tunnel Section with Parameter Uncertainty
QRA	Quantitative Risk Analysis
RRO	Risk Reduction Optimization
RTA	Road Traffic Act
SD	Singapore Dollars
SL	Slack Clearance
SR	Societal Risk
SVCF	Ignition Probability of Vehicles Involving in Chain Vehicle Collision
TTC	Time to Collision
USFA	United States Fire Administration
VD	Frequency of Vehicle defects
VROM	Dutch Ministry of Housing, Spatial Planning and Environment

GLOSSARY OF NOTATIONS

$\left(Ct\right)_i$:	the specific dose (concentration × time) required to produce lethality;
$C_{i,t}$:	the concentration of toxic component *i* at time τ;
D_n:	the K-S statistic with sample *n*;
D_p^j:	the purchase cost of the fire detection system with type *j*;
D_m^j:	the maintenance cost of the fire detection system with type *j*;
D_o^j:	the operating cost (the electrical cost and salaries of operators) of the fire detection system with type *j*;
D^j:	the annual worth of the fire detection system with type *j*;
E_{ij}:	the event j caused by H_i;
EV_k:	the expected value for the number of fatalities in road tunnel section *k* per year;
$EV_{\text{criterion}}$:	the safety target of expected number of fatalities.
$F_{i,\tau}$:	the FED caused by toxic component *i* for exposure time $[\tau, \tau + \Delta t]$;
$F_k\left(N\right)$:	the cumulative frequencies of all the accident scenarios occurred at tunnel section k with *N* or more fatalities;
F_{jk}:	the yearly frequency of accident scenario *j* occurred at tunnel section *k*;

$F_m\left(X_{CO}, X_{CO_2}, X_{O_2}, t\right)$: the fatality rate for exposure time period of [*0,t*] at location *m*;

F_p^k: the purchase cost of the fire verification system with type *k*;

F_m^k: the maintenance cost of the fire verification system with type *k*;

F_o^k: the operating cost (the electrical cost and salaries of operators) of the fire verification system with type *k*;

F^k: the annual worth of the fire verification system with type *k*;

$IG\left(\mu_i, \lambda\right)$: Inverse Gaussian distributed with parameters μ_i and λ;

IR_k: the IR of road tunnel section *k;*

$\hat{IR}$: the overall individual risk based on worst case scenario;

$\overline{IR}$: the overall individual risk based on weighting principle;

$IR_{\text{criterion}}$: the safety target of individual risk;

I: the number of vehicle types;

J_k: the total number of accident scenarios that could be occurred at tunnel section *k*;

K_α: the critical value;

l_{leader}: the length of the leading vehicle;

L_{leader}: the location of the leading vehicle at a particular time;

L_{follower}: the location of the following vehicle at a particular time;

$\dot{L}_{\text{follower}}$: the speed of the following vehicle at a particular time;

$\dot{L}_{\text{leader}}$: the speed of the leading vehicle at a particular time;

L_k: the length of tunnel section *k* (*km*);

n_k : the number of times that a given individual tunnel user passes through tunnel section *k* per year;

n_v^i : the study period for tunnel ventilation system with type *i*;

n_d^j : the study period for fire detection system with type *j;*

n_f^k : the study period for fire verification system with type *k;*

$N_{conflict}\left(\tau\right)$: the hourly exposure to traffic conflicts with TTC threshold τ ;

N_{jk} : the number of fatalities when scenario *j* occurred at tunnel section k ;

p_{ij} : the probability that the user loses his life under the event E_{ij} ;

$P\left(H_i\right)$: the probability that hazardous situation H_i occurs;

$P(E_{ij}\left|H_i\right.)$: the probability that event E_{ij} is triggered by situation H_i ;

Q_{ki}: the yearly travel rate of all type *i* vehicles passing through tunnel section *k* (*veh·km/ year*);

$\hat{SR}$: the overall societal risk based on worst case scenario;

$\overline{SR}$: the overall societal risk based on weighting principle;

$SR_{\text{criterion}}$: the safety target of societal risk;

S_e: the excess risk;

Δt : the time increment (min) and $t = m\Delta t$;

V_p^i: the purchase cost of the tunnel ventilation system with type *i*;

V_m^i : the maintenance cost of the tunnel ventilation system with type *i*;

V_o^i : the operating cost (the electrical cost and salaries of operators) of the tunnel ventilation system with type *i*;

V^i : the annual worth of the tunnel ventilation system with type *i*;

x_{jk} : the number of fatalities caused by accident scenario j occurred at tunnel section k ;

X_{CO} : the concentration of carbon monoxide (in *ppm*);

X_{CO_2} : the concentration of carbon dioxide (in *volume percent*);

ω_k : the weight of tunnel section k *;*

λ_i : the average number of travelers using vehicle type *i* vehicle;

CHAPTER 1 INTRODUCTION

1.1 Urban Road Tunnels

Road tunnels are critical transportation infrastructures, which provide underground vehicular passageways for motorists and commuters. This is especially important in cities where there are limitations on the land allocated to road transportation (PIARC, 2008; Meng et al., 2009). Some of their advantages include increasing traffic capacity, improving accessibility, and thus reducing travelling time. In addition, the negative impacts of traffic on the environment, such as air and noise pollution, which are becoming a major concern for the general public and the authorities, can be efficiently reduced by containing traffic in road tunnels underground. With the growing traffic volume and urban development, as well as increasing demands on land use, especially in urban areas, constructing road tunnels is becoming more and more popular. For example, in Singapore, the Central Expressway (CTE) and Kallang Paya Lebar Expressway (KPE) road tunnels have been open since September 21st, 1991 and September 20th, 2008, respectively, while the Marina Coastal Expressway (MCE) and Central Expressway II (CTE II) are under construction and due to open in 2012.

The urban road tunnels in Singapore are different from those in other countries, from the viewpoints of the following two aspects. Firstly, Singapore is a city nation, with scarce land and a high population density, which results in heavy traffic in road tunnels, especially during peak hours. A road tunnel in Singapore has many conjunctions, at which the main tunnel merges with slip roads, and the distance between consecutive conjunctions is comparatively short. For example, the KPE road tunnel has 19 slip roads along a nine-kilometre main tunnel bore. Road tunnels in Singapore may be linked together with major roads and/or expressways and hence, unlike most tunnels that only have one entry and one exit, possess multiple entries and exits. Accordingly, the traffic flow and tunnel geometries possess obvious non-homogeneity, that is the tunnel parameters and traffic flows are different from one section to another. Secondly, several slip roads may be attached to a main tunnel section and these can also be regarded as tunnel-like road sections. Thus, the whole tunnel may be branched into several sections, with distinct geometric and traffic characteristics. Such road tunnels, characterized by non-uniform tunnel parameters - for example tunnel configurations, geometries, tunnel safety provisions (e.g. tunnel ventilation system, fire detection system, etc.), traffic volumes and accident frequencies, among others - are referred to as non-homogeneous urban road tunnels in this dissertation.

Their safe operation is of utmost concern, due to the heavy traffic volume that the road tunnels carry. Accidents occurring in a road tunnel may lead to severe consequences, due to the enclosed nature of the tunnel structure. For example, in 1999, 39 people lost their lives in a fire disaster in the Mont Blanc Tunnel between France and Italy, and another disaster in the Tauern Tunnel in Austria resulted in 12 fatalities (Leitner, 2001; Vuilleumier et al., 2002). These accidents have raised awareness among the public and the government of the safety aspects of the tunnels and their consequences for the users. Thus, quantitative risk analysis for road tunnels has been one of the requirements under the European Union (EU) Directive (2004/54/EC) and the Netherlands' legislation on road tunnels. In Singapore, a safety target is required to be met by all major road tunnels longer than 240 metres, in accordance with the Project Safety Review (PSR) procedure manual for roads in the country (LTA, 2005).

1.2 Fires in Urban Road Tunnels

The French (Perard, 1996), German (Elbtunnel, 2006), Swiss (Ruckstuhl, 1990), Italian (Arditi, 2003), and Singaporean (HCD, 2009) accident statistics analysis shows that the frequency of accidents in road tunnels is lower than that on the open road[1]. Yet, there is no doubt that the consequences of a fire in a road tunnel are likely to be far more serious than those of a fire on an open road. In reality, once a fire has started, the concentration of oxygen (O_2) will decrease dramatically because tunnels are enclosed spaces; at the same time, the concentration of toxic gases, such as carbon monoxide (CO) and carbon dioxide (CO_2), will increase. CO is one of the major narcotic gases in fires and is believed to be one of the prime causes of incapacitation and death. CO reacts with haemoglobin in the blood to form carboxyhemoglobin (COHb), which reduces the blood's ability to supply critical organs with oxygen. According to the Fire Protection Handbook (National Fire Protection Association, 2008), CO_2 is quite low in terms of its own toxicological potency and is not, by itself, normally considered a toxicant in fire atmospheres. However, it does stimulate both the rate and depth of breathing, thereby increasing the fatality rate caused by CO. Lack of oxygen is another contributing cause to incapacitation and death. Indeed, it has been well recognized and reported that toxic gases are responsible for most fire fatalities (Babrauskas et al., 1998; Besserre and Delort, 1997), and fire is inarguably considered the most disastrous hazard in urban road tunnels (PIARC, 1999; PIARC, 2008). The 51 fatalities in the Mont Blanc and Tauern tunnels in 1999 were all the result of toxic gases generated by vehicle fires.

[1] Possible reasons for this include the following: motorists in road tunnels are more cautious; road tunnels are not affected by complications caused by the weather; the gradients of road tunnels are usually gentle.

In view of the high consequences of fires in road tunnels, various types of tunnel safety provisions have to be implemented, as required by land transport authorities. These tunnel safety provisions can be categorized into fire detection systems, fire verification systems, tunnel ventilation systems (also referred to as ventilation and smoke extraction systems), and fire fighting systems.

Fire detection systems are vital for tunnel safety, since other systems (e.g. tunnel verification systems, tunnel ventilation systems, etc.) used in road tunnels depend on detection systems for their operation. There are many types of fire detection devices which can be implemented in road tunnels. For example, automatic incident detectors (AID) work on the basis of traffic videos, while linear heat detectors (LHD) are activated when the temperature becomes higher than a given threshold. Fire detection systems should meet the following requirements:

(1) 30-60 second detection times;

(2) Guaranteed operation in case of cable breakage, through failsafe functions;

(3) Monitored integration into a fire alarm system;

(4) A maximum repair time of 30 minutes for mechanically damaged cables.

Details of fire detection systems can be found in Chapter 5 of the Handbook of Tunnel Fire Safety.

If an accident occurs, it is important that a tunnel operator is able to quickly assess the situation, and respond to the problem immediately (fire verification system). Real-time information about events is essential so that tunnel operators can make appropriate response plans. CCTV and emergency telephones installed in road tunnels provide the means to verify the severity of a tunnel fire. A 60-second time line is allocated in which to verify and identify fires.

There are two basic types of ventilation airflow systems applied in road tunnels: longitudinal and transverse. In a longitudinal ventilation system, the airflow moves through the tunnel and essentially moves pollutants and/or heated gases along using incoming fresh air taken from the beginning of the tunnel or tunnel section, and discharges heated or polluted air at the tunnel portal, or at the end of the tunnel section (see Figure 1-1). Longitudinal ventilation can be configured either portal to portal (short road tunnel sections), portal to shaft, or shaft to shaft (long road tunnel sections). In a transverse ventilation system, the transverse flow is created by the uniform distribution of fresh air and/or uniform collection of vitiated air, along the length of the tunnel. The uniform distribution and collection of air throughout the length of the tunnel will provide a consistent level of temperature and pollutants throughout. Normally, tunnel ventilation systems will take between 60 and 120 seconds from standstill to full rotational speed.

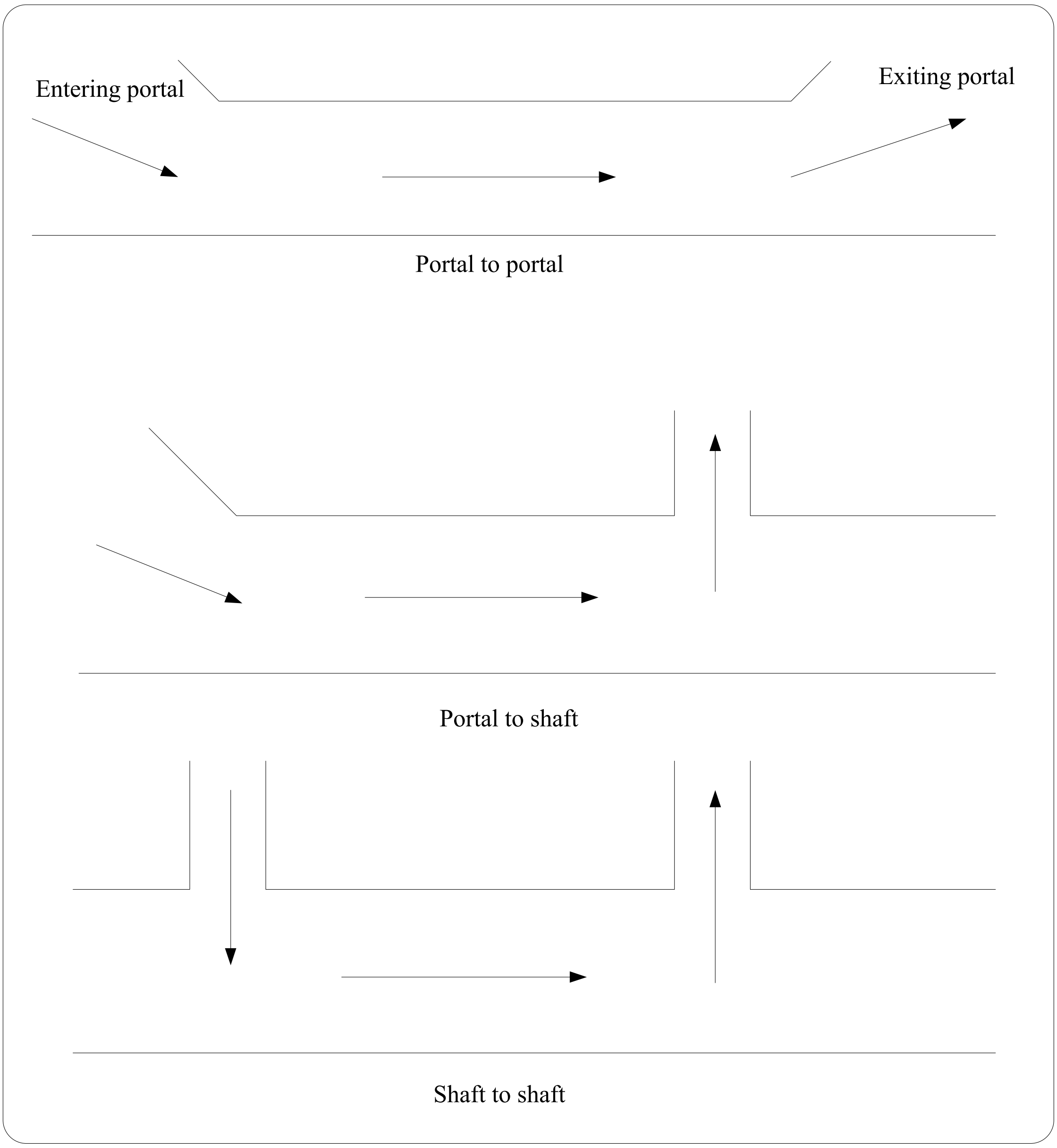


Figure 1-1: An example of a longitudinal ventilation system

Fire fighting systems can be categorized into five types: extinguishers, hose reels, fire hydrants, suppression systems, and water spray / water mist.

1.3 Quantitative Risk Analysis Models

Quantitative risk analysis (QRA) models have evolved from the application of reliability and statistics to engineering design, and are proven to be an efficient and effective methodology for quantitatively assessing the risks of hazardous installations. In the 1950s, a report issued by the US Atomic Energy Commission proposed a model to estimate risks (in terms of deaths, injuries and land contamination) of catastrophic accidents at nuclear power plants, with major radioactive releases. However, it was only in 1975 that a full-scale study, using numerical techniques to evaluate the probabilities and consequences of large accidents involving nuclear power reactors, was published in the US (US Nuclear Regulatory Commission, 1975). This landmark study introduced QRA, essentially in the form that we use today, as a numerical tool for evaluating the safety level of hazardous installations. Since then, we have seen a number of methodological applications in various industries (e.g. Collins and Cooley, 1983; Beim and Hobbs, 1997; Zhang and Yan, 1999; Persson, 2002; Zhang et al., 2004; etc.).

Figure 1-2 shows the standard framework illustrating how a QRA model is applied using four typical steps. Jonkman et al. (2003) and Vrouwenvelder et al. (2001), described how a QRA model can be decomposed into four steps, namely, qualitative analysis, quantitative analysis, risk evaluation, and risk control/reduction. Similarly, discussions about the standard framework for carrying out QRA can also be found in references published by NASA (2002), Molag and Trijssenaar-Buhre (2006), Beard and Cope (2007), and Botschek et al. (2007). Qualitative analysis focuses on attempting to find out the top event which may cause a severe accident, that is fires in road tunnels, through historical accident analysis and/or expert judgment. In Step 2, quantitative analysis, a fault tree is built to estimate the frequency of the top event, and an event tree is constructed to fractionize the top event into a number of accident scenarios which may lead to high consequences. Consequence estimation models are developed to calculate the consequences of each possible accident scenario (by spreadsheet model, numerical model, or simulation model). Having obtained the frequency and consequences of each possible accident scenario, risk indices are proposed and used in Step 3 to assess the risks. If the risks estimated by the model are not acceptable, based on a predetermined safety target, risk control/management measures are implemented (Step 4).

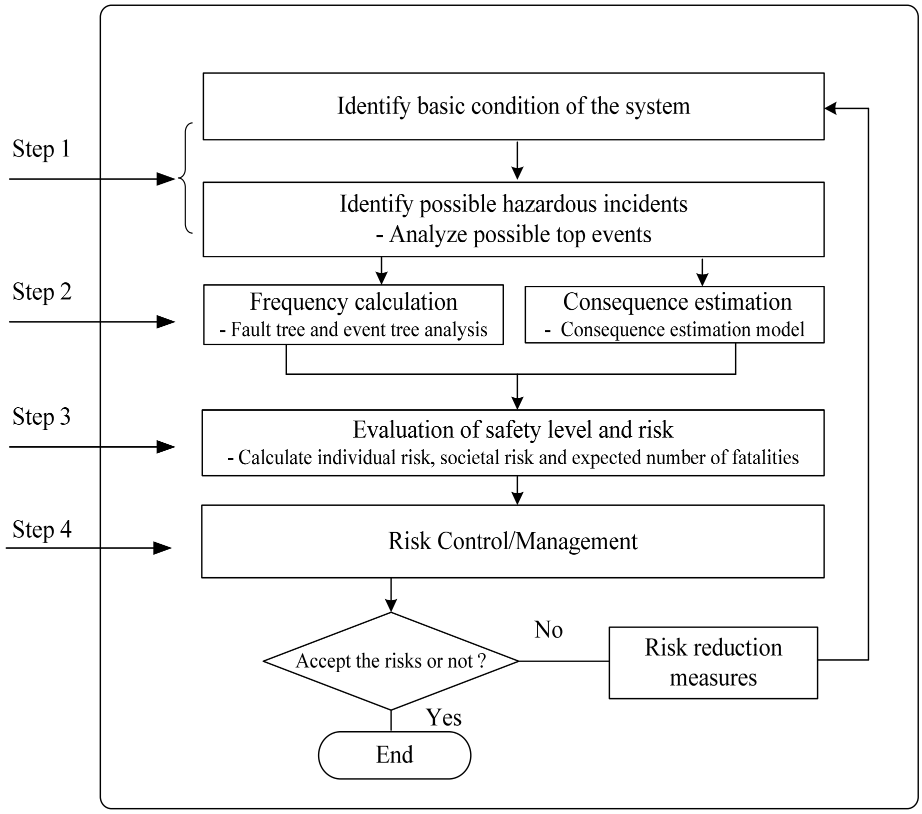


Figure 1-2: Demonstration of the framework for conducting QRA

1.4 Research objective and research methodology

The research objectives of this study is, in accordance with the PSR procedure manual for roads in Singapore, to build a quantitative risk assessment and quantitative risk control/management strategies for Singapore's road tunnels to support decision makers from Land Transport Authority of Singapore. The methodology could also be generalized to the risk analysis for other types of road tunnels.

The traditional four-step QRA modelling framework is applied in this study. First, fire is indentified as top event. Second, the fault tree and event tree are built in this step. The fault tree is built to estimate the frequency of fire in road tunnels, which is an important input parameter for a QRA model. The event tree is constructed to divide the top event into a number of accidental scenarios (leaf nodes of the tree) with certain frequencies and consequences. Third, the risk index is proposed to combine the frequencies and consequences of various possible scenarios to evaluate the risk level of a road tunnel. Fourth, if the tunnel risks exceed a predetermined safety target, the quantitative risk control/management would be done accordingly.

1.5 Flow of the thesis

According to Jonkman et al. (2003), there are two components of quantitative risk analysis models: quantitative risk assessment and quantitative risk control/management. This thesis addresses both components in the context of quantitative risk analysis for urban road tunnels. As can be seen in Figure 1-3, there are 8 chapters in the thesis. Following the introduction and literature review in Chapters 1 and 2, the frequency estimation model for fire in road tunnels is proposed in Chapter 3. According to the model proposed in this chapter, the frequency of fire in one particular road tunnel section could be calculated, given the traffic conditions in this tunnel section are available. The frequencies of fire in tunnel sections are the most important input parameters for the two risk assessment models: QRAM-I developed in Chapter 4 and QRAM-II developed in Chapter 6. QRAM-I could estimate the individual risk and societal risk for a whole road tunnel by taking into account the non-homogeneous characteristics of the tunnel. QRAM-II aims to evaluate the impact of parameter uncertainty by looking into a particular road tunnel section (normally the riskiest tunnel section or the longest tunnel section) to capture more information about the risks. On the basis of the two quantitative risk assessment models, two quantitative risk control/management strategies are proposed in Chapters 5 and 7, respectively. Chapter 5 focuses on the risk control/management strategies for existing road tunnels and Chapter 7 put forth the risk control/management strategies for planning road tunnels.

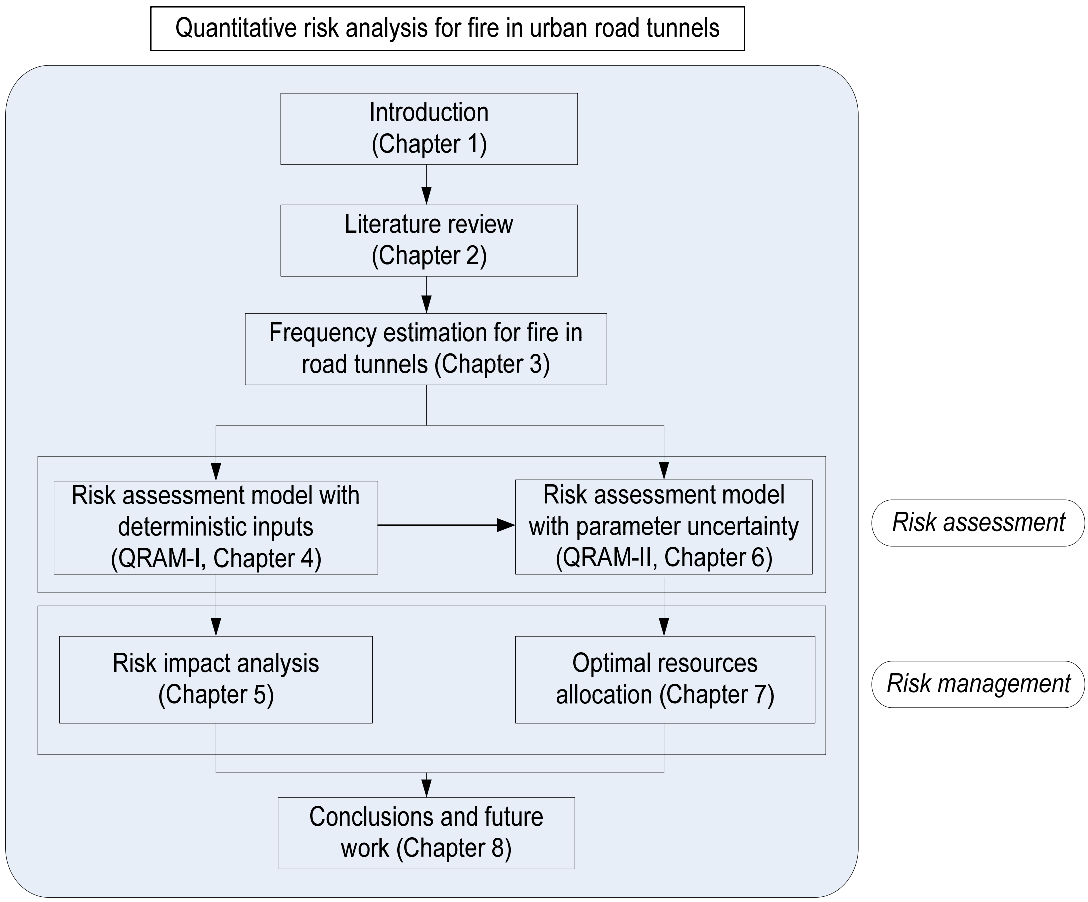


Figure 1-3: Flowchart of the thesis

Chapter 1 describes the research objective and motivations of this study. First, the characteristics of non-homogeneous urban road tunnels are introduced. Second, fire, the most disastrous event in road tunnels, is discussed. Third, the research motivations are pointed out - QRA for urban road tunnels has become an explicit requirement recently in the EU, the Netherlands and Singapore. Chapter 2 summarizes and reviews relevant studies on the topic. First, the causes of fire disasters are presented. Accordingly, it is of great importance to develop a robust and accurate model to estimate vehicle crash frequencies (as detailed in Chapter 3). Second, the tunnel safety provisions and accident response plan for Singapore's road tunnels are introduced. Third, the existing QRA models and risk indices for urban road tunnels are examined. Fourth, the issue of parameter uncertainty, and the fact that deterministic numbers are not appropriate to represent them, is pointed out.

Chapter 3 develop a model to estimate the frequency of fires in urban road tunnels. The fault tree model developed by Land Transport Authority of Singapore is applied to estimate the frequency of fire. According to LTA (2006), the vehicle crash frequency is the most important contributing factor to fires in urban road tunnels. Thus, a new vehicle crash estimation model is proposed, using detailed traffic data. According to the proposed model, the frequencies of fire occurred in different tunnel locations (with different traffic volumes) could be estimated. These fire frequencies are the most important input parameters for QRA models of road tunnels.

Chapter 4 builds a deterministic QRA model (QRAM-I) for non-homogeneous urban road tunnels. In the proposed model, a non-homogeneous urban road tunnel is segmented into a number of homogeneous road tunnel sections, based on a proposed tunnel segmentation principle. For distinct tunnel sections with different traffic volumes, the corresponding crash frequencies can be estimated using the model proposed in Chapter 3; then, a fire simulation model and the fractional effective dose (FED) methodology are applied to estimate the number of fatalities under different accident scenarios, by taking into account the different working statuses of tunnel safety provisions. Having obtained the frequencies and consequences of each possible accident scenario for the homogeneous tunnel section, the individual risk and societal risk of that tunnel section can be calculated. Finally, an aggregate QRA model is built by integrating the section-based QRA models. The model is further computerized as software, to help tunnel operators evaluate risks in urban road tunnels. The model and software have been applied by the Land Transport Authority of Singapore to assess the risks of urban road tunnels in the country.

Chapter 5 addresses the risk control/management strategies for operating tunnels, on the basis of QRAM-I. Once a tunnel is open to traffic, the only parameters that tunnel operators can adjust to control/manage the risks are traffic volumes and the proportion of Heavy Goods Vehicles (HGV). A risk impact analysis methodology is proposed in this chapter. An excess risk index is defined, to quantify the severities of unacceptable scenarios, which place road tunnels above a predetermined safety target. A contour chart, based on the excess risk index, could be used to help tunnel operators implement suitable risk control/management solutions. The analysis shows that the maximum tolerable traffic volume is 1,200 vehicles/hour·lane, and the maximum acceptable proportion of HGVs is 18% of the total traffic volume.

Chapter 6 develops a QRA model for a particular road tunnel section with parameter uncertainty (QRAM-II). In QRAM-I, a number of input parameters possess epistemic or aleatory uncertainty. In QRAM-II, aleatory uncertainty is formulated using probability distribution functions, while parameters with epistemic uncertainty are represented by fuzzy numbers. A hybrid Monte Carlo simulation-based approach is designed to propagate the parameter uncertainty in the framework of the QRA model, by taking into account the dependencies among these uncertain parameters. Finally, percentile-based individual risk and α-cut based societal risk are considered the most appropriate indices to support tunnel operators with distinct risk attitudes.

Chapter 7 addresses the optimal selection of tunnel safety provisions on the basis of QRAM-II. Tunnel safety provisions are features of urban road tunnels, which are installed and implemented to reduce tunnel risks. In practice, the selection of these safety provisions is based on expert judgment. In this study, an optimization model is proposed to obtain the optimal solution for the selection of tunnel safety provisions. The objective function minimizes the life-cycle costs of tunnel safety provisions, subject to the requirements for tunnel safety provisions, and the safety targets. Finally, by taking advantage of the special structure of the optimization model, a Bi-Section Search and Bound Algorithm (BSSBA) is designed, to efficiently solve the problem.

Chapter 8 draws conclusions and recommends future research work.

CHAPTER 2 LITERATURE REVIEW

2.1 The Causes of Fire Disasters

According to the US Fire Administration (USFA, 1999), the causes of vehicle fires can be divided into four categories: vehicle defects, an act of carelessness, arson, or the aftermath of a collision. A damaged fuel line, resulting in a spray of flammable fuel on a hot engine, the overheating of braking systems, and sparks, are all possible vehicle defects which could result in vehicle fire. Careless acts include causes such as dropped lights, naked lights, and cigarettes discarded on upholstery. Kocsis (2002) proposed that there are six types of intentional act: a profit motive, animosity crime, crime concealment, vandalism, personality disorder, and political objectives such as terrorism.

Based on statistics compiled in the Handbook of Tunnel Fire Safety, 55 out of 61 cases of fires in road tunnels are caused by vehicle crashes. According to the Design Safety Submission for tunnels (LTA, 2005), vehicles crashes also contributed to around 2/3 of tunnel fires. Therefore, vehicle crashes are considered as the major cause for tunnel fire in this study.

2.2 QRA Models and Risk Indices

2.2.1 QRA Models

As mentioned in the introductory section, in 1975, a full-scale study, using numerical techniques to evaluate the probabilities and consequences of large accidents involving nuclear power reactors, was published in the US (US Nuclear Regulatory Commission, 1975). This landmark study introduced QRA, essentially in the form that we use today, as a numerical tool for evaluating the risks of hazardous installations. In the past thirty years, we have seen a number of applications of the QRA model. Such studies have included electrical accident countermeasure systems for mines (Collins and Cooley, 1983), fusion fission hybrid reactor failures (Yang and Qiu, 1993), water resource planning (Beim and Hobbs, 1997), steam generator tube ruptures (Zhang and Yan, 1999), and emergency response in the context of chemical hazards or spills (Raman, 2004; Zhang et al., 2004). In the 1990s, researchers began to apply the methodology to assess the risks in homogeneous road tunnels (Arends et al., 2005; PIARC, 2008; Saccomanno and Haastrup, 2002). All these case studies show the usefulness and suitability of the QRA methodology to this type of problem.

The conventional four-step QRA framework includes qualitative analysis, quantitative analysis (frequency and consequence analysis), risk evaluation, and risk control/management, with the fault tree analysis, event tree analysis, and consequence estimation models in Step 2 the critical components. Fault trees, which are used to estimate the frequencies of top events, are made up of several photographical diagrams showing how the undesired states of a system can be analysed, using Boolean logic to combine series of low-level sub-events. They present all possible causes of a single event, using binary logic gates controlled by the Boolean values, resembling a "root system rising to a main stem". The tree starts from the top event and works downwards towards the various scenarios. These scenarios can be further defined until the basic events are reached. Figure 2-1 shows an example of a fault tree for a fire in a road tunnel. The top event may trigger a series of simple events with distinct results (frequencies and consequences). These simple events can be represented logically by an event tree, which is a tree diagram referring to complex events that can be fractionized in terms of their distinction by subsequent events. Figure 2-2 shows an event tree for a fire in a tunnel. Consequence estimation models are developed to estimate the consequences of each possible accident scenario (the leaf node of the event tree). Once the frequencies and consequences of all possible accident scenarios have been obtained, a risk assessment can be carried out.

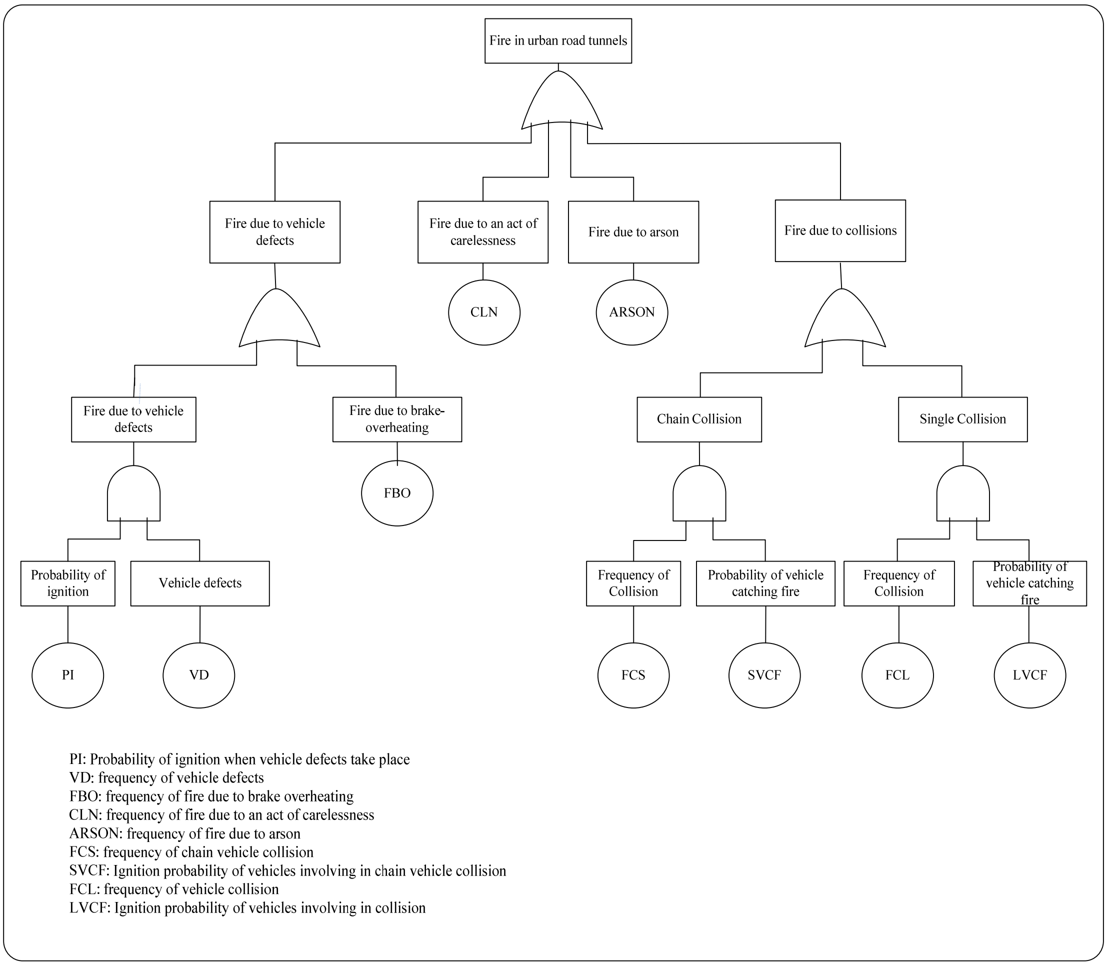


Figure 2-1: A fault tree

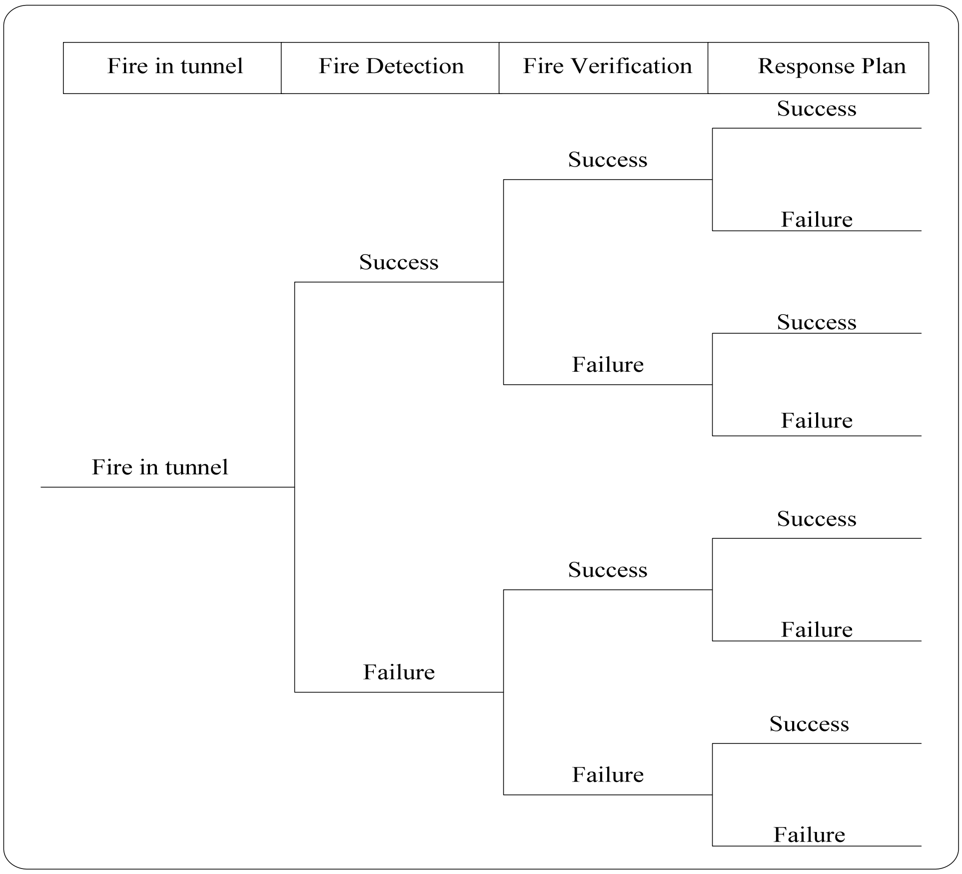


Figure 2-2: An event tree

2.2.2 Risk Indices

Risk indices have evolved in parallel with the development of QRA, as an integral analytical technique. In 1967, Farmer's pioneer paper defined the concept of risk in terms of a "probability consequence diagram" (Farmer, 1967). Individual risk (IR) and societal risk (SR) were defined and have gradually been recognized by researchers and industry as two risk indices that can be used to evaluate the safety level of a hazardous installation (Meng et al., 2009; PIARC, 2008).

The individual risk (IR), as used by the Dutch Ministry of Housing, Spatial Planning and Environment (VROM), is defined as the probability that an average unprotected person, permanently present at a certain location, is killed due to an accident resulting from a hazardous activity (Bottelberghs, 2000; Jonkman et al., 2003). Assuming that, during the use of a tunnel, say, a hazardous situation H_i may cause a set of events E_{ij} (for example, a fully developed fire, or explosion), let p_{ij} denote the probability that the user loses his life. Then, the individual risk of that person can be estimated using the following formal expression (Holický, 2007):

$$IR = \sum_{ij} p_{ij} P\left(E_{ij} \middle| H_i\right) P\left(H_i\right) \tag{2.1}$$

where $P\left(H_i\right)$ denotes the probability that the hazardous situation H_i occurs, e.g. the collision in the road tunnel, $P(E_{ij}|H_i)$ denotes the probability that event E_{ij} is triggered by situation H_i, and p_{ij} denotes the probability that a tunnel user is killed because of event E_{ij}.

Another commonly used measure of IR is passenger fatalities per total passenger traffic. Thus, IR is a fatality rate, not a probability. Four other expressions of IR were also mentioned by Jonkman et al. (2003):

(1) the loss of life expectancy: this indicates a reduction in life expectancy due to various incidents;

(2) the delta yearly probability: the intensity with which a given activity would need to be executed in order to increase the probability of death by 10^{-6} per year;

(3) the activity-specific hourly mortality rate: this reflects the probability of becoming a fatality in a given time unit when engaging in a particular activity;

(4) the death per unit activity: for example, the risk of travel by car or train can be represented by the number of deaths per kilometre travelled.

The conventional measure of IR defined by eqn. (2.1) was originally used to evaluate the risk of residents living close to nuclear power plants, under the assumption that the residents were permanently present at the location (as they lived nearby), which is unrealistic for road tunnel motorists and passengers. Instead, motorists and passengers enter and exit road tunnels from time to time rather than being permanently present at one location. Accordingly, the definition is not suited to road tunnel risk assessment. In this case, IR should be considered as the risk to individual tunnel users with distinct travel profiles.

The other widely-used risk index, SR, is defined as the relationship between frequency and the number of people suffering from a specified level of harm, in a given population, due to the realization of specified hazards (Ball and Floyd, 1998). SR can be sub-classified into the following four categories:

(1) Collective Risk: The risks associated with diffuse effects as a result of normal activities. For example, risks related to the radioactive discharges from incinerators working under normal conditions.

(2) Simple Societal Risk: This is related to hazardous installations where the predominant issue is human safety. This is the most widely used type of risk and is based on likelihood. Simple societal risks are illustrated by an *F/N* curve, which provides a graphical method of evaluating the consequences of incidents.

(3) Diverse Societal Risk: This can be applied to more complicated situations where other kinds of harm need to be considered, such as oil spills from tankers. The *F/N* curve is not sufficient in such situations. For example, in incidents involving maritime oil transport, the total harm is not only a function of human fatalities, but also of environmental pollution. In such cases, diverse societal

risk can be used to evaluate the impact of incidents on human beings and the environment.

(4) Societal Concerns: This is associated with strategic-level decision making where political and other factors are involved.

In risk assessments for road tunnels, researchers usually apply simple societal risk to represent the risks to all tunnel users. Simple societal risk (shortened to societal risk hereafter) can be represented graphically in the form of an F/N curve. The concept of using F/N curves to represent societal risk has been applied in all the existing QRA models. The curve reflects the relationship between the frequencies and number of fatalities for all possible scenarios on a double logarithmic scale. Let $F_k(N)$ denote the cumulative frequency of all accident scenarios in tunnel section k with N or more fatalities. We thus have:

$$F_k(N) = \sum_{j=1}^{J_k} \left[F_{jk} \times \delta\left(x_{jk} - N\right) \right], k = 1, 2, \cdots, K \tag{2.2}$$

where x_{jk} is the number of fatalities caused by accident scenario j in tunnel section k and the indicator function $\delta\left(x_{jk} - N\right)$ has the expression:

$$\delta\left(x_{jk} - N\right) = \begin{cases} 1, & \text{if } x_{jk} \geq N \\ 0, & \text{otherwise} \end{cases} \tag{2.3}$$

Using the frequency shown in eqn. (2.2), the expected value of the number of fatalities in road tunnel section k per year (EV_k) can be calculated as

$$EV_k = \sum_{j=1}^{J} \left(F_{jk} \times x_{jk} \right) \tag{2.4}$$

The upper bound curve for societal risk has been adopted by various countries as a safety target, namely,

$$F\left(N\right) \le \frac{C}{N^k} \tag{2.5}$$

where the parameters *k* and *C* specify the steepness and intercept of the safety target. Equivalently, eqn. (2.5) can also be represented as

$$k \log\left(N\right) + \log\left(F\left(N\right)\right) \le \log\left(C\right) \tag{2.6}$$

It should be noted that *k* represents the slope, that is the gradient of the safety target, and *C* denotes the intercept, that is a constant value that determines the position of the target. Different combinations of *k* and *C* express various degrees of strictness of the safety target. As a result, different countries can propose their own safety targets by choosing these parameters.

There are two principles to choose risk indices: straightforward and representative. A good risk index should be a straightforward value or simple figure representing the risk level of the hazardous installations. In this regards, the individual risk and simple societal risk are good risk indices with simple form and a practical meaning to represent risk levels.

2.3 QRA Models for Road Tunnels and Safety Targets

2.3.1 QRA Models for Road Tunnels

QRA models for road tunnels have been carried out and financially supported by various international and national organizations, including the OECD, PIARC, TNO in the Netherlands, and INERIS in France. In addition to academic studies on the use of QRA for road tunnels, some countries have developed their own QRA models specifically for their own road tunnels. Some examples include the OECD/PIARC model, the Dutch TUNprim model, Austria's TuRisMo model, the Italian risk analysis model, the French model, and the TUSI model (Meng et al., 2009; PIARC, 2008), among others. Out of these, the Dutch model and the OECD/PIARC model are well recognized by researchers and the authorities for land transport in various countries (Meng et al., 2009).

The Dutch scholars have dedicated a lot of effort to the development of QRA models for road tunnels, and a significant body of work is based on their study experiences. An integrated safety philosophy was proposed by Worm and Hoeksam (1998), to provide a concept for analysing the Westerschelde Tunnel in Southwest Netherlands. The potential for the concept to be used for future underground projects was also addressed. With the aim of building a basis on which to establish safety objectives and criteria for underground infrastructures, the TUNprim QRA model, programmed in a spreadsheet, was designed to calculate internal safety in two-bore tunnels with uni-directional traffic in each bore, during normal operation (Weger et al., 2001; Brussaard et al., 2001). To probe the possibility of improving QRA for tunnels, Soons et al. (2006) compared QRA modelling of tunnel safety with its applications in the food industry, the chemical industry, and the aviation and nuclear industry. They found that QRA modelling of tunnel safety is limited by the uncertainties in inputs and outputs, due to data shortages. The paper suggested that human factors, probabilities of failures of tunnel safety provisions, and people's self-rescue activities, should all be included, to improve the performance of the models. However, to date, no QRA models for road tunnels exist that address the uncertainty representation and propagation problem. Accordingly, the representation and propagation of parameter uncertainty needs to be addressed and discussed so as to improve QRA models for urban road tunnels.

In a project launched in 1995 regarding the transport of dangerous goods through road tunnels (Project ERS2), co-sponsored by the PIARC Tunnel Committee and the Road Research Division of the OECD, a PIARC/OECD/EU QRA model was developed for risk estimates associated with the transport of dangerous goods through road tunnels, incorporating 13 fire-related hazardous top events; spreadsheet-based software was created to computerize the model (Lacroix et al., 1999; Knoflacher et al., 2002; PIARC, 2008). The software was applied to the existing tunnels in Austria, France, the Netherlands, Norway, Sweden and Switzerland. This model and the accompanying software have significantly promoted the development of QRA models for road tunnels. In order to examine the risk levels in Austrian road tunnels, and the risk mitigation measures required, Knoflacher and Pfaffenbichler (2004) applied the software to analyze the risks in 13 selected Austrian tunnels. It has also been employed to analyse potential risk in road tunnels in the UK, France and the US (Colorado DoT, 2006; PIARC, 2008). Furthermore, the model is discussed with respect to different aspects, such as risk reduction measures and engineering applications, by Cassini (1998) and Saccomanno and Haastrup (2002). Botschek et al. (2007) presented a new QRA model, which can be applied to all tunnels equipped with mechanical ventilation systems and catered to the demands of the Austrian Ministry.

Table 2-1 lists the model structures, consequence estimation models, and safety targets of two of the above models, OECD/PIARC and TUNprim. As can be seen in the table, the OECD/PIARC model focuses on the risk analysis of hazardous material transportation in road tunnels, while the Dutch TUNprim model was built for homogeneous road tunnels. The Centre for Chemical Process Safety (CCPS) had earlier proposed the idea of dividing a tunnel into a number of homogeneous portions, for the risk assessment of the transportation of hazardous materials, in 1995 (CCPS, 1995). In their model, all of the parameters involved in risk calculations (accident frequency, scenario probability, population at risk, etc.) for each homogeneous portion, were assumed to be constant.

Table 2-1: Model structures, consequence estimation models, and risk indices in existing QRA models

Models	Procedure	Consequence estimation	Risk index
PIARC/OECD/EU QRAM	(1) Option of a restricted number of dangerous goods. (2) Option of representative accident scenarios involving those dangerous goods. (3) Identification of physical effects of those scenarios on an open-air or road tunnel section. (4) Evaluations of their physiological effects on road or rail users and on the local population, taking into account possibilities for escape/sheltering; (5) Determination of yearly frequency of occurrence of each scenario.	The consequences of a restricted number of scenarios is examined, including: (1) Physical modelling of the effects: explosions, fire or toxic releases. (2) Effects on road/rail users and local population.	Individual risk Societal risk Expected number of fatalities
Dutch TUNprim model	(1) Identification of initial events. (2) Identification of accident scenarios in an event tree, each branch of the event tree is a scenario. (3) Frequency calculation for each scenario. (4) Consequence estimation for each scenario. (5) Calculation of the overall risk.	Consequence for each scenario is calculated as the number of fatalities. Evacuation possibilities: (1) Free fleeing distance (2) Traffic jam	Individual risk Societal risk

2.3.2 Safety Targets

In order to evaluate whether or not a hazardous installation is risky, various countries have proposed their own safety targets. Table 2-2 lists the different individual risk values published in various research papers. Table 2-3 gives the upper and lower bounds of the F/N curve (societal risk) used in various countries. The upper bound and lower bound curves can be expressed by a general formula, whereby C_1/N^k and C_2/N^k show the minimum and maximum acceptable societal risk.

$$\frac{C_1}{N^k} \leq f_x(N) \leq \frac{C_2}{N^k} \tag{2.7}$$

Table 2-2: Safety targets for individual risks

Presented in	Explanations	Individual Risk
ISO 2394 (1998)	Loss of life due to structural failure or due to electric power and radiation.	$\leq 10^{-6}$
Trbojevic (2003)	In industrial conditions.	$\leq 10^{-3}$
Holický (2007)	Most industrial areas.	$[10^{-6}, 10^{-3}]$
Jonkman et al. (2003)	Proposed by the Dutch Ministry of Housing, Spatial Planning and Environment.	$\leq 10^{-6}$
Arends et al. (2005) and Vrouwenvelder et al. (2001)	Employees (Rail).	$\leq 10^{-4}$
	Passengers or users.	$\leq 10^{-5}$
	Persons living near the tunnel.	$\leq 10^{-6}$

Table 2-3: Upper and lower bounds used in various countries

COUNTRY	Tolerable	Non-tolerable
	Lower bound	Upper bound
Austria	$10^{-4}/N$	$10^{-1}/N$
Denmark	NA	$10^{-2}/N^2$
Hong Kong	NA	$10^{-2}/N$
Netherlands	NA	$10^{-3}/N^2$
Switzerland	NA	$10^{-4}/N$
United Kingdom	NA	$10^{-1}/N$

Source: All safety targets were obtained from Beard and Cope (2007) and Jonkman et al. (2003)

The standards by Austria, Hong Kong, Switzerland, and UK are called risk neutral. The safety targets by Denmark and Netherlands are called risk averse. In these cases, larger accidents are weighted more heavily and are thus only accepted with a relatively lower probability.

2.4 Parameter Representations in Existing QRA Models

In the existing QRA models for road tunnels, all input parameters are taken to be deterministic numbers, with no account taken of parameter uncertainty (PIARC, 2008). However, quite a number of the input parameters possess various types of uncertainty. For example, the failure probability of the tunnel safety provisions, which are considered hardware-failure-dominated (HFD) events, includes randomness caused by inherent variability, while some other parameters may include other types of uncertainty, due to lack of information. Accordingly, as suggested by Ferson and Ginzburg (1996), distinct representation models are needed to adequately account for this random variability (also referred to as aleatory uncertainty) and imprecision (also referred to as epistemic uncertainty). It is unrealistic and inappropriate to represent the input parameters to a QRA model as deterministic numbers. Thus, distinct approaches should be applied to represent and propagate both aleatory and epistemic uncertainty.

2.5 Limitations of the Existing Literature

Based on the literature review presented above, it can be concluded that there are four limitations in the existing QRA studies relating to road tunnels, as follows:

(1) Majority of the tunnel fires are caused by vehicle crashes. Evidently, vehicle crashes are the most important contributing factor behind fires in urban road tunnels and should be include in any risk assessment. As this is so important, it may not be appropriate to estimate the frequency of vehicle crashes by taking an average of historical records, especially for newly-opened road tunnel sections, with little historical data. Therefore, a robust model of the frequency of vehicle crashes is needed (as detailed in Chapter 3).

(2) Non-homogeneous urban road tunnels are different from traditional road tunnels due to their non-homogeneity of traffic and geometric parameters. Previous QRA models cannot simply be applied to assess the risks in non-homogenous urban road tunnels, and non-homogeneous urban road tunnels cannot be examined homogeneously without taking the multifarious geometric layouts of their tunnel sections into account. In addition, the conventional definition of IR is not suitable for the risk assessment of road tunnels, as tunnel users are not permanently present at a specific location in

a tunnel. Necessary revisions to the definition of IR need to be made in order to assess the risks for road tunnel users. Therefore, a new QRA model need be developed for non-homogeneous urban road tunnels (as detailed in Chapter 4).

(3) Parameter uncertainty should also be taken into consideration. A number of the parameters involve uncertainty from various origins. It is inappropriate to neglect this parameter uncertainty in risk assessments, as it may lead to unreliable results. Accordingly, the representation and propagation of parameter uncertainty should be addressed in the QRA framework (as detailed in Chapter 6).

(4) The existing QRA models mainly focus on risk assessment, and little has been quantitatively analyzed in the area of risk control/management in urban road tunnels. In practice, risk control/management solutions need to be implemented if tunnels do not pass the predetermined safety target. These risk control/management strategies have to be quantitatively discussed in relation to the risk assessment models (as detailed in Chapters 5 and 7).

2.6 Research Scope

The research scope of this study can be summarized as follows.

(1) A model is developed to estimate the frequency of vehicle crashes in road tunnel sections. As a result, the frequency of fires in urban road tunnels is estimated using the fault tree technique (as detailed in Chapter 3).

(2) A QRA model (QRAM-I) is developed for fires in non-homogeneous urban road tunnels, taking into account the distinct tunnel parameters in each section (as detailed in Chapter 4).

(3) A QRAM-I based risk impact analysis approach is proposed to examine the traffic flows in Singapore's road tunnels. A risk contour chart is provided to support the tunnel operators from the Land Transport Authority of Singapore in controlling/managing the risks (as detailed in Chapter 5).

(4) A QRA model for a road tunnel section, with parameter uncertainty (QRAM-II) is developed in order to address uncertainties due to inherent variability and lack of knowledge. A Monte Carlo simulation-based approach is applied to propagate the parameter uncertainties in the QRA model. Percentile-based individual risk and α-cut-based societal risks are also proposed; these risk indices are considered the most appropriate solutions for tunnel operators with distinct risk attitudes to assess the safety level of a road tunnel (as detailed in Chapter 6).

(5) A QRAM-II based approach is proposed to optimally select the tunnel safety provisions in non-homogeneous urban road tunnels, under safety target constraints. By taking advantage of the special structure of the problem, a BSSBA is designed to efficiently solve the problem.

CHAPTER 3 FREQUENCY ESTIMATION FOR FIRE IN URBAN ROAD TUNNELS

3.1 Introduction

As acknowledged by the previous QRA models for road tunnels, frequency of fire in road tunnels is the most important contributing factor for the risks (Meng et al., 2009; PIARC, 2008). Therefore, frequency analysis is crucial to the reliability of a QRA model for urban road tunnels. Accordingly, it is important to develop a robust and reliable model to estimate the frequency of fire in road tunnels. In this chapter, we first developed a fault tree model for fire in urban road tunnels on the basis of expert judgment by experienced tunnel operators from Land Transport Authority of Singapore. Based on statistics compiled in the Handbook of Tunnel Fire Safety, 55 out of 61 cases of fires in road tunnels are caused by vehicle crashes. In Singapore, 61.5% of tunnel fires are caused by vehicle crashes (LTA, 2005). Therefore, vehicle crashes are major cause for tunnel fire. In this regard, a method is further proposed to accurately estimate the frequency of vehicle crashes in urban road tunnels with distinct traffic conditions. The traffic videos collected from Singapore's road tunnels are applied to obtain the Time to Collision (TTC) distributions, concluding that Inverse Gaussian distribution is the best-fitted distribution to TTC samples. Then, an Inverse Gaussian regression model is used to establish the relationship between TTC samples and their corresponding contributing factors. We then proceed to introduce a new concept of *exposure to traffic conflicts* as the mean sojourn time in a given time period that vehicles are exposed to dangerous scenarios, i.e. the TTCs are lower than a predetermined threshold value. Finally, a crash frequency estimation method is proposed on the basis of the accident records provided by Historical Crash-Damage (HCD) database for Singapore's road tunnels.

3.2 Fault Tree for Fire in Road Tunnels

The fault tree for fire in urban road tunnels is built by experienced tunnel operators from Land Transport Authority (LTA) of Singapore, which is depicted in Figure 3-1. The circles attached to the leaf nodes of fault trees are the notations of input parameters to the fault tree. The meanings of notations in fault tree for fire in tunnel top event are explained in the figure. The probability of ignition when vehicle defects occur and probability of vehicle catching fire for collisions are constants provided by LTA. The frequencies of fire due to brake-overheating, an act of carelessness, and arson are relatively low in Singapore. Therefore, the frequency of vehicle crashes plays an essential role in the estimations of frequency of fire in urban road tunnels. In other words, the reliability of fault tree estimations relies on the credibility of frequency of vehicle crashes. Therefore, it is of great significance to develop a model to accurately estimate the frequency of vehicle crashes in urban road tunnels with distinct traffic conditions.

According to the Handbook of Tunnel Fire Safety (2006), fire could be resulted from vehicle defects, an act of carelessness, arson, and vehicle collisions. Thus, the first level of fault tree includes these four possible causes. The frequency of fire due to vehicle defects could be estimated by multiplying the frequency of vehicle defects (which could be obtainable from historical data) and probability of ignition when vehicle defects. Similarly, the frequency of fire due to vehicle collisions could be estimated by multiplying the frequency of vehicle collisions and probability of vehicle catching fire in a crash event. Thus, the fault tree could be built. This fault tree model has been applied by Land Transport Authority of Singapore for 10 years and relevant coefficients have been calibrated and adjusted year by year. This model could be generalized to be used in other road tunnels. However, the coefficients should be further calibrated in accordance with the vehicle and traffic conditions in the tunnel.

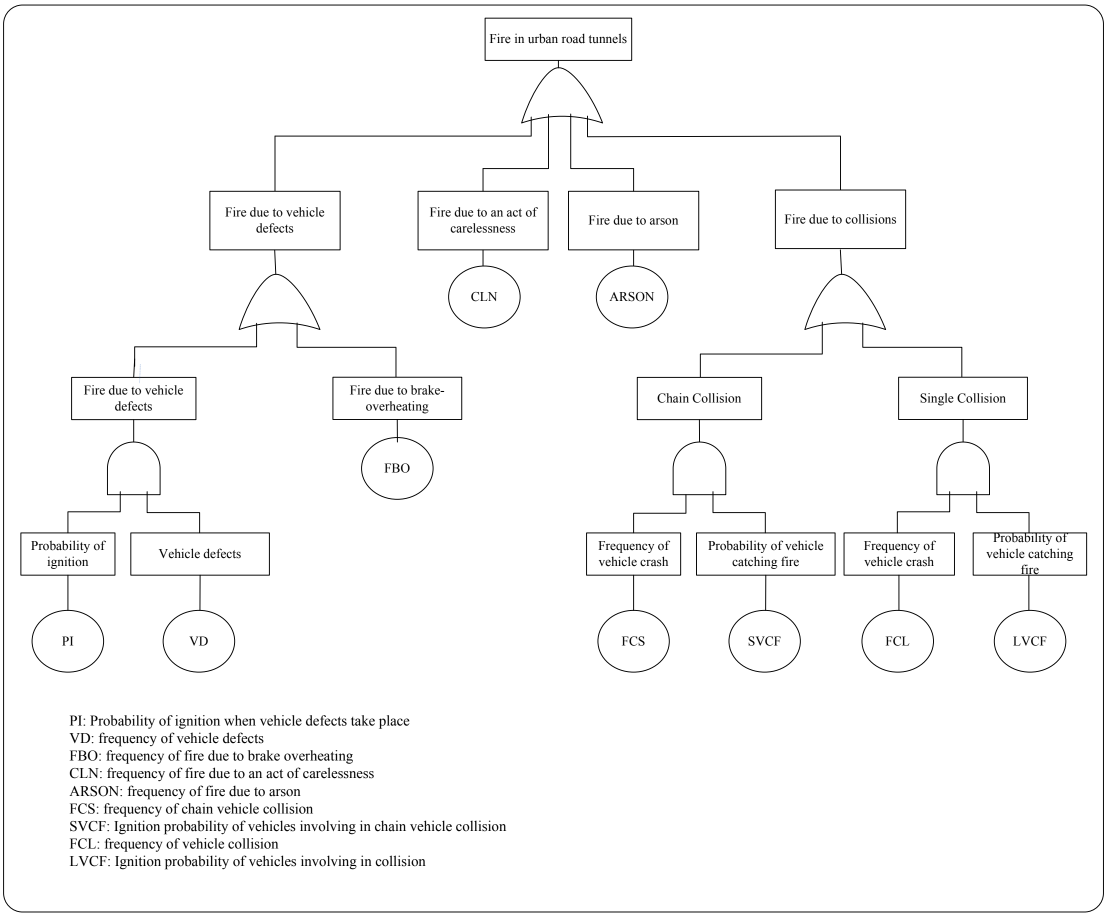


Figure 3-1: Fault tree for fire in tunnel top event

3.3 Estimations of Vehicle Crash Frequencies in Road Tunnels

3.3.1. Statistical Models for Crash Frequency Estimations in Open Roads

A number of studies have been conducted to predict/estimate vehicle crash frequency on highways using crash-frequency data. However, identification of the cause and effect relationships is typical unavailable due to lack of microscopic traffic information (or the detailed driving data). Consequently, as pointed out by Lord and Mannering (2010), researchers have framed their analytic approaches to study the factors that affect the number of crashes occurring in some geographical space over some specified time period by using various types of count-data regression models in accordance to some assumptions. These models include Poisson regression model (e.g. Miaou and Lum, 1993; Miaou, 1994), Negative binomial/Poisson-Gamma model (e.g. Maycock and Hall, 1984; Malyshkina and Mannering, 2010a; Daniels et al, 2010), Zero-inflated Possion and negative binomial models (e.g. Maiou, 1994; Shankar et al., 1997; Malyshkina and Mannering, 2010b; Lord et al., 2007), Conway-Maxwell-Poisson model (e.g. Lord et al., 2008; Lord et al., 2010), and others (e.g. Zhang and Xie, 2007; Guo et al., 2010; Haque et al., 2009). The lack of the detailed driving data on highways makes those statistical analysis models biased to reflect the fundamental cause and effect relationship. Lord and Mannering (2010) thus highlight that the entirely new direction of research could potentially open up if the anticipated availability of the detailed driving data and crash data are available.

More detailed traffic data are obtainable in road tunnels compared to highways because most of road tunnels are equipped with the closed circuit television (CCTV) cameras and/or an operation control centre (OCC). For example, each of Singapore’s road tunnels has been installed 2 to 4 CCTV cameras every 200 meters and monitored by a twenty-four-hour manned operation control centre (OCC). These CCTV cameras record real time and detailed traffic information. In addition to hourly traffic volume and density, we can precisely measure/estimate the time to collision (TTC) for two consecutive vehicles moving in the same lane of a road tunnel using traffic videos recorded by these cameras. The TTC is defined as *the time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained* (Hayward, 1972). The TTC has been one of the well-recognized safety indicators for traffic conflicts on highways (Farah, et al., 2009; Svensson, 1998; Chin et al., 1991; Chin et al., 1992; Chin and Quek, 1997). Minderhoud and Bovy (2001) further pointed out that it is inversely related to vehicle crash frequencies in road sections. It is widely accepted as a safety indicator in highways.

The objective of this study is to develop a crash frequency estimation method on the basis of TTC distributions. The TTC sample data are collected from the traffic videos in Singapore's road tunnels. Based on the statistical analysis, we find that the Inverse Gaussian distribution is the best-fitted distributions for the collected TTC samples. Accordingly, the Inverse Gaussian regression model is applied to establish the relationship between TTC distributions and the corresponding traffic volume. Having had the TTC distributions, a crash frequency estimation method is put up to establish the relationship between the TTC distributions and the crash frequencies.

3.3.2. TTC Data Collection

Assume that there are two consecutive vehicles moving in the same direction on the same lane of a road tunnel. Let L_{leader} and L_{follower} be the locations of the leading and following vehicles at a particular time, respectively. Correspondingly, let $\dot{L}_{\text{leader}}$ and $\dot{L}_{\text{follower}}$ denote the speeds of the leading and following vehicles at the particular time. According to the TTC definition, namely, the *time that remains until a collision between two vehicles would have occurred if the collision course and speed difference are maintained*, the TTC can be mathematically expressed by

$$TTC = \begin{cases} \dfrac{L_{\text{leader}} - L_{\text{follower}} - l_{\text{leader}}}{\dot{L}_{\text{follower}} - \dot{L}_{\text{leader}}}, & \text{if } \dot{L}_{\text{follower}} > \dot{L}_{\text{leader}} \\ \infty, & \text{otherwise} \end{cases} \tag{3.1}$$

where l_{leader} is the length of the leading vehicle. Eqn. (3.1) implies that the TTC is measurable if we have real time traffic information.

To collect the TTC data in a road tunnel, the Kallang/Paya Lebar Expressway (KPE) and the Central Expressway (CTE) in Singapore shown in Figure 3-2 and Figure 3-3 are selected. KPE and CTE are two vital infrastructures in Singapore's road system. The first one has a total length of 12 kilometers and 9 kilometers of the expressway (Figure 3-2) is built underground as a road tunnel, serving the growing traffic demand of the north-eastern sector of Singapore. The second one, a 17-kilometer expressway, links the north and south of Singapore through the Central Business District (CBD). 2.4 kilometers of the expressway (Figure 3-3) are laid underground and these portions of the CTE form the first road tunnel in Singapore. Both road tunnels are equipped with the 24-hour OOC systems.

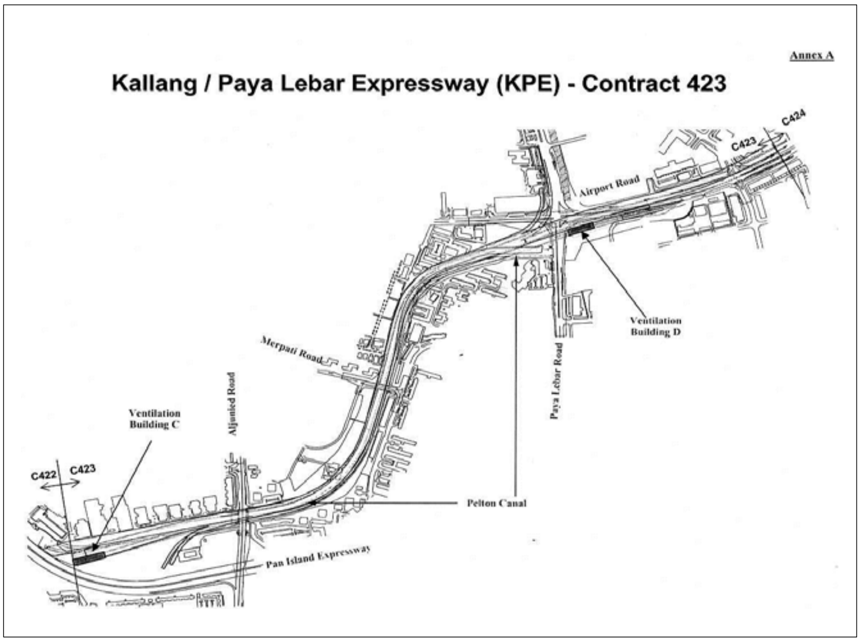


Figure 3-2: General arrangement of KPE road tunnel

Figure 3-3: Traffic videos recorded from CTE road tunnel

We request 42-hour tunnel traffic videos recorded by CCTV of these two tunnels from Land Transport Authority of Singapore, including 14 locations for 3 typical time periods - morning peak hour: 8:00 am to 9:00 am, off-peak hour: 14:00 pm to 15:00 pm, evening peak hour: 19:00 pm to 20:00 pm - in Mar 2011. The TTC samples are counted from these traffic videos in different time periods with different traffic conditions. The procedure of measuring a TTC with respect to a car-following scenario is summarized as follows. We first measure the length of the leading vehicle (l_{leader}) in a car-following scenario (per lane basis). After that, the spot speeds of the vehicles ($\dot{L}_{\text{follower}}$ and $\dot{L}_{\text{leader}}$) can be estimated by measuring the time taken by the vehicle to cover two lane-markers' distance in the video. Then, the time headway (h) between the leading and following vehicles is recorded. According to Vogel (2003), the gap size $\left(L_{\text{leader}} - L_{\text{follower}} - l_{\text{leader}}\right)$ can be estimated by $\left(\dot{L}_{\text{follower}} \times h - l_{\text{leader}}\right)$. Finally, the TTC for the car-following scenario could be calculated according to eqn. (3.1).

In the measurement, we display 30 frames per second to obtain a better data accuracy. To sum up, 1,433 car following scenarios occurred in various locations are analyzed in this study. From the analysis, 604 TTC samples with respect to different traffic volumes are obtainable (TTC samples with finite values). Statistically, the number of TTC samples with finite values should be equal to that of samples with infinite values. Infinite TTC values indicate that the following vehicle will not be possible catch up with the leading one, which are absolutely safe situations. Accordingly, we would focus on the probability distributions of TTC samples with finite values.

3.3.3. Inverse Gaussian Distribution for TTC

3.3.3.1 Statistical analysis for the TTC samples

A data analysis procedure is proposed in order to obtain the best-fitted TTC distributions. Five commonly used distributions are examined in this study: Inverse

Gaussian, Exponential, Normal, Triangular, and Lognormal. The maximum likelihood estimation (MLE) technique is employed to estimate the parameters involved in a distribution model. After obtaining the parameters for various types of distributions, the goodness-of-fit test is conducted to select the best-fitted distribution among the give candidate distributions. Kolmogorov-Smirnov (K-S) test, a nonparametric test, has been widely applied to compare a sample with a reference probability distribution in transportation studies (e.g. Ibeas et al., 2011; Páez et al., 2011). In this study, the K-S test is also adopted to perform the goodness-of-fit test. The K-S statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution. In this study, a distribution with the lowest K-S test statistic is regarded as the best-fitted distribution.

According to the above-mentioned procedure, we analyze five sets of samples collected at different locations with respect to different traffic volumes, shown in Table 3-1. Table 3-2 gives the best-fit analysis results.

Table 3-1: TTC samples

	Traffic volume (vehs/hour·lane)	Number of samples
Sample 1	894	104
Sample 2	963	65
Sample 3	1127	80
Sample 4	1374	79
Sample 5	1672	93
Sample 6	1028	61
Sample 7	1454	60
Sample 8	1298	62

Table 3-2: Statistical analysis for the TTC samples

Sa-mple	Inverse Gaussian		Lognormal		Triangular		Exponential		Uniform	
	Distributions	K-S	Distributions	K-S	Distributions	K-S	Distributions	K-S	Distributions	K-S
1	IG	0.0968*	Lognorm	0.1198	Triang	0.2385	Expon	0.1814	Uniform	0.3600
	(9.26, 12.21)		(9.27, 8.28)		(0, 2.30, 31.50)		(9.26)		(0, 29.82)	
2	IG	0.1003*	Lognorm	0.1138	Triang	0.2471	Expon	0.1764	Uniform	0.3746
	(9.69, 12.88)		(9.71, 8.62)		(0, 2.41, 32.80)		(9.69)		(0, 31.39)	
3	IG	0.1017*	Lognorm	0.1024	Triang	0.1756	Expon	0.2091	Uniform	0.3807
	(11.20, 14.06)		(11.53, 9.56)		(0, 2.10, 37.40)		(11.20)		(0, 36.84)	
4	IG	0.0813*	Lognorm	0.1097	Triang	0.1768	Expon	0.1408	Uniform	0.3449
	(12.30, 11.01)		(12.96, 13.86)		(0, 1.41, 40.60)		(12.30)		(0, 39.55)	
5	IG	0.0651*	Lognorm	0.0781	Triang	0.3199	Expon	0.1934	Uniform	0.4948
	(7.26, 9.24)		(7.24, 6.45)		(0, 1.65, 29.88)		(7.26)		(0, 29.57)	
6	IG	0.1208*	Lognorm	0.1287	Triang	0.1603	Expon	0.1461	Uniform	0.3133
	(11.27, 12.42)		(11.65, 11.42)		(0, 2.07, 36.38)		(11.27)		(0, 34.94)	
	IG	0.1095	Lognorm	0.1041*	Triang	0.3065	Expon	0.1836	Uniform	0.4343
	(13.16, 11.19)		(13.32, 14.21)		(0, 3.50, 51.32)		(13.16)		(0, 50.18)	
8	IG	0.1266	Lognorm	0.1035*	Triang	0.2873	Expon	0.1127	Uniform	0.4744
	(15.24, 12.86)		(15.76, 17.86)		(0, 2.21, 62.97)		(15.24)		(0, 62.25)	

* The K-S statistics of the best fitted distributions.

According to Table 3-1 and Table 3-2, we can find that

(1) The Inverse Gaussian distribution and lognormal distribution are considered as the best-fitted distributions for the cases[2]. Figure 3-4 depicts the histograms and empirical cumulative distribution function (CDF) for data samples with the best-fitted distributions (traffic volume = 963 vehs/hour·lane).

(2) The TTC samples collected at different locations with respect to similar traffic volumes generally follows the same Inverse Gaussian distribution with the same parameters (e.g. Sample 1 and Sample 2, sample 3 and sample 6). In other words, the traffic volume could be considered as the contributing factor for TTC distributions.

(3) The TTC sample mean and its inverse both have a parabola relationship with traffic volume, as shown in Figure 3-5 and Figure 3-6. This is because two contributing factors to TTC, distance headway and speed dispersion, are both dependent of the traffic volume. When traffic volume is low (<1000 vehs/hour·lane), the great speed dispersion could result in low TTC values. However, when traffic volume is high (>1600 vehs/hour·lane), the small distance headway would lead to low TTC values.

(4) The shape parameters (λ) of best fitted Inverse Gaussian distributions with respect to different traffic volumes are within a relatively small range from 9.24 to 14.06.

---

[2] Inverse Gaussian Distribution is a two parameter family of continuous probability distributions with support on (0, ∞). Its probability density function is given by

$$f(x;\mu,\lambda)=\left(\frac{\lambda}{2\pi x^3}\right)^{1/2}\exp\left(\frac{-\lambda(x-\mu)^2}{2\mu^2 x}\right), 0<x<\infty.$$

where μ >0 is the mean and λ >0 is the shape parameter. The distribution can be viewed as the distribution of first passage time of a Wiener process with an absorbing barrier, i.e., while the Gaussian describes a Brownian Motion's level at a fixed time (Wiener process), the inverse Gaussian describes the distribution of the time the Brownian Motion takes to reach a fixed positive level.

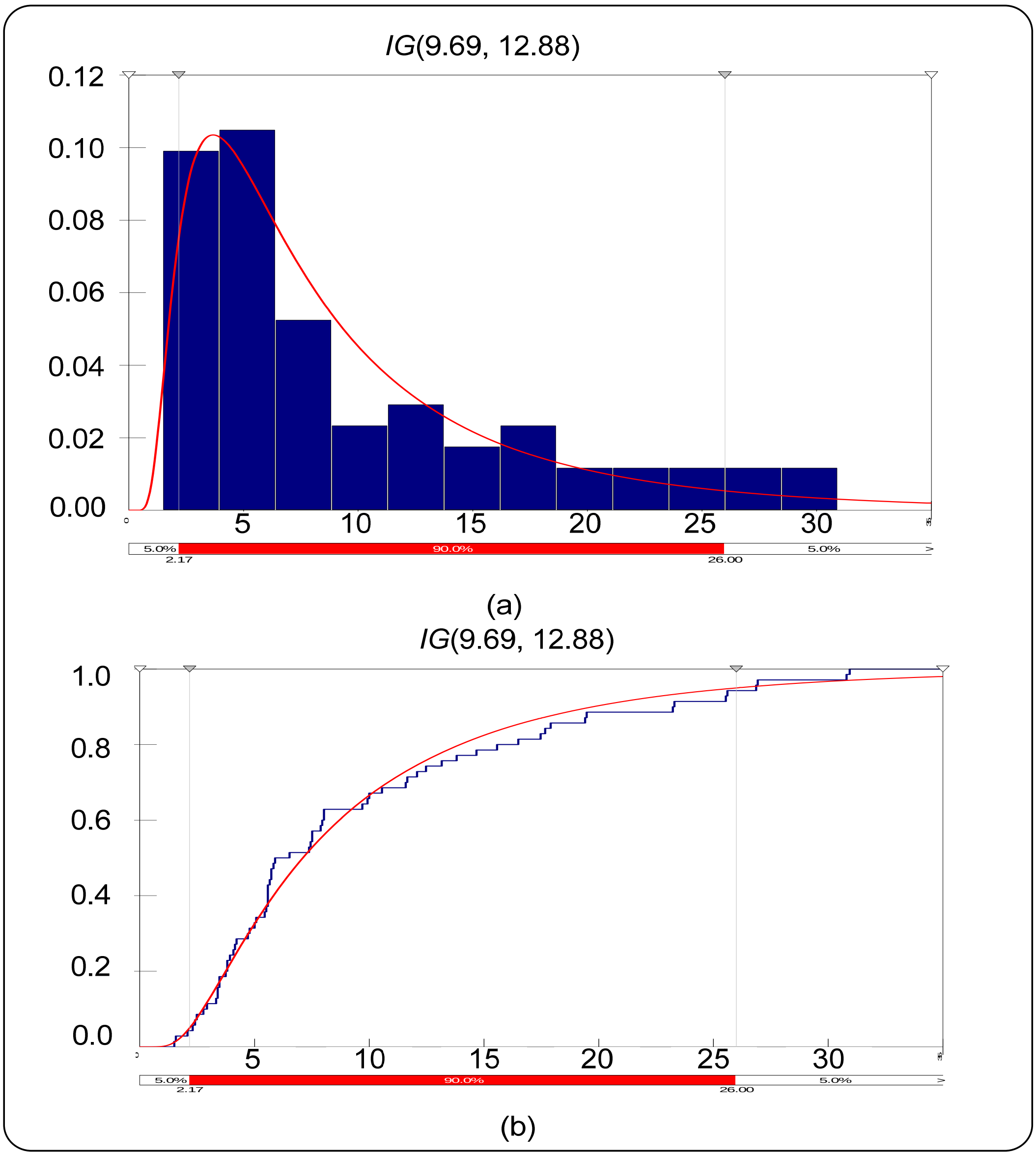


Figure 3-4: The histograms and empirical CDF (traffic volume = 963 vehs/hour·lane)

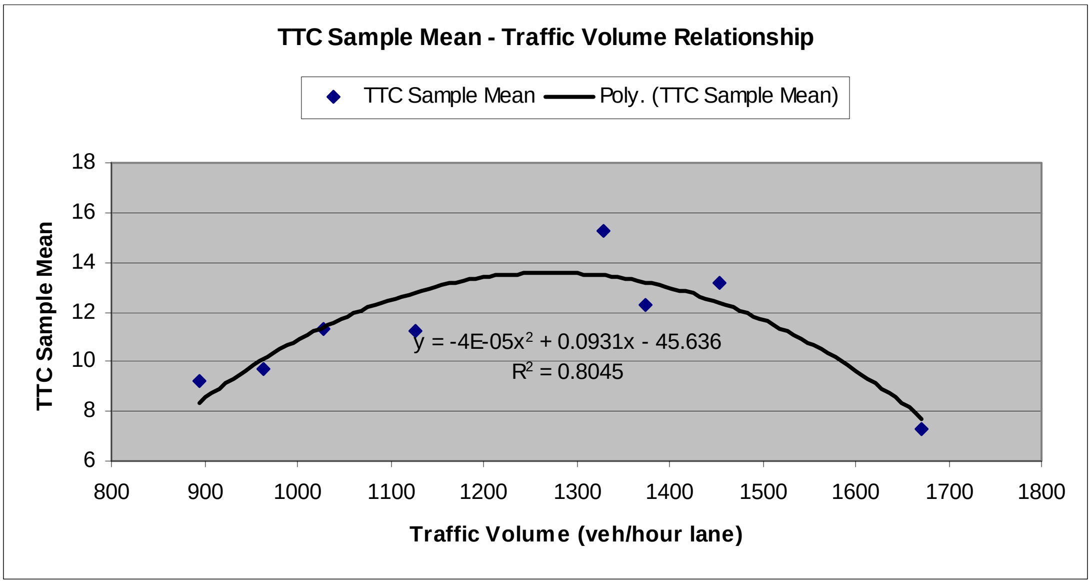


Figure 3-5: TTC sample mean – traffic volume relationship

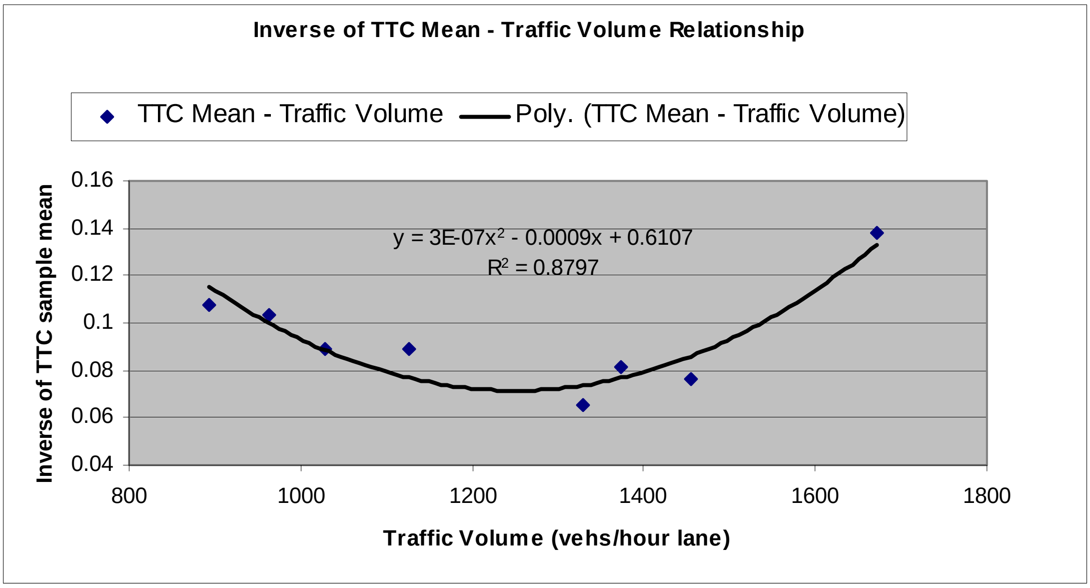


Figure 3-6: Inverse of TTC mean – traffic volume relationship

3.3.3.2 Estimation of the parameters defining Inverse Gaussian distribution

To establish the relationship between TTC and traffic volume, an Inverse Gaussian regression model is formulated by assuming that traffic volume is the contributing factor to TTC. To formulate the inverse Gaussian regression model, let $y_i,\ i=1,\cdots,n,$ be n independent observations (TTC samples) distributed as $IG(\mu_i,\lambda)$, where the inverse of sample mean has a parabola relationship with traffic volume, represented by $\frac{1}{\mu_i}=\beta_0+\beta_1 x_i+\beta_2 x_i^2>0$. Here x denote traffic volume. Whitmore (1983) derived the pseudo maximum likelihood estimators of β and λ as

$$\hat{\beta}=\left(X'YX\right)^{-1}X'1 \tag{3.2}$$

$$\hat{\lambda}=n\Big/\left(\mathbf{1}^T Y^{-1}1-1'X\hat{\beta}\right) \tag{3.3}$$

where Y is the diagonal matrix with i-th diagonal elements being y_i, 1 is the n-vector of all ones and $X=\left(1,x_i,x_i^2\right)'$. These are called pseudo maximum likelihood estimators because the condition $\hat{\beta}_0+\hat{\beta}_1 x_i+\hat{\beta}_2 x_i^2>0$ for all i is not guaranteed to be satisfied[3]. According to our TTC data with different traffic volumes (421 data samples for Locations 1 to 5), the estimated coefficients are

$$\hat{\beta}_0=5.606\times10^{-1} \tag{3.4}$$

$$\hat{\beta}_1=-7.900\times10^{-4} \tag{3.5}$$

$$\hat{\beta}_2=3.21\times10^{-7} \tag{3.6}$$

$$\hat{\lambda}=12.17 \tag{3.7}$$

[3] The condition is guaranteed in this study since the traffic volume is with the range from 800 to 1700 vehs/hour·lane.

Having had the estimated coefficients, the TTC distributions could be determined for different traffic conditions reflected by their traffic volumes. In order to evaluate how well the Inverse Gaussian regression model estimates the TTC distributions, we compare the derived TTC distributions with the TTC samples with different traffic volumes - 894 vehs/hour·lane, 963 vehs/hour·lane, 1,127 vehs/hour·lane, 1,374 vehs/hour·lane, and 1,672 vehs/hour·lane) - by using the hypothesis test.

The K-S test is applied to conduct the hypothesis test. The null hypothesis is rejected at level α if

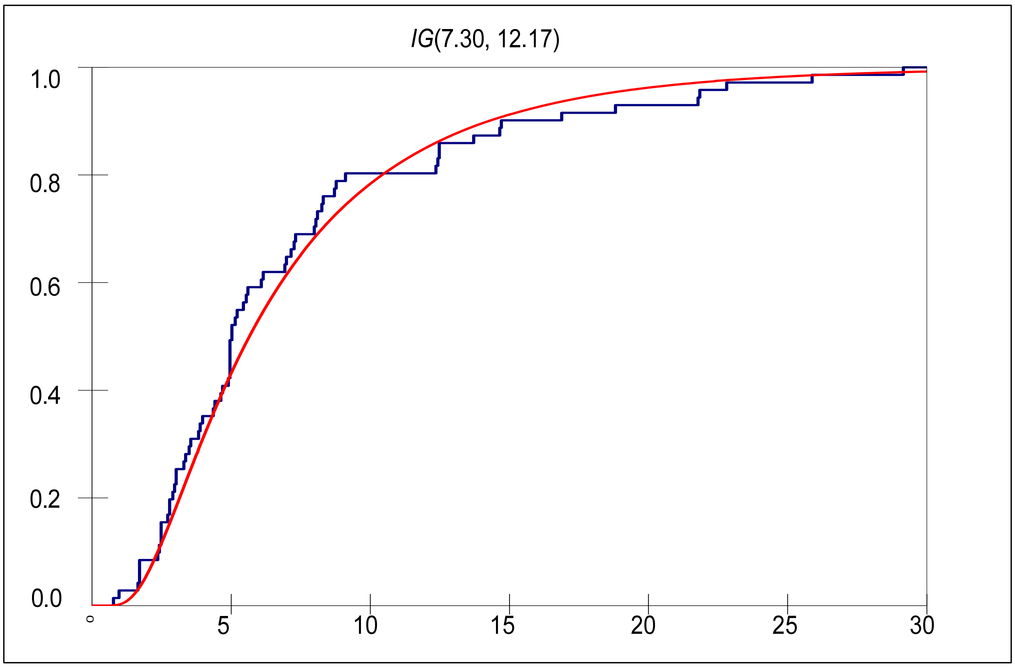
$$\sqrt{n}D_n > K_\alpha \tag{3.8}$$

where n is the number of samples, D_n is the K-S statistic, and K_α is the critical value. The results of K-S tests are reported in Table 3-3.

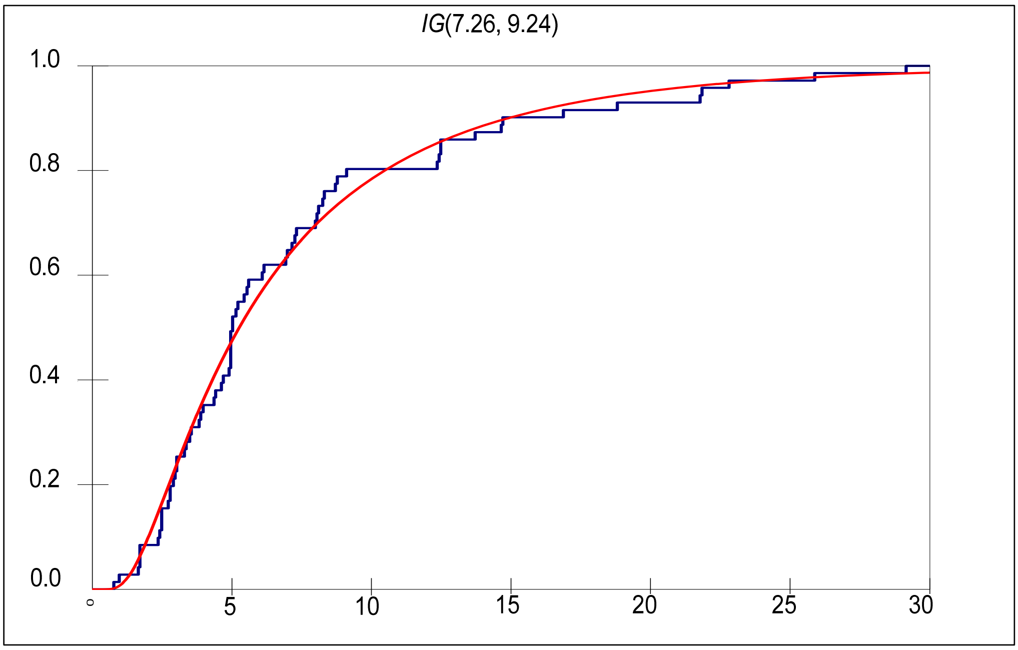
Table 3-3: K-S tests

Traffic volume (vehs/hour·lane)	Number of samples (n)	Distributions	K-S values (D_n)	Critical value (K_α)	Test results
894	104	IG(9.02, 12.17)	0.0977	1.36	1.00<1.36
963	65	IG(10.26, 12.17)	0.1086	1.36	0.88<1.36
1,127	80	IG(12.33, 12.17)	0.1496	1.36	1.34<1.36
1,374	79	IG(12.83, 12.17)	0.0821	1.36	0.73<1.36
1,672	93	IG(7.30, 12.17)	0.1026	1.36	0.99<1.36

As can be seen from Table 3-3, the K-S tests suggest the regression model performs well. Figure 3-7 depicts the CDF of the best fitted Inverse Gaussian distribution and the CDF generated by Inverse Gaussian regression for a TTC sample (traffic volume = 1,672 vehs/hour·lane), respectively. The two distributions both fit the TTC samples very well, namely, the distribution generated by Inverse Gaussian regression model is a good approximation of the best-fitted Inverse Gaussian distribution.



(a) Empirical CDF & CDF generated by IG regression model



(b) Empirical CDF & Best fitted IG CDF

Figure 3-7: Empirical CDF with Inverse Gaussian distributions (traffic volume = 1,672 vehs/hour·lane)

3.3.4. Crash frequency estimation model

3.3.4.1 TTC threshold value and exposure to traffic conflicts

A TTC threshold value is usually chosen to distinguish relatively safe situation and dangerous scenarios exposed to traffic conflicts (or critical encounters). Various opinions can be found from the literature as to which value should be used as the threshold value. Hirst and Graham (1997) reported that a time-to-collision measure of 4 seconds could be used to discriminate between cases where drivers unintentionally find themselves in a dangerous situation from cases where drivers remain in control. Hogema and Janssen (1996) presented a minimum TTC value of 3.5 seconds for non-supported drivers and 2.6 seconds for supported drivers. It is widely acknowledged that the TTC threshold should be 2 seconds to 5 seconds (Minderhoud and Bovy, 2001; Vogel, 2003).

We define the *exposure to traffic conflicts* as the mean sojourn time in a given time period (e.g. an hour) that vehicles are exposed to dangerous scenarios (or critical encounters), i.e. the TTCs are lower than a predetermined threshold value τ . Having had the TTC distributions for road tunnel sections (Section 3.3.3), the hourly *exposure to traffic conflicts* can be quantified by eqn. (3.9).

$$N_{conflict}\left(\tau\right)=(K\times L-1)\times \Pr\left(TTC\left(x\right)\le\tau\right)\times 0.5\times 1 \tag{3.9}$$

where K denote the traffic density; L is the length of a road tunnel section; $P\left(TTC\left(x\right)\le\tau\right)$ represents the probability of TTC less than the threshold value τ ; x is the traffic volume of the time period in the road tunnel section. Note that only half of car following scenarios will result in finite TTCs and the other half is considered as absolutely safe situations (infinite TTCs).

3.3.4.2 Historical Crash-Damage database

Historical Crash-Damage (HCD) database is applied in order to examine the relationship between *exposure to traffic conflicts* and crash frequencies. According to the Motor Claims Framework (MCF) introduced by the General Insurance Association of Singapore (GIA), in the event of a crash in expressways, everyone involved must inform the insurance company within one day using the GIA Motor Accident Report form. In addition, according to Road Traffic Act in Singapore, another report must be made within 24 hours of a crash if an injury has occurred. The HCD database (2006-2008) has all the reported crash records, by means of either ways, occurred at Singapore expressways from 2006 to 2008, which includes the time of crash, location of crash, crash type (e.g. rear-end, skidded, chain collision, etc.), vehicle type (e.g. car-car, car-truck, etc.), number of slight injuries, number of serious injuries, and number of fatalities. To sum up, there are 2,324 crashes (4,650 vehicles involved) in the 17 km CTE expressways from 2006 to 2008, causing 6 fatalities, 160 severe injuries, and 1,486 slight injuries.

3.3.4.3 Relationship between exposure to traffic conflict and crash frequency

In this section, we take 2 seconds, 3 seconds, and 4 seconds as examples of the TTC threshold values to illustrate the methodology. From the HCD database we get the crash frequencies in a one-km road tunnel section in CTE road tunnel are 11, 5, 8, 20, 17, and 4 for he time period 7:00 am to 8:00 am, 1:00 pm to 2:00 pm, 5:00 pm to 6:00 pm, 8:00 pm to 9:00 pm, 9:00 am to 10:00 am, and 11:00 pm to 12:00 am from 2006 to 2008, respectively. In the one-km tunnel section, there is a 2.4 meters wide shoulder and three 3.6 meters traffic lanes in each carriageway with a tunnel structural height of approximately 6 meters high. Both the curvature and gradient are very gentle in this section. We assume the TTC distributions follow the same pattern in shoulder lane, middle lane, and median lane. Therefore, we just measure the TTC for vehicles in the middle lane to represent the traffic state.

We assume that the traffic volumes in the road tunnel section in a specific time period would not have significant daily variations. According to eqn. (3.9), the exposure to traffic conflicts could be calculated. The estimated traffic volumes, densities, and number of crashes are summarized in Table 3-4.

Table 3-4: Traffic volumes, density, length, crash records, and exposure to traffic conflicts for different time periods

Time period	R-E Crash records (2006-2008)	Estimated Traffic volume (vehs/hour·lane)	Density (vehs/km·lane)	Average Speed (km/hour)	Exposure to Traffic Conflicts		
					2s	3s	4s
7:00am - 8:00am	11	1600	25	62	657	2024	3548
1:00pm - 2:00pm	5	1200	16	73	263	829	1502
5:00pm - 6:00pm	8	1400	20	70	364	1155	2070
8:00pm - 9:00pm	20	1700	45	39	1566	4673	7998
9:00pm - 10:00pm	17	1600	50	34	1341	4131	7243
11:00pm - 12:00am	4	900	11	78	252	777	1374

We further analyze the relationship between *exposure to traffic conflicts* and the crash frequencies in a linear manner, which is presented in Figure 3-8 and

Figure 3-9. The statistical results are reported in Table 3-5. Surprisingly, the *P*-values of the coefficients with respect to constant for the three linear regression models are all greater than 0.035. By contrast, the *P*-values of coefficients with respect to crash frequency are all close to 0. That is to say, the coefficients with respect to intercept are very significant. The linear regression model with 0 intercept is depicted in Figure 3-9. According to the linear regression analysis, a linear relationship is observed between the crash rate and the proposed *exposure to traffic conflicts*. The corresponding proportional coefficient is defined as causation factor ($P(t)$) in a linear manner, which could be considered as the conditional probability that vehicle crashes could not be avoided under dangerous encounters for one hour.

Table 3-5: Statistical results of linear regression models

	Constant		Crash frequency		R-Sq Coefficient
	Coefficient	P-value	Coefficient		
2s	2.5929	0.035	0.0111	2s	2.5929
3s	2.4085	0.044	0.0037	3s	2.4085
4s	2.2446	0.058	0.0022	4s	2.2446

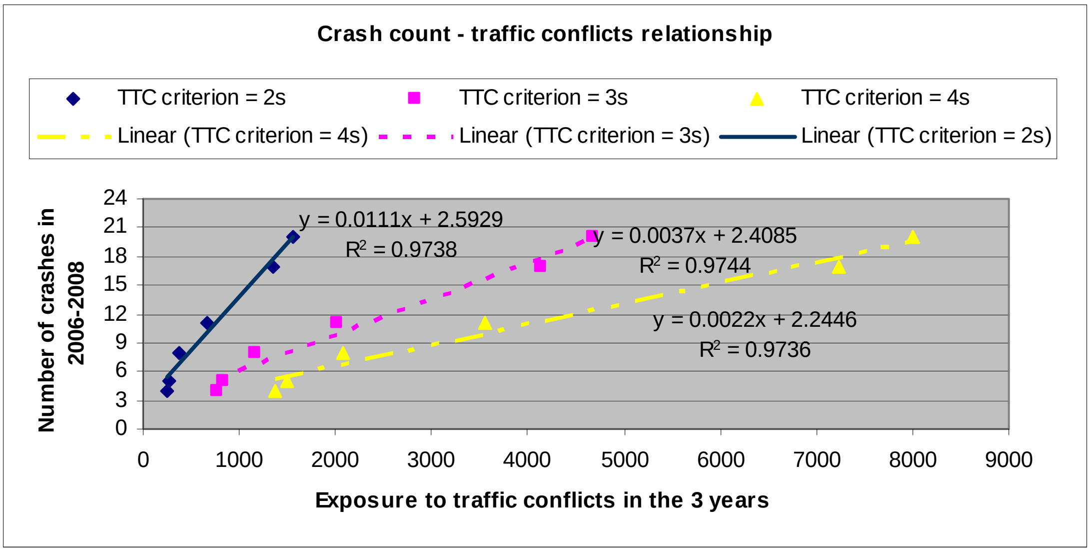


Figure 3-8: Crash count – traffic conflicts relationship with linear fit

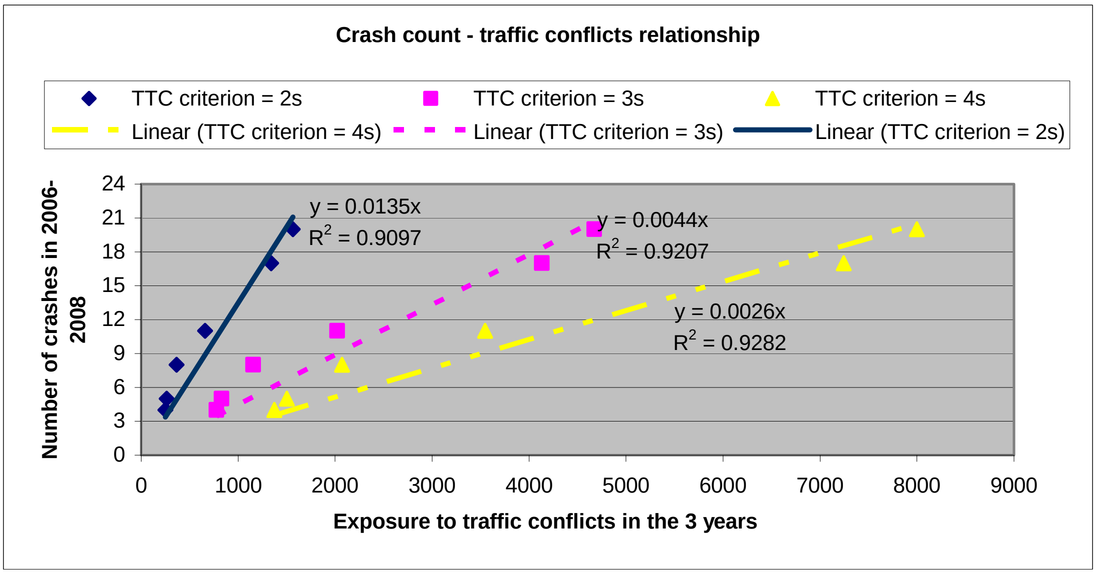


Figure 3-9: Crash count – traffic conflicts relationship with linear fit (0 intercept)

As suggested by Hauer et al. (1988), Lord and Mannering (2010), and Miaou and Lum (1993), it is theoretically inappropriate to model discrete and non-negative crash count data using the conventional linear regression method. Generalized linear modelling techniques (GLIM) have the advantages of overcoming the shortcomings associated with linear models. Therefore, the GLIM is applied to fit the model using a negative binomial distributed error structure.

The Negative Binomial regression model considered in this study has the form as presented by Miao (1994).

$$p(Y_i = y_i) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma(y_i+1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{1}{1+\alpha\mu_i}\right)^{1/\alpha} \left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)^{y_i} \tag{3.10}$$

$$y_i = 0,1,2,\cdots \tag{3.11}$$

$$\mu_i = E(Y_i) = N_{conflict,i} \exp(\beta) \tag{3.12}$$

and the variance of Y_i is

$$Var(Y_i) = \mu_i + \alpha\mu_i^2 \tag{3.13}$$

where Y_i is a random variable representing the number of crashes in time period i; y_i is the actual number of crash count in the time period; $N_{conflict,i}$ is the exposure to traffic conflicts in the time period; $\alpha \geq 0$ and is referred to as dispersion parameter. According to the analysis in Section 4.3.1, it is reasonable to assume the mean value of crash count μ_i or $E(Y_i)$ to be proportional to the exposure to traffic conflicts. This model assumes an exponential rate function $\exp(\beta)$, which ensures that the crash rate is always non-negative.

The parameters (α and β) are estimated by the three approaches (hybrid, fisher, and Newton Raphson methods) using the SPSS software. The three approaches deliver the same estimators for the two parameters, presented in Table 3-6.

Table 3-6: Results of Negative Binomial regression models

	α	β	p-value	Log-likelihood	AIC

Model 1 (2s)	0.044	-4.114	0.000	-19.777	41.554
Model 2 (3s)	0.036	-5.244	0.000	-19.760	41.519
Model 3 (4s)	0.031	-5.814	0.000	-19.767	41.493

From Table 3-6, we can see the p-values are close to 0, indicating that the three models perform well. The Log-likelihood value and the Akaike Information Criterion (AIC) value for each model are also given in the table. Note that estimated models with high Log-likelihood and low AIC values are preferred. Accordingly, the performances of the three models with respect to different TTC thresholds do not have substantial differences. Table 3-7 depicts the estimated expected values of crash counts by the three models and the actual crash count for the six data points in this study, which also indicate that the models perform very well. The proportional coefficients of the expected values of crash counts (with negative binomial assumption) over the exposure to traffic conflicts are $e^{-4.114} = 0.0163$, $e^{-5.244} = 0.0053$, and $e^{-5.814} = 0.0030$, respectively. These coefficients are the causation factors in regression models with generalized linear manner.

Table 3-7: Estimated expected values of crash counts

R-E Crash records (2006-2008)	Estimated by model 1 (2s)	Estimated by model 2 (3s)	Estimated by model 3 (4s)
11	10.74	10.68	10.59
5	4.30	4.38	4.48
8	5.95	6.10	6.18
20	25.59	24.67	23.87
17	21.91	21.81	21.62

4	4.12	4.10	4.10

3.3.4.3 Remark: sensitivity analysis for TTC threshold values

According to the literature, the TTC threshold values range from 2 seconds to 5 seconds (Minderhoud and Bovy, 2001; Vogel, 2003). Thus, a sensitivity analysis for TTC threshold values – 2 seconds, 2.5 seconds, 3 seconds, 3.5 seconds, 4 seconds, 4.5 seconds, 5 seconds, 5.5 seconds, 6 seconds - is conducted to choose an appropriate TTC threshold value for the linear model. The average relative error method is a well recognized method to examine the goodness of fit of models in transportation studies (e.g. Wang et al., 2011), mathematically represented by

$$E = \frac{1}{n}\sum_{i}\frac{\left|y_i^{'} - y_i^{*}\right|}{\left|y_i^{*}\right|} \tag{3.14}$$

where n is the number of samples; $y_i^{'}$ is the actual crash count in the time period i; y_i^{*} is the predicted crash count in the time period i.

The average relative errors for different TTC threshold values are given in Table 3-8 and Figure 3-10.

Table 3-8: average relative errors for different TTC threshold values

TTC threshold values	The average relative errors
2.0 seconds	0.1362
2.5 seconds	0.1302
3.0 seconds	0.1323
3.5 seconds	0.1220
4.0 seconds*	0.1175*
4.5 seconds	0.1177

5.0 seconds	0.1225
5.5 seconds	0.1379
6.0 seconds	0.1437

According to the sensitivity analysis, the model performs best if the TTC threshold takes value of 4.0 seconds. As can be seen in Figure 3-10, the errors are sensitive to the TTC threshold values, especially if the values fall out of the range 3.5 seconds to 4.5 seconds.

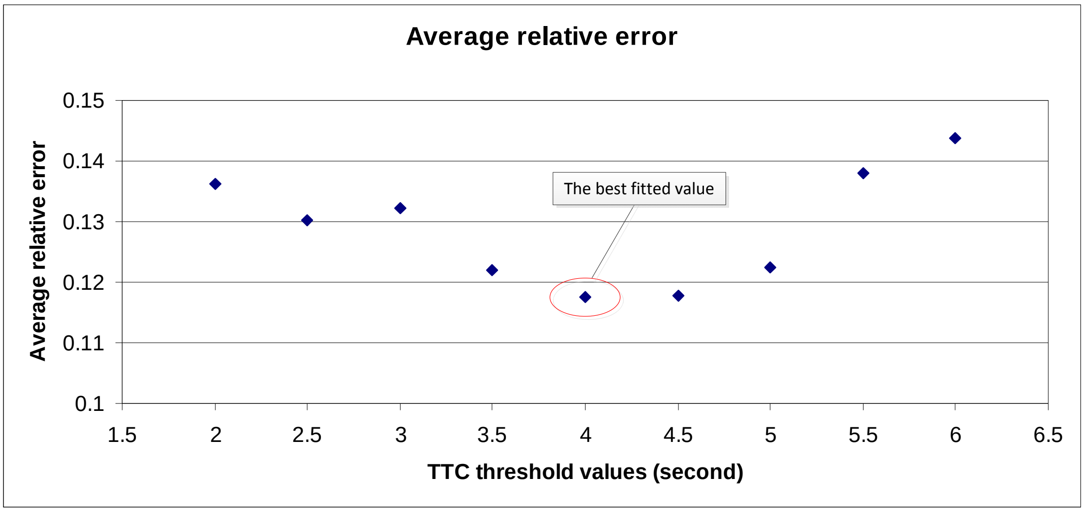


Figure 3-10: average relative error – TTC threshold values chart

3.3.5 Yearly crash frequency estimation

As shown in Figure 3-9, there is a proportional relationship between the proposed index and crash count, mathematically

$$N_{crash,\,time} = \alpha\left(\tau\right) \times N_{conflict}\left(\tau\right) \tag{3.15}$$

where $\alpha\left(\tau\right)$ is the proportional coefficient with respect to the TTC threshold value τ (e.g. $\alpha\left(4\right) = 0.0026$ for linear model). Thus the number of crashes in this time period is obtainable given the traffic volume, density, and length of the tunnel section. The yearly crash frequency could be approximated by

$$N_{crash,\,year} = \sum_{i=1}^{n} \frac{\alpha(\tau) \times (K_i \times L - 1) \times \Pr\left(TTC\left(x_i\right) \le \tau\right) \times 0.5 \times 1}{T_d} \tag{3.16}$$

where *i* refers to different time periods; K_i and x_i is the density and volume in the time period *i*, respectively; T_d is the number of years with respect to analyzed crash data in HCD database (e.g. T_d = 3 years for the model in Section 3.3.4.3).

3.3.6. Discussions

Theoretically, linear regression models are not appropriate to model discrete and non-negative crash count data. GLIM is proven to be more effective to formulate the rare events such as crash count. However, as illustrated in Section 4.3.1, the linear regression models also perform well according to the CURE method and correlation coefficients. Therefore, it is also acceptable to formulate the relationship between crash count and proposed index in this study. The coefficients between crash counts (or expected values of crash counts) and the exposure to traffic conflicts are defined as the causation factor in this study. The proposed causation factor $P(t)$ reflects the conditional probability that vehicle crashes have occurred when the vehicle are exposed to dangerous scenarios for one hour. The probability would be dependent on vehicle conditions, drivers' abilities, and the road geometries. We conjecture that this factor could be a constant for a given road tunnel section in the long run with a given TTC threshold value. The TTC values would generally have a parabola relationship with traffic volume because they will be affected by not only speed dispersion but also distance headways. For non-interrupt traffic flows with traffic volume from 900 vehs/hour·lane to 1,700 vehs/hour·lane, the TTC distributions may follow the Inverse Gaussian distributions (lognormal distributions are also a good approximation) and traffic volume could be considered as the contributing factor to the distribution parameters. It should be pointed out that these perspectives need to be validated using more actual data from other expressways and/or urban road tunnels.

The crash data from Singapore's road tunnels shows that linear or proportional relationship may not be good enough to reflect the relations between crash count and traffic volume. Instead, the linear and proportional relationships perform very well between crash count and exposure to traffic conflicts. This may be because not only traffic volume but also density is taken into consideration in the proposed exposure to traffic conflicts.

Other than the TTC, the deceleration rate to avoid the crash (DRAC) and the post encroachment time (PET) have also been considered as good safety indicators to measure the safety level in roads (Meng and Weng, 2011; Cunto and Saccomanno, 2008). Further study may be conducted to establish the relationship between crash frequency and the above-mentioned two safety indicators. The comparative analysis of these three safety indicators could also be studied accordingly. In addition, the model can also be applied to identify the hotspots in the urban road tunnels and/or expressways (Cheng and Washington, 2005; Montella, 2010).

3.4. Conclusions

In this chapter, we developed a fault tree to estimate the frequency of fire in urban road tunnels. According to the fault tree, we find that the reliability of frequency estimations for fire in road tunnels would be determined by the credibility of the estimated frequency of vehicle crashes. Accordingly, we shift our aim to find a better way to estimate the frequency of vehicle crashes. On the basis of literature review, pure statistical models are usually applied to estimate the vehicle crash frequencies since the detailed driving data are generally unavailable in open roads. However, more detailed traffic data are obtainable in road tunnels compared to highways because most of road tunnels are equipped with the closed circuit television (CCTV) cameras and/or an operation control centre (OCC). Based on the available data, a crash estimation model is developed to estimate the frequency of vehicle crashes in urban road tunnels.

According to the proposed model, density, traffic volume, tunnel length, and causation factor are the input parameters for the crash frequency for a particular road tunnel section. Therefore, the crash frequency for any tunnel sections could be estimated if all these traffic parameters are available. The frequency of fire in this road tunnel section could be estimated by the fault tree accordingly. This model will provide an important input parameter – frequency of fire in a road tunnel section.

One limitation of this study is that the tunnel geometric characteristics are not taken into account. Future study could be focused on analyzing the impact of the parameters such as lane width, curvature, gradient, etc. Another limitation of this study is that the daily variation of traffic flow and the variation of traffic volume within one hour are not taken into account due to the difficulties in data collection. We assume that there do not exist substantial variation in traffic volume within one hour and from day to day.

CHAPTER 4 QRA MODLE WITH DETERMINISTIC PARAMETERS FOR ROAD TUNNELS

4.1 Introduction

As mentioned in Chapter 2, there is no generic QRA model which is able to assess the risks of non-homogeneous road tunnels. In addition, the conventional definition of individual risk is not applied to risk assessment for road tunnels. Accordingly, a QRA model is proposed to deal with the issues mentioned above. In the proposed model, a non-homogeneous road tunnel is segmented into a number of homogeneous road tunnel sections based on the tunnel segmentation principle in Section 4.2. For each particular tunnel section, a QRA model is developed to assess the individual risk and societal risk based on event tree analysis and consequence estimation models. An aggregated QRA model (QRAM-I) is thus built by integrating the section-based QRA models. The model has been applied to Singapore MCE road tunnels.

4.2 Tunnel Segmentation Principle and Risk Indices

4.2.1 Tunnel Segmentation Principle

A non-homogenous urban road tunnel comprises multiple entry and exit slip roads as well as main tunnel bores hence possesses the non-homogeneous characteristics. The urban road tunnel segmentation principle aims to divide the whole road tunnel into several individual homogeneous sections. These homogeneous sections can be classified into 3 types according to their geographical layouts and characteristics. Type I represents slip road sections, which is an enclosed roadway section entering or leaving the main road tunnel. Type II refers to road tunnel intersections. This section is where the traffic from slip road tunnels merges with main tunnels or leaves main tunnels to slip road tunnels. Type III represents main road tunnel sections. Figure 4-1 gives an example of how a road tunnel can be segmented according to the principle. The most substantial differences among tunnel sections are traffic conditions and geometric characteristics.

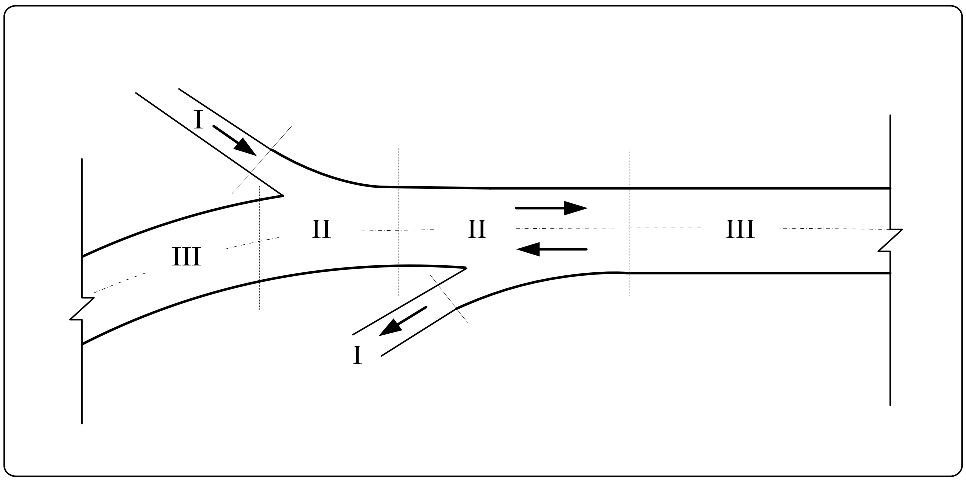


Figure 4-1: An example for tunnel segmentation

According to the model proposed in Chapter 3, the frequency of vehicle crash could be obtainable for any tunnel sections, given the tunnel length, density, and traffic volume. Thus the frequency of vehicle crash in the tunnel section could be considered as the input parameters of the fault tree. The frequency of fire in this particular tunnel section could be estimated by using the fault tree accordingly, which provide the most important input parameters for the frequency analysis in the event tree model.

4.2.2 Risk Indices

The conventional definition of individual risk for road tunnels is not suited for road tunnel risk assessment. Assume that a non-homogenous urban road tunnel has K homogenous tunnel sections where K is a positive integer. IR for a particular homogeneous road section is defined as follows: "Individual risk of a road tunnel section is the probability that a particular unprotected individual is killed due to an incident resulting from a hazardous activity in the road tunnel section". Different from the conventional definition of individual risk, the IR for road tunnel does not assume that a tunnel user is permanently present at a location. Instead, it reflects the risks exposed to individual tunnel user with distinct travel profiles. Let IR_k denote the IR of road tunnel section k and it can be expressed by

$$IR_k = \frac{n_k \times L_k}{\sum_{i=1}^{I} Q_{ki}\lambda_i} \times \sum_{j=1}^{J_k} F_{jk} N_{jk}, k = 1, 2, \cdots, K \tag{4.1}$$

where n_k is the number of times that a given individual tunnel user passes through tunnel section k per year; L_k is the length of tunnel section k (km); I is number of vehicle types; Q_{ki} is yearly travel rate of all type i vehicles passing through tunnel section k ($veh \cdot km/ year$); λ_i is average number of travelers using vehicle type i vehicle; F_{jk} is the yearly frequency of accident scenario j occurred at tunnel section k; N_{jk} is number of fatalities when scenario j occurred at tunnel section k ; J_k is the total number of accident scenarios that could be occurred at tunnel section k.

In this study, the simple societal risk defined by eqn. (2.2) and *EV* defined by eqn. (2.4) are applied. In order to measure severity of societal risk, slack clearance index is defined as the minimum gap from safety target to the F/N curve, namely,

$$SL = \min_{i \in A} \left\{ \log(C) - k \log(N_i) - \log(F(N_i)) \right\} \tag{4.2}$$

where A is the set of the selected values of number of fatalities, $F(N_i)$ is the cumulative frequency of all the accident scenarios occurred at the road tunnel with N_i or more fatalities. The index indicates the slack clearance between safety target and *F/N* curve. *SL* takes non-negative values if the tunnel is considered safe according to the predetermined safety target. The less *SL* is, the riskier the tunnel is in terms of societal risk.

The authorities for road tunnel may require an integrated index to evaluate the individual risk and societal risk for the road tunnel as a whole. Therefore, we define two types of integrated risk indices for the entire non-homogenous road tunnel after obtaining the IR and SR values expressed in the eqns. (4.1) and (2.2) for each homogeneous tunnel section. Eqns. (4.3) and (4.5) illustrates the risk in the worst section of the tunnel while eqns. (4.4) and (4.6) defines the risk for overall road tunnel by weighing the risk indices for each tunnel section. Therefore, two integrated IR risk indices can be mathematically expressed as follows:

$$\hat{IR} = \max_{k=1,2,\cdots K} \left\{ IR_k \right\} \tag{4.3}$$

$$\overline{IR} = \sum_{k=1}^{K} \left[\omega_k \times IR_k \right] \tag{4.4}$$

where parameter ω_k is the weight of tunnel section k. Note that these weights are determined by tunnel risk evaluators. For example, the section travel rate (veh·km/year) is considered as the weight in Singapore road tunnel risk assessment. In reality, the tunnel section length, traffic volume of tunnel section, accident rate of tunnel section, etc. can also be considered as the weight. Similarly, two integrated societal risk indices can be equally defined below.

$$\hat{F}(N) = \max_{k=1,2,\cdots K} \{F_k(N)\} \tag{4.5}$$

$$\overline{F}(N) = \sum_{k=1}^{K} \left[\omega_k F_k(N) \right] \tag{4.6}$$

Eqns. (4.3) and (4.5) represent a pessimistic principle from the viewpoint of tunnel designers, who adopted the risk of the worst section in the road tunnel. This principle is attractive to those who wish to guard against the "worst case" at least for contingency planning. Evidently, tunnel designers are more concerned about the high consequence events (worst case). Eqns. (4.4) and (4.6) express a mean value principle from the standpoint of tunnel managers, which defines the risk for overall road tunnel by weighing the risk indices for each tunnel section. Tunnel managers focus on minimizing the total fatalities of the road tunnel. These two principles are widely used in game theory and statistics (Howe et al., 1996; Johnson and Chess, 2003).

4.3 QRA Model for a Particular Tunnel Section

Given a particular homogeneous tunnel section k of a non-homogeneous urban road tunnel, its QRA model is built according to the following procedures. Firstly, the top event, i.e. fire in road tunnels, is identified based on the expert judgment. Subsequently, fault tree and event tree for the top event are built. An event tree consists of a number of particular accident scenarios triggered by fire in road tunnels. Fault tree is used to estimate the frequency of fire in road tunnels. The frequency of each particular accident scenario can be calculated by multiplying the frequency of fire in road tunnels and the fractions / probabilities of sequential events (e.g. peak hour, fire detection failure, etc.) associated with this scenario. Furthermore, consequence estimation models are required to calculate the number of fatalities for various accident scenarios involved in an event tree. After obtaining the frequency and fatality of each accident scenario, the IR and SR expressed by eqns. (4.1) and (2.2) can be calculated.

4.3.1 Event Tree Building

The top event (fire in road tunnels) may trigger a series of simple events with different results (frequencies and consequences). These simple events can be represented logically by an event tree. An event tree is simply a tree diagram referring to complex events that can be discretized in terms of their distinction by sequential events into a series of simple events. Figure 4-2 depicts the event tree starting from "Fire in tunnel" and terminating at Fire Fighting Column. Because A4 page cannot accommodate the event tree, the tree is decomposed into two sub-event trees, namely, sub ET 1 and sub ET 1.1. Sub ET 1.1 continues from all the leaf nodes of sub ET 1. There are 240 scenarios (leaf nodes of the tree) in the event tree. Note that the event tree is not the same with a conventional event tree representing a sequential logic. Column 1, period of day, represents the accident occurred at peak hour (7:00 am to 9:30 am, 5:00 pm to 8:00 pm), night (9:30 am to 5:00 pm, 8:00 pm to 12:00 am), or night (12:00 am to 7:00 am), which is used to determine number of people at risk. Column 2, vehicle composition, represents the fire type (e.g. motorcycle fire: Heat Release Rate = 1 MW, car fire: Heat Release Rate = 5 MW, bus and HGV fire: Heat Release Rate = 50 MW, Hazmat fire: Heat Release Rate = 100 MW), which is an important input for fire simulation model. The rest subsequent events are related to the tunnel safety provisions working conditions, which affect the delay time (duration of people in danger).

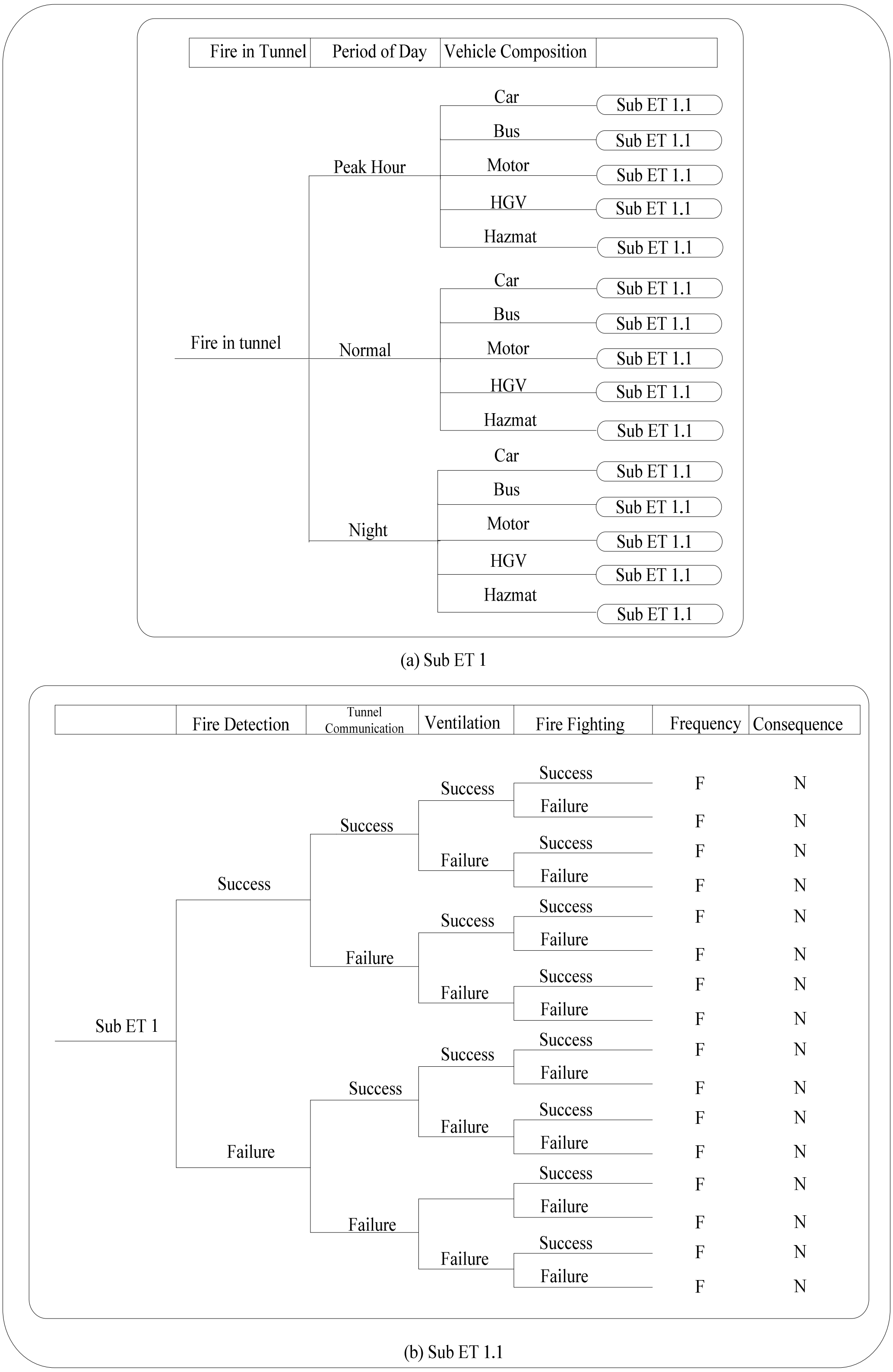


Figure 4-2: Event tree for fire in tunnel top event

The frequency of each scenario can be regarded as the product of frequency of fire in the tunnel section (estimated by the model proposed in Chapter 3) and conditional probabilities/fractions of sequential events (input parameters). The conditional probabilities/fractions of sequential events can be calculated by historical statistics or instruction manuals of tunnel mitigation facilities (See Appendix A). As for the number of fatalities for each scenario, it can be computed by the consequence estimation models (Section 4.3.2).

4.3.2 Consequence Estimation Method

4.3.2.1 Accident response plan in Singapore's road tunnels

In the event of a fire accident, traffic downstream of the fire site will be able to drive away while traffic upstream of the fire site would be trapped. Prompt detection of a fire in the tunnel is an important factor in preventing a catastrophic fire incident. According to the conceptual design of the tunnel, two types of fire detection systems, i.e. the automatic incident detectors (AID) and linear heat detectors (LHD), are provided in the tunnel and the fire detection time is set at 30 to 60 seconds. Closed Circuit Televisions (CCTVs) and emergency telephones installed in the tunnel are used to verify the occurrence of tunnel fire. The fire verification system would take around 60 seconds to respond after receiving the notice from fire detection systems. Then, the tunnel will be ventilated in two minutes and the smoke caused by the fire will be released to the atmosphere via exhaust stacks in the ventilation buildings. If the tunnel ventilation systems fail to work, which would be highly unlikely, the tunnel officers will begin to inform and guide the motorists and passengers to evacuate from the cross passenger doors. The timeline of the response plan for a fire accident is illustrated in Figure 4-3. In Singapore, most motorists and passengers would not evacuate from the tunnel bore until they are informed to do so. The timings and functional parameters of tunnel safety provisions would be the input parameters for consequence estimation models.

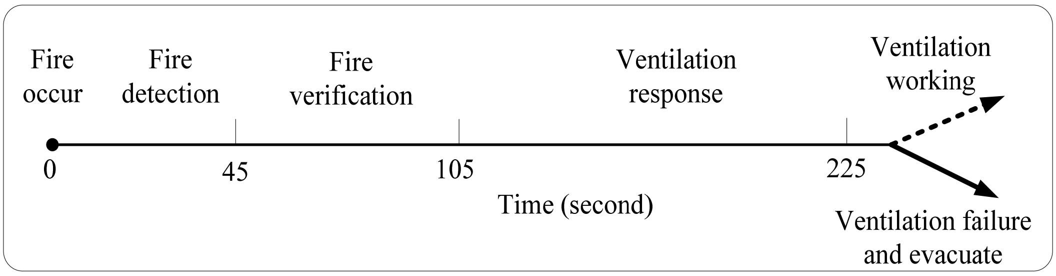


Figure 4-3: The timeline of incident response plan

4.3.2.2 Estimation of number of people at risk

The people downstream of cross passage doors could easily evacuate from one tunnel bore to the other. Thus, the downstream vehicles of the fire site will not be affected by the fire accident and those in upstream will be trapped. Accordingly, the area between fire site and the nearest cross passenger door downstream (Figure 4-4) should be considered as the risk area. A deterministic queuing model is adopted to estimate the people at the area at risk as follows.

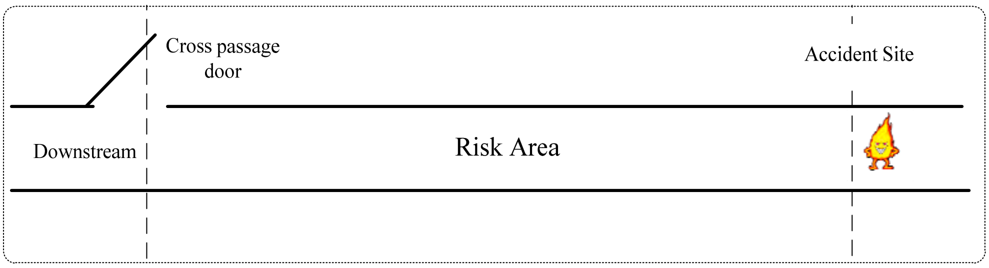


Figure 4-4: The schematic diagram for the queuing model

The number of vehicles (*M*) in one lane can be estimated by

$$M\left[\sum_{i=1}^{I} P_i L_i\right] + (M-1)H = D \tag{4.7}$$

where I is number of vehicle types (car or truck), L_i is the average length of vehicle type i, P_i is the proportion of vehicle type i, H is distance between two successive vehicles when the vehicles stop due to the emergent incidents, and D is the distance of risk area. Thus, the vehicles at the risk area in the traffic lanes (M_v) are estimated by

$$M_v = 3 \times \frac{D+H}{H+\left[\sum_{i=1}^{n} P_i L_i\right]} \tag{4.8}$$

Accordingly, the number of people at risk (M_{par}) is

$$M_{par} = M_v\left(\sum_{i=1}^{n} P_i O_i\right) \tag{4.9}$$

where O_i is the average people in vehicle with type i. In this study, we assume that the vehicles are located uniformly when they stop due to the emergency incidents in urban road tunnels.

4.3.2.3 Fire simulation models

The estimation of concentrations of toxic gases generated by fire in road tunnels has been studied since 1990s (Modic, 2003). In general, the models for estimating the concentrations are based on empirical or semi-empirical “hand calculations” using spreadsheets or more advanced computational fluid dynamics (CFD) models (Nilsen and Log, 2009). For example, Ingason et al. (2001) proposed a hand calculation model based on a collocation and further refined the model in spread sheets; Migoya et al. (2009) developed a CFD model to simulate the accidental fires in road tunnels. In this study, the CFD model is applied and a fire simulation model is built by using the Fire Dynamics Simulator (FDS) developed by National Institute of Standards and Technology (NIST). The FDS has been widely used for fire simulations (e.g. Tsukahara et al., 2011). The process of fire growth and spread could be formulated by conservation equations for mass, momentum, energy, and species coupled with the equation of state, which are introduced as follows.

The conservation of mass is written as:

$$\frac{\partial \rho}{\partial t} + \nabla \rho u = 0 \tag{4.10}$$

The first term represents the density change with time while u in the second term is the velocity vector. This equation describes that the rate of mass storage within the control volume due to change in density is balanced by the net rate of inflow.

The conservation of momentum is written as:

$$\frac{\partial(\rho u)}{\partial t} + \nabla puu = -\nabla p + \rho f + \nabla \tau_{ij} \tag{4.11}$$

The equation for conservation of momentum is derived from Newton's second law of motion. This is also known as the Navier Stokes equation which states the sum of forces acting on a fluid element is equal to its rate of change of momentum (Cox, 1995). The first two terms on the left hand side of the equation define the rate of change of momentum and terms on the right hand side are the forces acting upon it where p represents pressure, τ_{ij} is the stress tensor acting on the fluid and f in the momentum equation consists of gravity plus other forces such as drag exerted by liquid droplets (McGrattan, 2005).

The conservation of energy is written as:

$$\frac{\partial(\rho h)}{\partial t} + \nabla \rho hu = \frac{\partial p}{\partial t} + \dot{q}''' - \nabla q + \Phi \tag{4.12}$$

The energy equation is derived from the first law of thermodynamics where the rate of energy change within the control volume is equal to the rate of heat added to the control volume minus the rate at which work is done within the control volume (Abbott and Basco, 1989). The term on the left hand side is the net rate of energy accumulation within the control volume while the terms on the right-hand side represent the heat release rate per unit volume from a chemical reaction ($\dot{q}'''$), the conductive and irradiative heat flux (∇q), and the dissipation function (Φ), the rate at which kinetic energy is transferred to thermal energy due to the viscosity of the fluid (McGrattan, 2005).

The equation of the state is written as:

$$p = \rho RT \tag{4.13}$$

According to Abbott and Basco (1989), thermodynamics is the study of equilibrium states of matter. The state of a given mass of fluid in the control volume in an equilibrium state is specified by two parameters (density ρ and pressure p). *R* is gas constant (287.05 $J/\left(kg \cdot K\right)$). *T* is the temperature (*K*).

The conservation of species is written as:

$$\frac{\partial \rho Y_i}{\partial t} + \nabla \rho Y_i u = \nabla \rho D_i \nabla Y_i + \dot{m}_i''' \tag{4.14}$$

where fluid consists of a mixture of species, the transport equations for each species will need to be solved. The Y_i is the mass of the *ith* species. D_i is the diffusion coefficient of species *i* into the mixture. $\dot{m}_i'''$ is the production rate of the species *i*.

The FDS program works as follows. First, the initial pressure and temperature, the tunnel geometry, fire size and location, materials of fuels, the type of fire detection systems, the type of ventilation systems, and simulation period are indicated in an FDS program. Second, the FDS will numerically solve the equations above and get the densities of various toxic gases and temperature of the smoke in different locations during the simulation period. Third, the output module could graphically and numerically represent the results (densities and temperature).

The cross sectional layout (tunnel geometry) of a simulated tunnel is presented by Figure 4-5. The fire size is determined by vehicle types involved in an accident (column 3 in the event tree) as depicted in Figure 4-2. The functional parameters (e.g. response time, air velocity of tunnel ventilations, etc.) would be the input parameters for the simulation model. The distributions and concentrations of CO, CO_2, and O_2 could be estimated by the model. Figure 4-6 presents the distributions of CO of an assumed truck fire (50 MW) in a particular time point (t = 19.8s).

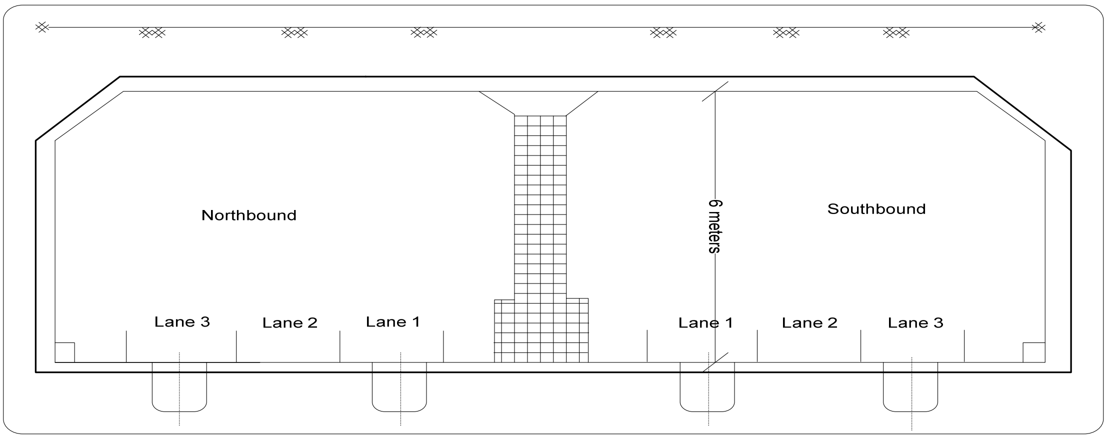


Figure 4-5: the cross sectional layout of a simulated tunnel

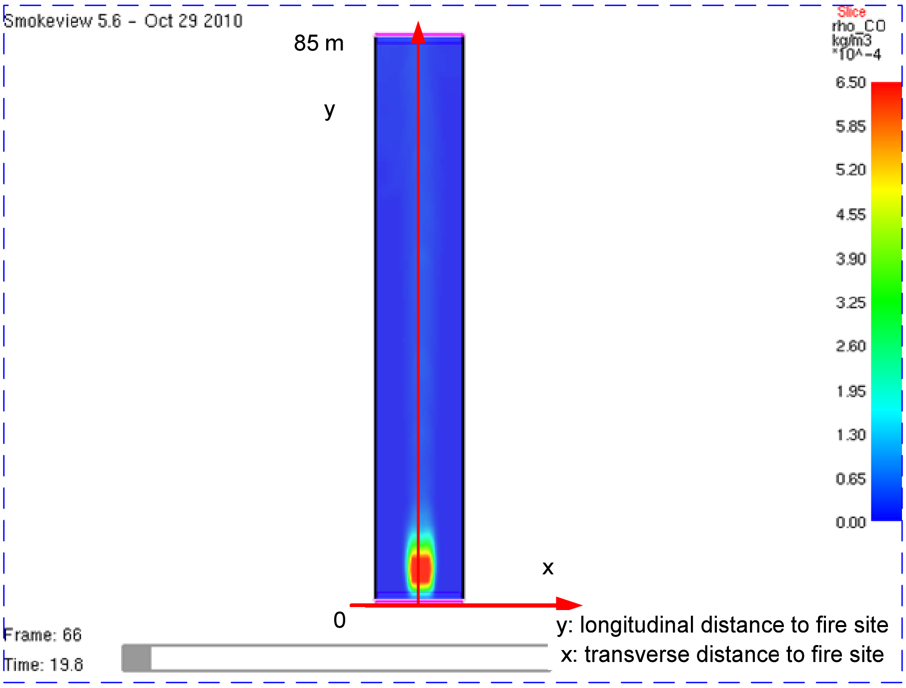


Figure 4-6: CO distributions of an assumed tunnel fire

According to the fire simulation model, the concentrations of other toxic gases at various locations could be recorded. For example, Figure 4-7 and Figure 4-8 present the distributions of CO_2 and O_2 of an assumed tunnel fire at different time point.

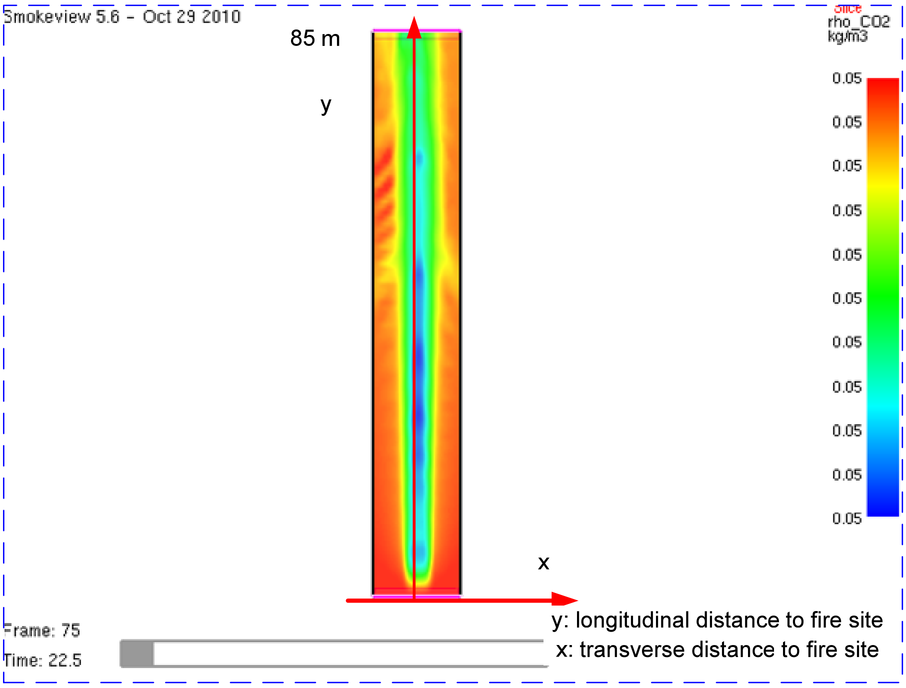


Figure 4-7: Concentrations of CO_2 (an assumed tunnel fire)

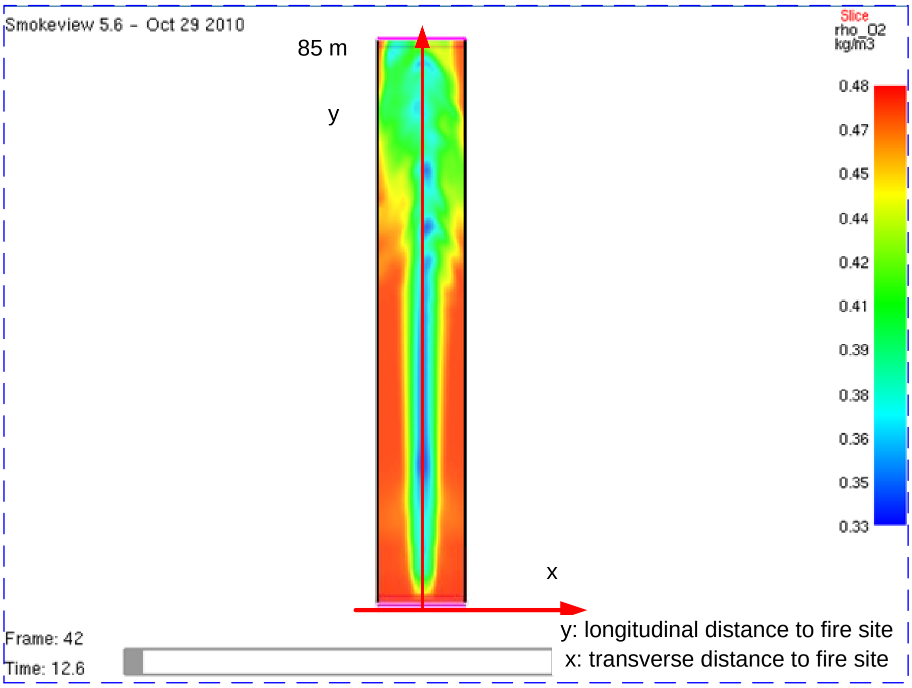


Figure 4-8: Concentrations of O_2 (an assumed tunnel fire)

4.3.2.4 Estimation of fatality rate

The fatality rate at various locations during the time period [*0,t*] should be estimated. Assume the concentrations of various types of gases (CO, CO_2, and O_2) are available for any locations at any time. The additive effects of combustion gases were demonstrated in a number of experiments using rodent (Hartzell et al., 1985; Levin et al., 1987), which was advanced to include consideration of exposure time. This strategy is commonly referred to as the fractional effective dose (FED) methodology. The FED is defined as the ratio of the *Ct* (concentration × time) for a gaseous toxicant produced in a given test to that *Ct* product of the toxicant that has been statistically determined from independent experimental data to produce lethality in 50% of test animals within a specified exposure and post exposure time (ASTM, 2002; Hartzell, 2001).

The additivity of FEDs has become a useful property in fire toxicology for estimations of number of fatalities, mathematically represented by

$$FED = \sum_{i=1}^{n} \sum_{\tau=0}^{m\Delta t} \frac{C_{i,\tau}}{\left(Ct\right)_i} \Delta t = \sum_{i=1}^{n} \sum_{t=0}^{m\Delta t} F_{i,\tau} \Delta t \qquad (4.15)$$

where $C_{i,t}$ is the concentration of toxic component *i* at time τ ; $F_{i,\tau}$ is FED caused by toxic component *i* for exposure time $[\tau, \tau + \Delta t]$; $\left(Ct\right)_i$ is the specific dose (concentration × time) required to produce lethality; Δt is time increment (min) and $t = m\Delta t$.

According to Fire Protection Handbook (2006), carbon dioxide (CO_2) is quite low in its own toxicological potency and is not, by itself, normally considered as a toxicant in fire atmospheres. However, it does stimulate both the rate and depth of breathing, thereby increasing the fatality rate caused by carbon monoxide (*CO*). Levin et al. (1987) developed an empirical FED function for exposure of 30 minutes caused by the combinations of carbon monoxide and carbon dioxide as follows.

$$F_{CO\&CO_2}(X_{CO}, X_{CO_2}, 30) = \frac{m \cdot X_{CO}}{X_{CO_2} - b} \tag{4.16}$$

where X_{CO} is the concentration of carbon monoxide (in *ppm*); X_{CO_2} is the concentration of carbon dioxide (in *volume percent*); *m* and *b* are two coefficients: if the concentration of carbon dioxide is less than 5%, $m = -18$ and $b = 122,000$; otherwise, $m = 23$ and $b = -38,600$. The confirmatory work using this model has been published by Pauluhn (1993).

Due to the additivity of FEDs, the FED function for exposure time period of [*0*,*t*] caused by the combinations of carbon monoxide and carbon dioxide is

$$F_{CO\&CO_2}(X_{CO}, X_{CO_2}, t) = \frac{m \cdot X_{CO}}{X_{CO_2} - b} \times \frac{t}{30} \tag{4.17}$$

According to Persson (2002), the FED with respect to low concentration of O_2 for exposure time period of [*0*,*t*] is

$$F_{O_2}(X_{O_2}, t) = \frac{t}{e^{8.13 - 0.54(20.9 - X_{O_2})}} \tag{4.18}$$

where X_{O_2} is the concentration of oxygen (in *volume percent*).

By substituting eqns. (4.12) and (4.13) to eqn. (4.10), the FED of the mixed effects by *CO*, *CO₂*, and *O₂* is obtainable. Due to the additivity of FEDs, the fatality rate for exposure time period of [*0,t*] at location *m* could be estimated by

$$F_m\left(X_{CO}, X_{CO_2}, X_{O_2}, t\right) = \left(F_{CO\&CO_2}(X_{CO}, X_{CO_2}, t) + F_{O_2}(X_{O_2}, t)\right) \times 50\% \quad (4.19)$$

4.3.2.5 Validation of the consequence estimation model due to tunnel fire

Validation of consequence models is difficult as the fire is a rare event and relevant data are not obtainable. In order to complete a validation study, we request the data - vehicle composition, distance between two consecutive exits, traffic volume, delay time for response, and tunnel configurations of Mont Blanc, Burnley, and Tauren road tunnels. Some other input parameters of the model, such as the ratio of different age group of Italy and French in the case study for Mont Blanc tunnel fire, can be obtained from internet search. The key input parameters are as follows shown in Table 4-1.

Table 4-1: Input parameters for simulating Mont Blanc, Burnley, and Tauern road tunnel fire incidents

Input Parameters	Mont Blanc	Burnley	Tauern
Car Proportion	0.385	0.79	0.76
Bus Proportion	0	0.02	0.02
Motorcycle Proportion	0.038	0	0

HGV Proportion	0.577	0.19	0.22
Distance Between Two Consecutive Exits	1200m	800m	400m
Traffic Volume	306 veh/hour lane	2000 veh/hour lane	882 veh/hour lane
Average Length-Bus	20m	20m	20m
Average Length-Car	3.5m	3.5m	3.5m
Average Length-Motorcycle	2m	2m	2m
Average Length-HGV	20m	20m	20m
Average Length-Hazmat	20m	20m	20m
Average Persons Per Bus	35	20	20
Average Persons Per Car	2.5	3	3
Average Persons Per Motorcycle	1.2	1.2	1.2
Average Persons Per HGV	1.8	1	1
Average Persons Per Hazmat	2	1	1
Delay Time for Response to Accidents	10 min	1min	1min
Wind Velocity in Tunnel	6 m/s	4m/s	4m/s
Number of Lanes	1	3	2

The vehicle composition, traffic volume, and distance between two consecutive exits are used to estimate the number of people at risk. The delay time, wind velocity, and tunnel ventilation status (Mont Blanc tunnel: failure; the other two tunnels: success) are used to estimate the fatality rate. The comparison between historical record of death and number of fatalities generated by the model is shown in Table 4-2.

To the best of our knowledge, this is the first attempt to rebuild real-case fire incidents for validation to some extent. Three cases are obviously not convincing to conclude that the consequence model performs well. However, due to data unavailability and such cases are really limited, we leave the further validation of the model as future studies.

Table 4-2: Comparison between number of fatalities generated by the proposed model and number of death of actual record

	Number of fatalities generated by the proposed model	Number of death of actual record
Mont Blanc road tunnel disaster	31.79	37
Burnley road tunnel disaster	2.76	3
Tauern road tunnel disaster	0.72	1

4.3.3 Aggregated QRA Model for Non-homogeneous Urban Road Tunnels

Having established the QRA model for homogenous road tunnel section, an aggregated QRA model for the non-homogeneous urban road tunnels can be developed. Figure 4-9 shows the customized framework for building the aggregated QRA model. Firstly, according to the proposed tunnel segmentation principle, a non-homogeneous road tunnel is segmented into a number of homogeneous sections, where all the parameters involved in risk calculations can be assumed to be constant. The QRA models for the various road tunnel sections are built separately and the IR and SR for each tunnel section are calculated independently. Subsequently, the integrated risk indices shown in eqns. (4.3) - (4.6) can be evaluated for the entire road tunnel. Table 4-3 shows the merits and explanations of the aggregated QRA model. The model is further computerized as a software tool to facilitate tunnel operators in Land Transport Authority of Singapore (Appendix C).

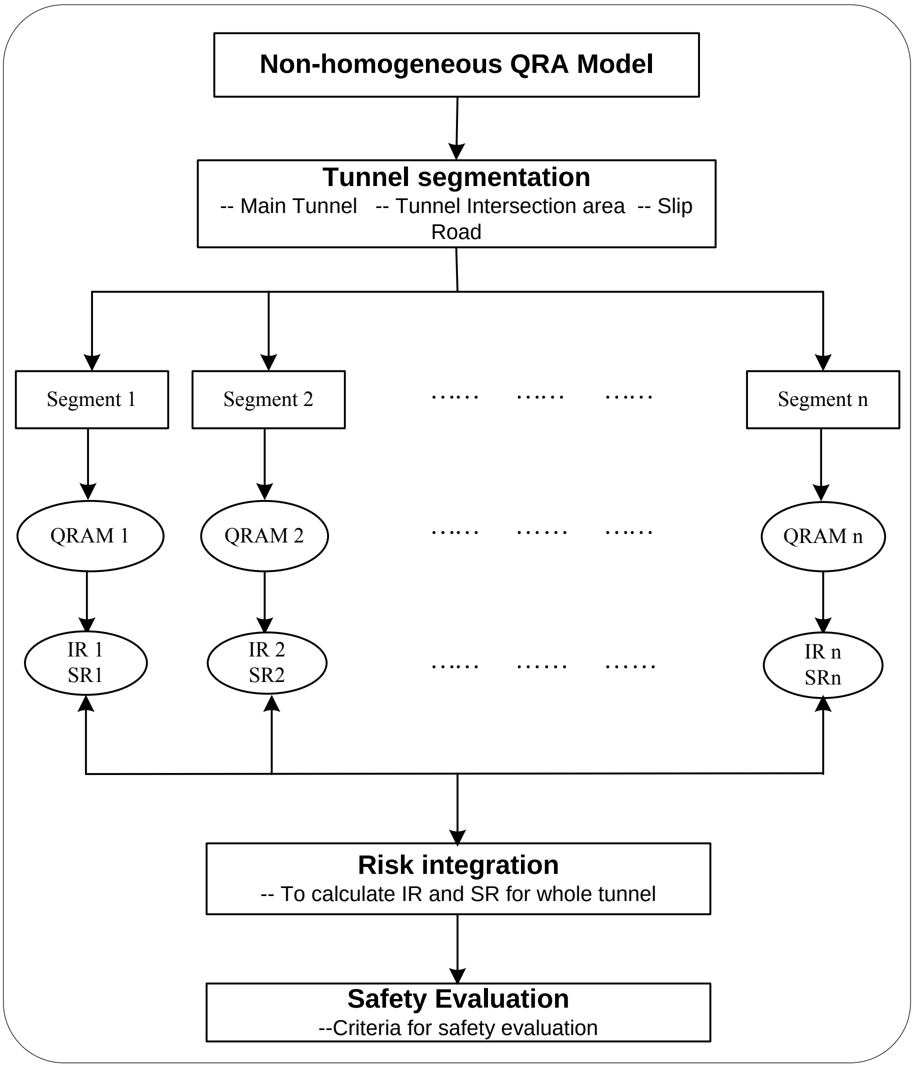


Figure 4-9: The QRA model for non-homogeneous road tunnels building procedure

Table 4-3: The differences of the new QRA model

Model	Differences of the model
Risk assessment method	QRA model incorporating more scenarios is more realistic; the revised definition of IR is more appropriate for tunnel risk assessment.
Input parameters	Consider more specific input parameters than previous developed models: tunnel configurations; traffic volume and vehicle composition; human and vehicle factors; tunnel safety provisions, etc.
Model building structure	Segment-based risk assessment is employed: the tunnel is divided into several segments, and the overall risk can be the combination of segment-based risks
Frequency estimation and consequences estimation	Event tree and fault tree particularly designed for Singapore is used; a model is built to estimate the frequency of vehicle crashes; fire simulation based consequence estimation model.

4.4 Applications

Marina Coastal Expressway (MCE) is built to serve the projected increase in traffic volume due to the large number of developments in the Marina Bay area, Singapore. As is shown in Figure 4-9, it also serves as a vital transport link from Marina Bay to other parts of the island. MCE will be the tenth expressway, which is the key element of the strategic island-wide road network to support the long-term growth of Singapore. It is a dual five-lane, 5km long expressway with 3.8km of it built underground. It will run through segments of reclaimed land as well as a 420m section that runs below the seabed of Marina Bay. The functionality and working profiles of the tunnel safety provisions can be obtained from their instruction manuals. The values of the vehicle profiles can be obtained from the planning department of LTA of Singapore. The distance between two emergency exits is 100 meters. The safety target of (10^{-3}/ N^2) is applied in this case study.

Figure 4-10: MCE road tunnel in Singapore

By adopting the tunnel segmentation principle, MCE can be divided into 16 sections, 7 sections of which are on the eastbound and 9 sections on the westbound tunnel. On the eastbound tunnel, there are 2 tunnel slip road sections, 2 tunnel intersection sections and 3 main tunnel sections are considered. As for the westbound tunnel, there are 3 tunnel slip road sections, 3 tunnel intersection sections and 3 main tunnel sections.

The geometry figure of the segmented MCE tunnel is as follows:

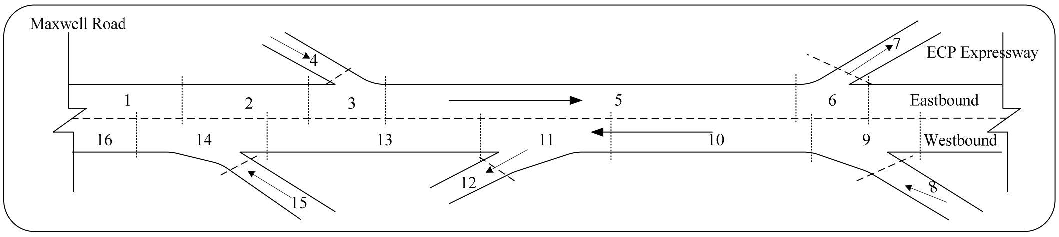


Figure 4-11: Geometry of MCE tunnel segmentation

Note that the parameters are different for various tunnel sections. The number of lanes, frequencies of fire in the section, and ventilation response time used in this study are presented in Table 4-4. The MCE road tunnel is not open to traffic yet. Therefore, we use the planning data provided by LTA to conduct this numerical example. The traffic volumes in normal periods and night periods are assumed to be 60% and 20% of that in peak hours. The other parameters, which take the same values for different tunnel sections, are presented in Table 4-5.

Table 4-4: Some important input parameters

Section No.	Number of lanes	Traffic volume in peak hour (planning data)	Frequency of fire (per year)	Ventilation response time
1	5	1500	0.122128	105 s
2	5	1500	0.082128	105 s
3	5	1900	0.279982	105 s
4	2	400	0.008586	225 s
5	5	1900	0.279982	105 s

6	5	1600	0.149594	105 s
7	2	300	0.017586	225 s
8	2	350	0.008586	225 s
9	5	1550	0.10266	105 s
10	5	1550	0.10266	105 s
11	5	1250	0.170729	105 s
12	2	300	0.007466	225 s
13	5	1250	0.059729	105 s
14	5	1600	0.141993	105 s
15	2	350	0.007466	225 s
16	5	1600	0.132662	105 s

Table 4-5: Input parameters (the same for distinct tunnel sections)

Input Parameters	Values
Fraction of Peak Hour	0.23
Fraction of Normal Period	0.52
Fraction of Night Period	0.25
Car Proportion	0.644
Bus Proportion	0.021
Heavy Goods Vehicle Proportion	0.164
Hazardous Materials Vehicle Proportion	0
Motorcycle Proportion	0.171
Distance Between Two Consecutive Exits	100m
Proportion of the Elderly Tunnel Users	0.3
Proportion of the Young Tunnel Users	0.7

Average Length-Bus	20m
Average Length-Car	3.5m
Average Length-Motorcycle	2m
Average Length-HGV	20m
Average Length-Hazmat	20m
Average Persons Per Bus	30
Average Persons Per Car	2
Average Persons Per Motorcycle	1.2
Average Persons Per HGV	1
Average Persons Per Hazmat	1
Fraction of Experienced Driver	0.98
Fraction of Inexperienced Driver	0.02
Air Velocity (Tunnel Ventilation Success)	1.2 m/s
Air Velocity (Tunnel Ventilation Failure)	4.5 m/s
Length of the tunnel	8 km
Delay time of fire detection system (success)	1 min
Delay time of fire detection system (failure)	2 min
Delay time of communication system (success)	0.8 min
Delay time of communication system (failure)	1.5 min

A QRA software tool (Appendix C) is developed to facilitate this study. Figure 4-11 to Figure 4-14 shows the expected value of number of fatalities per year, the individual risk, and societal risk represented by F/N curve. Figure 4-11 is the calculation results by QRA model for non-homogeneous road tunnels proposed in this paper. Figure 4-13 depicts the results if the MCE road is regarded as one tunnel section. Figure 4-14 shows the result of the section with the highest risk in terms of societal risk.

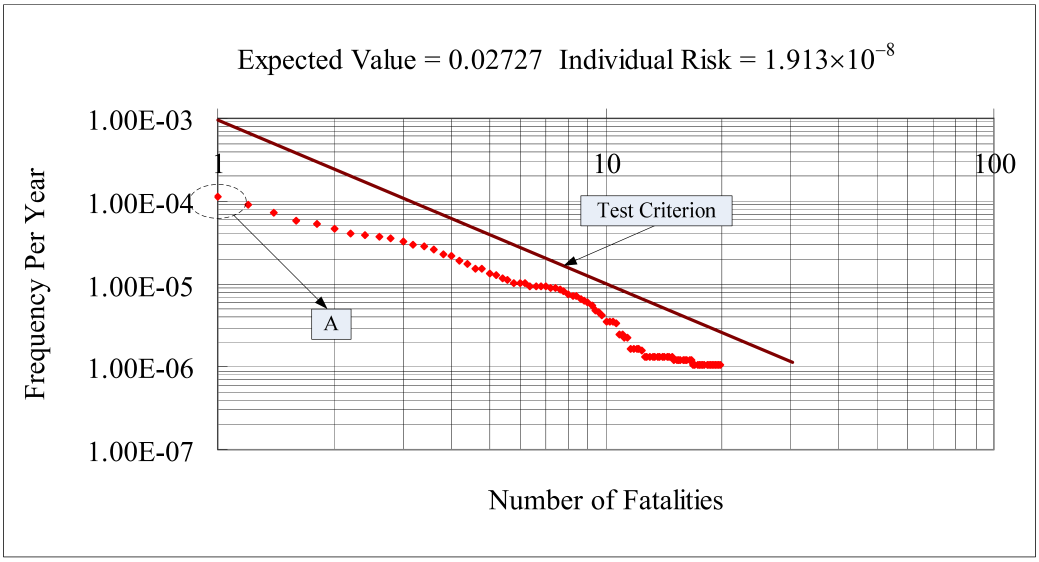


Figure 4-12: Risks of MCE road tunnel by the non-homogeneous QRA model

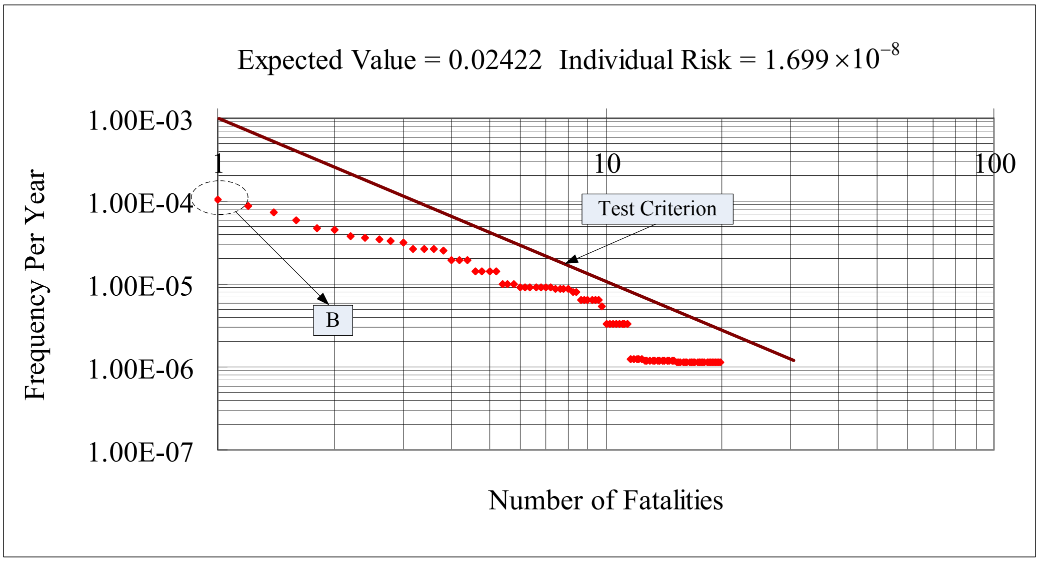


Figure 4-13: Risks of MCE road tunnel by the homogeneous QRA model

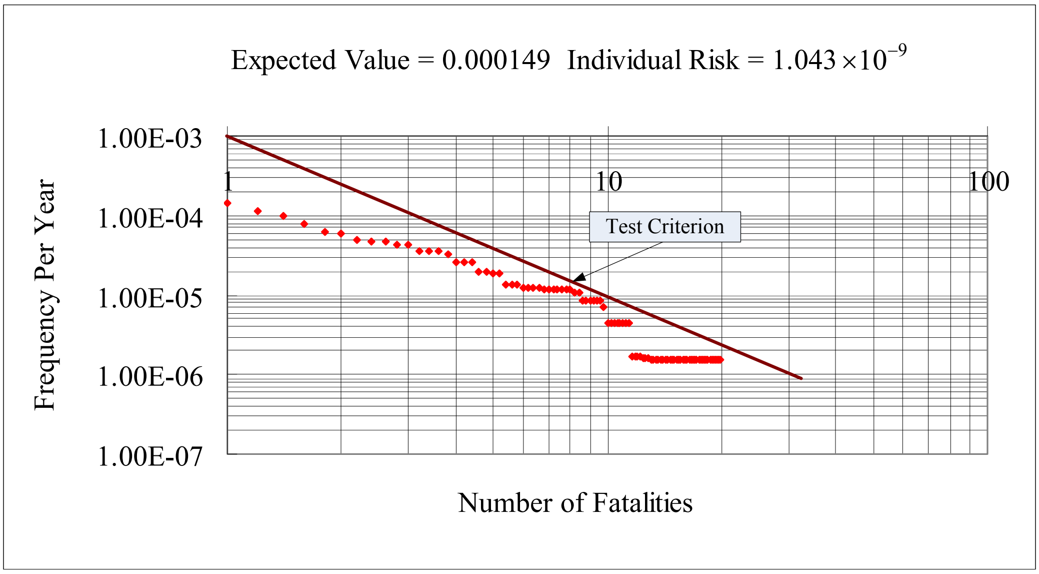


Figure 4-14: Risks of the riskiest tunnel sections

As shown in Figure 4-11 and Figure 4-13, both the individual risk and societal risk generated by the two models are different, which is reflected by the frequency intercept of the F/N curve and the value of individual risk. It draws the conclusion that QRAM-I for non-homogeneous road tunnels such as MCE road tunnel is necessary. Ellipses A and B display the first point of the F/N curves shown in Figure 4-12 and Figure 4-13, respectively. The corresponding frequencies for the two points are 1.41×10^{-4} /yr and 1.01×10^{-4} /yr respectively. This means the frequencies of lower consequence events may significantly vary with respect to different tunnel segmentations. QRA model for non-homogeneous road tunnel can further generate the risks of individual section. Hence, the most risky sections can be identified. This is very important for tunnel manager to decide risk reduction strategy.

From the results, we found that tunnel sections 1, 6, 7, 8, 10, 11, 14, and 16 have higher tunnel risks in terms of individual risk (individual risks are greater than 6×10^{-9}). All the tunnel sections are considered safe according to the test safety target. Tunnel sections 6, 8, 10, 11, 14, and 16 have smaller slack clearances (less than 0.2) which indicate that they are riskier in terms of societal risk. Compared to other tunnel sections, the above-mentioned sections have higher traffic volume and frequencies of collisions. In reality, the traffic volumes of eastbound are indeed less than that of westbound from the planning data. This is because more traffic transits from the East Coast Expressway, one of the busiest expressways in Singapore, to MCE road tunnel. In addition, there are limited tunnel mitigation facilities in slip roads. These may also result in higher risks in slip road tunnel section. However, the total travel rates (weights for risk integration) of tunnel section 7, 8 (slip roads), 6, 11, 14 (tunnel intersection), and section 1 (short main tunnel) are much smaller than those of tunnel section 10 and 16 (long main road tunnel). Therefore, tunnel section 10 (41,686,921 veh·km/year) and section 16 (12,161,137 veh·km/year) contribute most to the overall road tunnel risk.

4.5 Conclusion

In this chapter, a deterministic QRA model (QRAM-I) for non-homogeneous urban road tunnels is developed. In the proposed model, a non-homogeneous urban road tunnel is segmented into a number of homogeneous road tunnel sections based on the proposed tunnel segmentation principle. For each particular tunnel section, the frequency could be estimated by using the model proposed in Chapter 3; fire simulation model and fractional effective dose (FED) methodology are applied to estimate the number of fatalities under different accidental scenarios by taking into account the different working status of tunnel safety provisions. Having had the frequency and consequence of each possible accidental scenario for the homogeneous tunnel section, the individual risk and societal risk of the tunnel section can be calculated accordingly. Finally, an aggregated QRA model is thus built by integrating the section-based QRA models. The model is further computerized as software to facilitate tunnel operators to evaluate risks in urban road tunnels (Appendix C). The model and software has been applied by Land Transport Authority of Singapore to assess the risks of urban road tunnels in the country.

CHAPTER 5 RISK IMPACT ANALYSIS OF TRAFFIC FLOW

5.1 Risk Index and Risk Control/Management Strategies

Road tunnels are vital infrastructures providing underground vehicular passageways for commuters and motorists. They contribute to transportation systems, both economically and practically, because they enhance capacity and accessibility. However, fatal accidents occurring in road tunnels may result in catastrophic consequences. According to *The Handbook of Tunnel Fire Safety*, the consequences of tunnel incidents may include: (1) fatality, (2) injury, (3) property loss, and (4) disruption of operations, with the number of fatalities being the predominant concern of Land Transport Authority of Singapore. In addition, all the preventive and/or protective safety provisions (e.g. fire detection systems, tunnel ventilation systems) installed in a road tunnel aims specifically to reduce number of fatalities. Accordingly, from the perspective of land transport authorities, societal risk is usually used to evaluate the safety level of a road tunnel. Most countries have chosen an upper bound for societal risk as a safety target for their road tunnels (Meng et al., 2009; PIARC, 2008). If the societal risk generated by a QRA model is below the chosen safety target, the road tunnel is considered safe. Otherwise, risk reduction measures need to be implemented.

Under the QRA model, the risk of a given road tunnel is determined by its geometries, traffic volume, vehicle composition, hazmat transportation, E&M systems, the distance between evacuation exits, and other parameters. The tunnel geometries and safety provisions are designed at the planning stage. Once the tunnel is open to traffic, these parameters are considered to be un-adjustable - it would be difficult, if not impossible, to adjust these parameters to reduce the risks. By contrast, critical components of traffic flow can be controlled conveniently through the use of entry controls and traffic regulations. Total traffic flow has an important bearing on societal risk because as the traffic volume in a road tunnel increases there tends to be an increase both in the frequency of accidents and in the number of injuries and fatalities in any given accident (Davis, 2000; Abdel-Aty and Pande, 2007). The number of Heavy Goods Vehicles (HGVs) in proportion to total traffic is an important factor within this general pattern, both because HGVs as such increase the risk of accident, and because an accident involving an HGV tends to be more severe in terms of fatalities than one involving only smaller vehicles. These elements are recognized in Singapore, where prior notice must be given to the Land Transport Authority (LTA) for approval before an HGV can enter a road tunnel (thus the proportion of HGV is a controllable parameter in Singapore), and overall traffic flow through the tunnel can be controlled using the normal signalling system..

The traffic volume and proportion of HGVs are two important contributing factors to the risks of road tunnels. It is thus important to capture a picture of how these two factors affect societal risk. Towards this end, a risk impact analysis approach is proposed, not only to support the design considerations of new tunnels by varying these two factors (planning data), but also to evaluate various road tunnel traffic control schemes and HGV transport regulations, which may provide helpful information to decision makers. In addition, given a combination of the traffic volume and the proportion of HGVs, the F/N curve generated by a QRA model may not fulfill a predetermined road tunnel safety target. In this case, we need an index to measure how far the risk is from the safety target. Accordingly, the “excess risk index” is defined to quantify the danger levels of road tunnels relative to the safety target. Based on this index, a contour chart is plotted, incorporating possible combinations of the two contributing factors. This chart could further facilitate LTA's decision making.

5.2 Risk Impact Analysis Methodology

In this section, we first propose an excess risk index in order to quantify the magnitude of risk for road tunnels which do not meet safety targets. Based on the proposed index, an excess risk-based risk impact analysis is presented, to examine how the traffic flow parameters influence risks.

5.2.1 Excess Risk Index

Societal risk, represented by an F/N curve, reflects the risks of hazardous installations. It is convenient for decision makers to recognize whether societal risk of a road tunnel passes a predetermined safety target. However, it can only provide a binary judgment and cannot reflect the degree of danger quantitatively in terms of the risks of hazardous installations. Horn et al. (2008) proposed a measure defined as the total extent to which the constraint is violated, expressed by

$$v = \sum_{\substack{n=1 \\ F(n)>C(n)}}^{M} \left(F(n) - C(n)\right) \tag{5.1}$$

where M is the upper limit on the number of fatalities per incident; $C(n)$ is the risk limit (safety target). Following Horn et al.'s work, another risk index, excess risk index, is defined as weighted summation of distances between the predetermined safety target and F/N points which are above the safety target. Let us take an example to intuitively illustrate the excess risk index. Figure 5-1 depicts an F/N curve diagram generated by QRAM-I software tool. The diamonds on the F/N curve are generated by the software in the case that traffic volume is 1800 vehs/hour·lane. The asterisks on the F/N curve are generated when traffic volume is 1600 vehs/hour·lane. As per the safety target shown by the straight line in Figure 5-1, both scenarios are unacceptable since both curves have some points higher than the safety target. However, the F/N curve with diamonds is much more dangerous than the asterisks curve (all diamonds are significantly higher than asterisks, e.g. $F_{1800}(3)=1.5\times10^{-4} > F_{1600}(3)=8.8\times10^{-5}$).

The mathematical expression of excess risk index is shown by eqn. (5.2).

$$S_e=\sum_{i=1}^{n}\max\left\{\left(F\left(N_i\right)-\frac{C}{N_i^{\,k}}\right)\times N_i,\,0\right\} \tag{5.2}$$

where S_e is the excess risk index; N_i is the selected value of number of fatalities; n is the number of fatalities, C and k are two constants representing the intercept and slope of the safety target. For an acceptable F/N curve, S_e takes the value of 0. As shown in Figure 5-1, with increasing numbers of fatalities the *F(N)* curve is shifted to the right, while with increasing frequency it is shifted upwards, and wherever *F(N)* surpasses the target curve the exceeding risk value becomes non-zero. In reality, excess risk basically refers to the area of any regions where *F(N)* lies above the predetermined safety target.

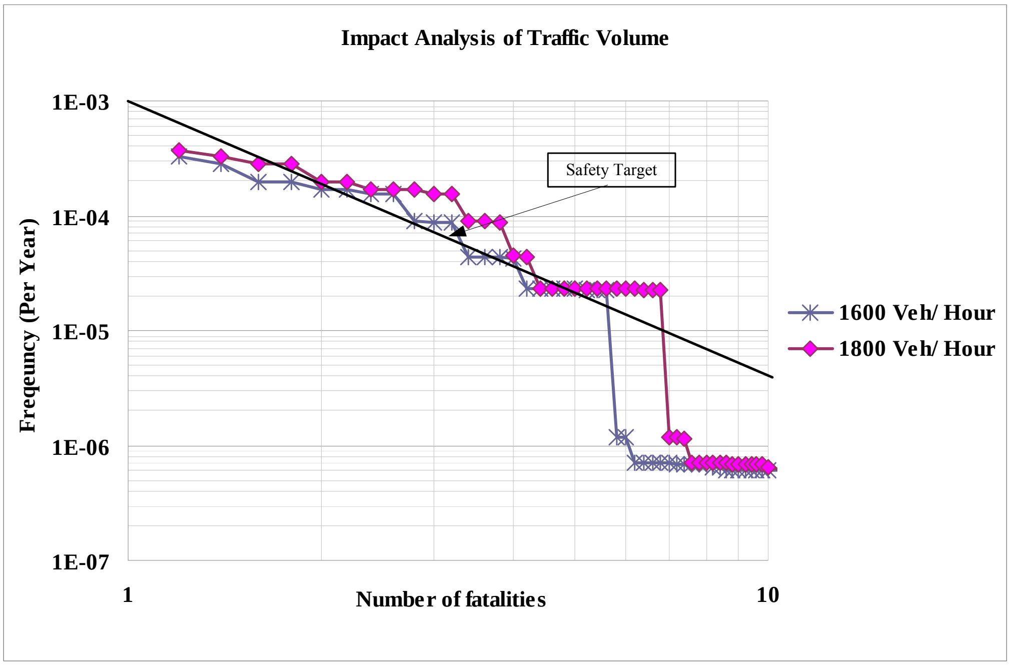


Figure 5-1: An F/N curve example

5.2.2 Excess Risk Index-Based Risk Impact Analysis

A risk impact analysis of the two contributing factors, traffic volume and proportion of HGVs, to the societal risk of a road tunnel can be implemented easily using the QRAM-I software tool. The F/N curve can be generated using the tool on a case by case basis. The risk impact analysis procedure works as follows. Firstly, determine the ranges of traffic volume (X_i) and proportion of HGVs (Y_j) and discretize these ranges. The range of traffic volume may be assumed to be between 1,000 and 1,800 vehs/hour·lane, based on historical data, and the step is taken to be 200 vehs/hour·lane, based on expert judgment. The examined traffic volumes are thus taken to be 1,000, 1,200, 1,400, 1,600, and 1,800 vehs/hour·lane. The values of the other input parameters required in the QRAM-I (as described in Chapter 4) can be acquired from historical data and the design documents of the road tunnels. These values are held constant in this risk impact analysis.

Next, a quantitative risk analysis is performed for all possible combinations of the two major contributing factors (traffic volume and proportion of HGVs). The societal risk for all combinations is generated using the QRAM-I software tool and the excess risk (R_e) can thus be calculated using Equation (5.2). Excess risk can thus be considered as the output of the various combinations of the two contributing factors.

Finally, an excess risk contour chart is introduced to illustrate the changing pattern of excess risk. We plot points (combinations of the two contributing factors) which produce the same excess risk, that is, for a given value of excess risk α, we plot the points (X_i, Y_j) where $R_e(X_i, Y_j) = \alpha$. Then, the B-spline curve fitting method, a process of constructing a smooth curve with the best fit to a series of data points, is adopted to generate a smooth contour line. Finally, the excess risk contour chart is drawn using these curve fitting methods for varying values of α. Figure 5-2 illustrates the two-factor impact analysis procedure.

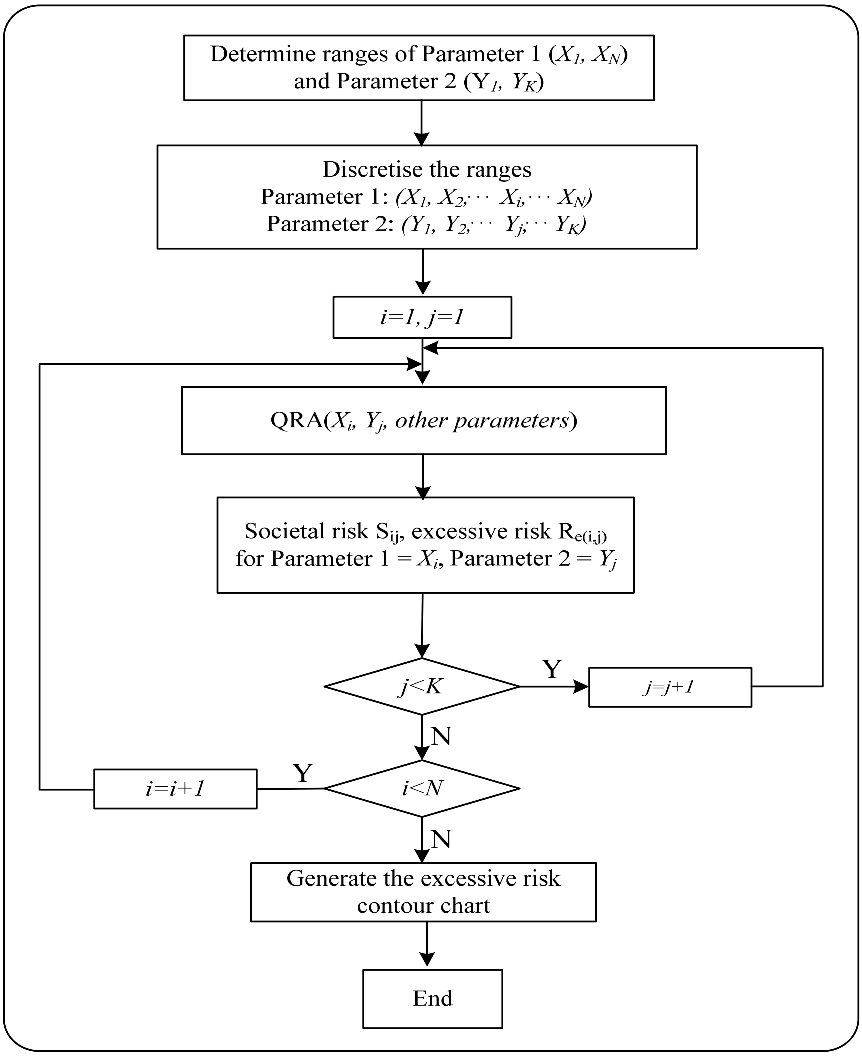


Figure 5-2: Two-factor sensitivity analysis procedure

It should be pointed out that this method and the proposed index could also be applied to analyze the impact of other input parameters, and could also be generalized to analyze three or more parameters as well.

5.3 Applications to KPE road tunnels in Singapore

We have applied this methodology in conjunction with LTA of Singapore to evaluate the effect of the two above-mentioned important contributing factors: traffic volume and the proportion of HGVs. Thereby, the traffic capacity and acceptable proportion of HGVs in terms of risk in the three existing non-homogeneous urban road tunnels in Singapore have been derived.

The Kallang/Paya Lebar Expressway (KPE) in Singapore, shown in Figure 5-3, has a total length of twelve kilometres, and is 36 meters wide. Nine kilometres of the expressway is built underground as a road tunnel, serving the growing traffic demands of the north-eastern sector of Singapore. It is the longest road tunnel in South East Asia. The KPE road tunnel is a dual three-lane underground passageway and has nine entry slip roads, eight exit slip roads and six longitudinal ventilation buildings. The cross-sectional area of the tunnel is around 306 meters squared. The distance between emergency exits is one hundred meters. There is a twenty-four hour manned operation control centre (OCC) in one of the ventilation buildings and an unmanned hot standby OCC located in another ventilation building. The major safety provisions of the KPE tunnel include a tunnel ventilation and environmental control system, a fire protection system, an electrical system, an integrated traffic and plant management system and a communications system.

Figure 5-3: KPE road tunnels in Singapore

5.3.1 Traffic Volume Impact Analyses

In order to quantify the impact on societal risk of the road tunnel's traffic volume, measured as total number of vehicles at peak hour, an impact analysis is performed. All the other input parameters (default values) are based on operational data collected from Singapore's KPE road tunnel. As mentioned earlier, the traffic volume varies from 1,000 to 1,800 vehs/hour·lane. The F/N curves associated with different traffic volumes are shown in Figure 5-4. A safety target of $10^{-3} / N^2$ is adopted in this case study.

Figure 5-4(a) depicts the F/N curves for traffic volumes varying from 1,000 to 1,400 vehs/hour·lane. In these three scenarios, the KPE tunnel can be considered safe based on the chosen safety target. Figure 5-4(b) shows the F/N curves for traffic volumes of 1,600 and 1,800 vehs/hour·lane. It can be seen that these two scenarios are not acceptable based on the selected safety target. Therefore, it can be concluded that the maximum tolerable traffic volume of the KPE road tunnel is 1,400 vehs/hour·lane.

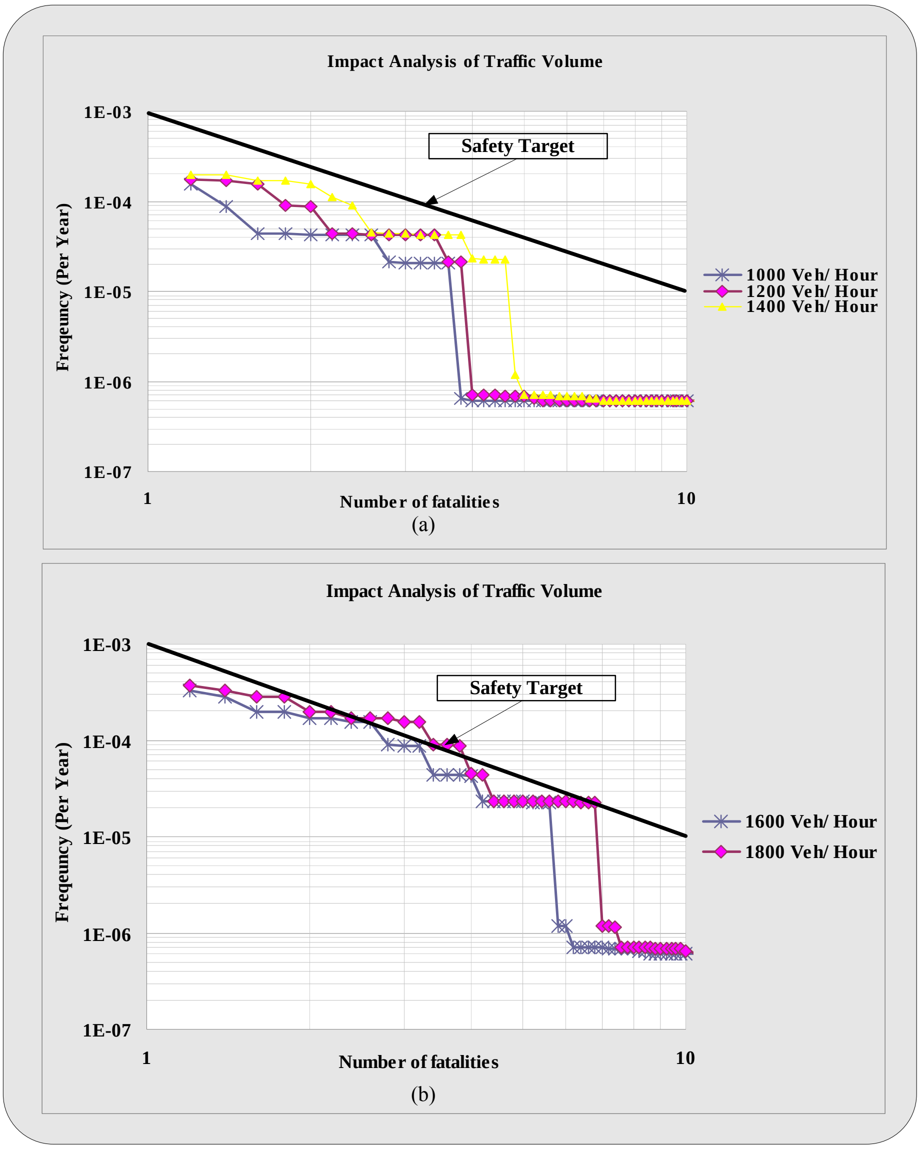
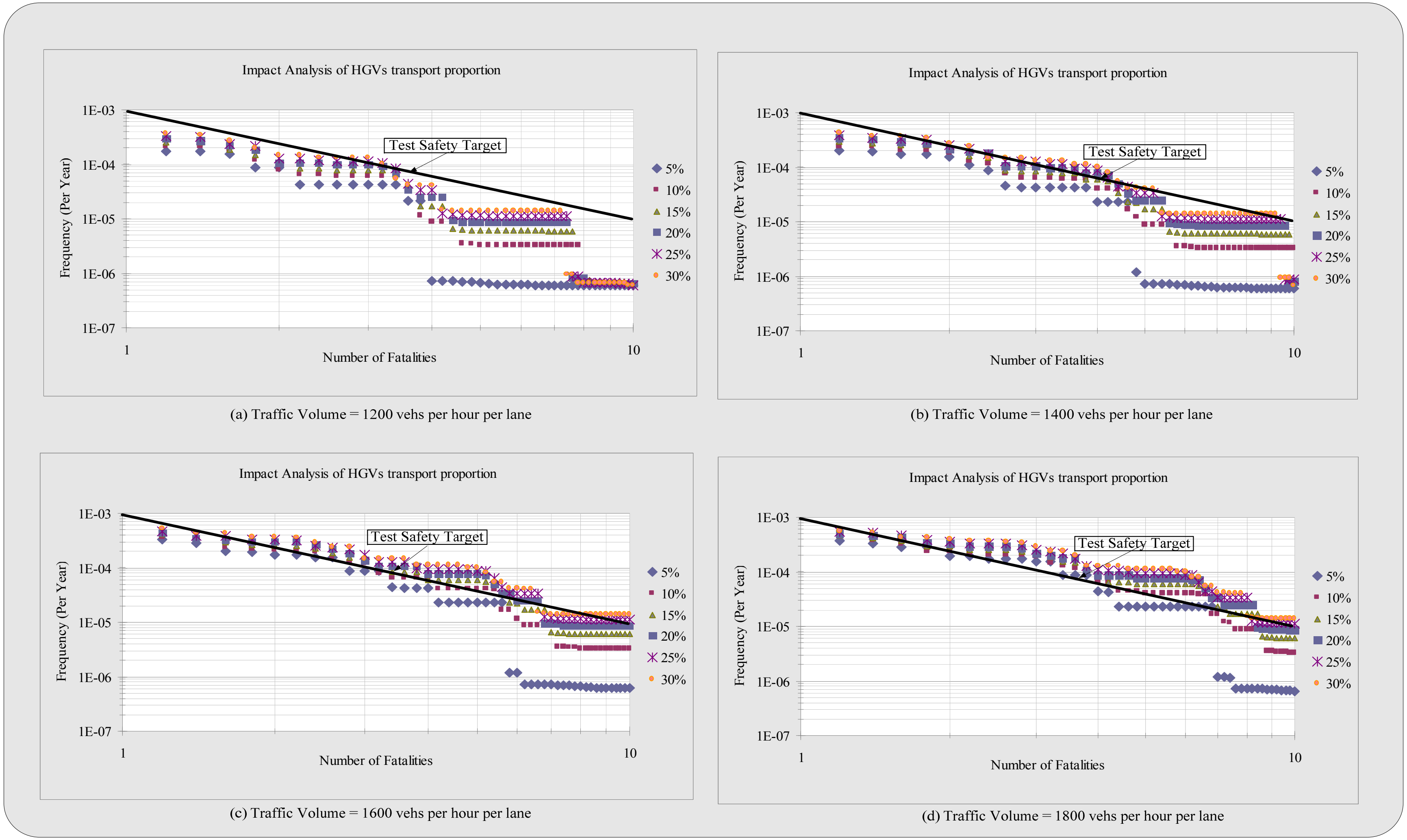


Figure 5-4: Two F/N curve diagrams for the KPE road tunnel

5.3.2 Impact Analyses on the Proportion of HGVs

As mentioned in the introductory section, according to the Road Traffic Act of Singapore, a form of notice is required to be submitted to the LTA of Singapore before an HGV enters the KPE road tunnel. According to the impact analysis, the maximum proportion of HGVs is obtainable, which can be used to support the LTA's decisions regarding how many HGVs it allows to enter the tunnel. The proportion of HGVs ranges from 5 to 30%. Meanwhile, the traffic volume takes values of between

1,200 and 1,800 vehs/hour·lane. Figure 5-5 represents the F/N curves for scenarios with traffic volumes of 1,200, 1,400, 1,600, and 1,800 vehs/hour·lane for varying proportions of HGVs. Figure 5-5(a) shows that if the traffic volume is relatively low, even with a 30% proportion of HGVs, the F/N curve stays below the safety target. However, at 1,400 vehs/hour·lane (which is likely, due to the densely populated nature of Singapore), even 15% HGVs could impose a significant threat to the tunnel's users, since some of the F/N points exceed the safety target (Figure 5-5(b)).



(a) Traffic Volume = 1200 vehs per hour per lane

(b) Traffic Volume = 1400 vehs per hour per lane

(c) Traffic Volume = 1600 vehs per hour per lane

(d) Traffic Volume = 1800 vehs per hour per lane

Figure 5-5: Four F/N curve diagrams of the KPE road tunnel

5.3.3 Excess Risk Index Contour Chart

The above impact analysis indicates that traffic volume and the proportion of HGVs have a significant impact on the tunnel risk. Therefore, both parameters should be taken into consideration in the impact analysis. For each combination of these two parameters, the excess risk index is calculated using the QRAM-I. The excess risk index-based contour chart is drawn by varying the traffic volume from 1,000 to 1,800 vehs/hour/lane in steps of 200 and the proportion of HGVs from 5% to 30% in steps of 5%. After obtaining the excess risk value for all thirty possible combinations of the two variables, the risk contour chart is drawn using the curve fitting method (as described earlier). The contour chart is shown in Figure 5-6. Region 1 is considered to be the safe region. The excess risk index will become bigger as the traffic volume and proportion of HGVs increase. This contour chart can assist decision-makers in deciding on the most appropriate combination of traffic volume and proportion of HGVs for any given safety target.

As the population of Singapore increases, more road tunnels will be built due to the need for more efficient land use. Furthermore, the proportion of HGVs passing along Singapore’s expressways is relatively high, due to the need to transport containers to and from the port of Singapore, the busiest container port in the world. It is thus important to determine the most suitable combinations of the two most important contributing factors to societal risk. Considering the urban nature of Singaporean road tunnels, traffic volume tends to be at the higher end of the range that we have considered in our impact analysis. This means that the road tunnels may be operating near to the risk contour line 0, which shows the maximum allowable traffic volume based on the selected safety target. If the traffic volume or the proportion of HGVs increases, then the risk index may increase beyond the risk contour line 0, which will no longer satisfy the safety target. If effective operational procedures are implemented, this would help to reduce the transportation of HGVs through road tunnels, then this would effectively shift the excess risk index from risk contour line 10^{-5} to risk contour line 0 and thus the chosen safety target would still be satisfied. For example, if the tunnel were operating with 1,200 vehs/hour/lane and 20% HGVs (Point A in Figure 5-6), the operational status would be unsafe and risk reduction solutions would need to be implemented. Based on Figure 5-6, the LTA could either reduce the traffic volume from 1,200 to 1,117 vehs/hour/lane or reduce the proportion of HGVs from 20% to 17%. Based on this contour chart, therefore, the LTA can examine the operational status of a tunnel and implement suitable risk reduction solutions.

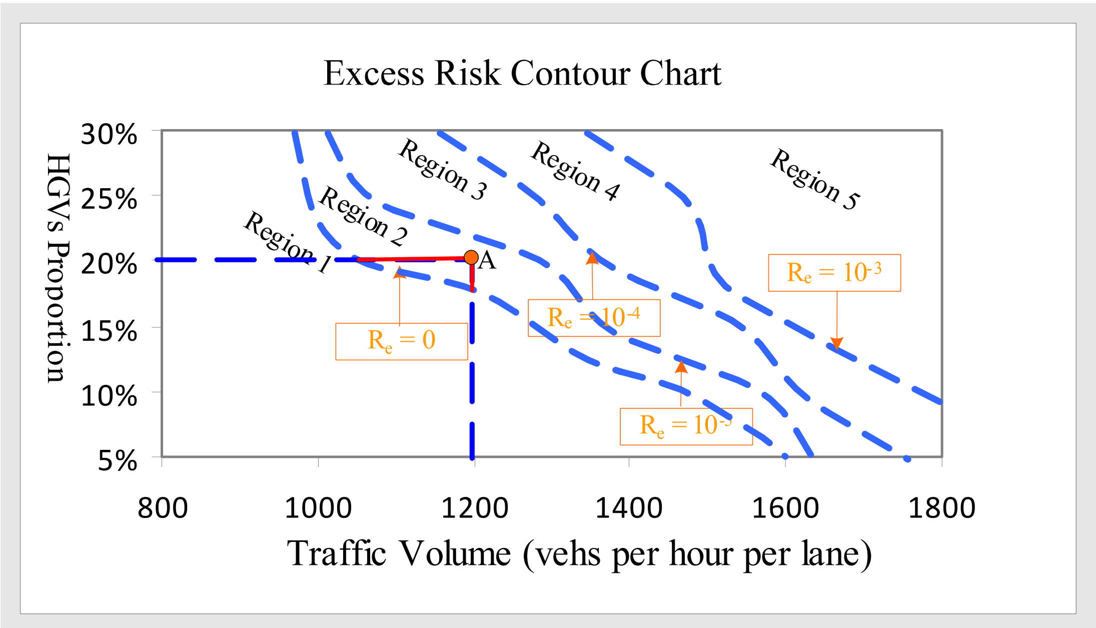


Figure 5-6: Risk contour chart based on the excess risk index

5.4 Implications for Tunnel Management

Risk impact analysis is of great significance for tunnel management. The tunnel risk is dependent on traffic flow (traffic volume and the proportion of HGV vehicles). If a tunnel operates with an unsafe status, tunnel authorities may either reduce the traffic volume or the proportion of HGV vehicles passing through the tunnel. For example, three operational procedures have been considered to reduce tunnel risks in Singapore. Firstly, as presented in the introductory section, in Singapore, a form of notice is required to be submitted to the LTA for approval before an HGV can enter a road tunnel, in accordance with the Road Traffic Act. Accordingly, the LTA can insist that HGVs pass through road tunnels only during off-peak hours when traffic volumes are lower. Secondly, a tunnel entry control could be used in the entrance of the road tunnel during peak times, to ensure a safe distance of more than one hundred meters, or at least the braking distance based on the speed limit of the road tunnel. Thirdly, electronic road pricing (ERP) and ramp metering could be used to limit the traffic flow. The risk index contour chart could be used to examine the efficiency of a road pricing strategy from the viewpoint of risk reduction.

5.5 Conclusions

This chapter has developed a QRAM-I model based risk impact analysis methodology to evaluate the impact of contributing factors on societal risk. In addition, an “excess risk index” has been defined to quantify the severities of unacceptable scenarios which place road tunnel operations above a predetermined safety target. A contour chart, based on the excess risk index, could be plotted using all possible combinations of two different parameters. The contour chart can be used to help decision makers to implement suitable risk reduction solutions so as to better manage/control the risks in urban road tunnels. Finally, the QRAM-I was used to generate the F/N curves (societal risk) and the values of the excess risk index for the KPE road tunnel in Singapore. The risk impact analysis shows that the maximum tolerable traffic volume is 1,200 vehs/hour·lane and the maximum acceptable proportion of HGVs is 15% of the total traffic volume, which suggests the current operational status of KPE road tunnels is within the safety targets.

CHAPTER 6 QRA MODEL WITH PARAMETER UNCERTAINTY FOR A ROAD TUNNEL SECTION

6.1 Introduction

The individual risk (IR) and societal risk (SR) for road tunnels could be obtainable the QRAM-I (Chapter 4). IR is a crisp value which refers to the risk to an individual tunnel commuter or motorist and SR is represented graphically in the form of frequency/number of fatalities (F/N) curve which is considered as an index to measure the safety level of a road tunnel. The risk assessment of a road tunnel is determined by a variety of input parameters such as tunnel geometries, traffic volume, vehicle composition, hazmat transport, tunnel safety provisions, distance between two evacuation exits, etc. It is universally acknowledged that uncertainty is an unavoidable component in risk analysis (Baraldi and Zio, 2008; Lemming et al., 2010; Baudrit et al., 2006). There are two distinct kinds of uncertainty affecting parameters (Ferson and Ginzburg, 1996; Hoffman and Hammonds, 1994). The first kind refers to randomness resulting from inherent variability, e.g. the failure probability of the hardware-failure-dominated (HFD) events (Huang et al., 2001). The other kind of uncertainty, i.e. imprecision due to lack of information, results from systematic measurement errors or expert opinions (Möller et al., 1999). Both types of uncertainty are very common in risk assessment for fire in road tunnels. For example, most tunnel E&M systems (e.g. fire detection systems, tunnel ventilation systems, etc.), which are HFD systems, are implemented to reduce the threats from fire in tunnels; in addition, there are few fire accident records according to historical data (imprecision due to lack of information). In fact, the tunnel operators may want to look into a particular tunnel section (they concerned) to obtain more information about the risks (e.g. lower and upper bounds, percentile based values, etc.), rather than a crisp value *IR* and a figure *SR*, by taking into account the parameter uncertainty .

As suggested by Ferson and Ginzburg (1996), distinct representation models are needed to adequately account for random variability (also referred to as *aleatory uncertainty*) and imprecision (also referred to as *epistemic uncertainty*). However, in the aforementioned QRA models for fire in road tunnels, parameters with both types of uncertainty are represented by crisp values (worst case or most probable values) without considering inherent random uncertainty and/or imprecision of parameters due to lack of information, which is unrealistic and could result in erroneous and unreliable assessment. Therefore, suitable approaches should be applied to represent the input parameters in a QRA model.

In this chapter, distinct approaches are applied to represent and propagate aleatory and epistemic uncertainty in a QRA model for fire in road tunnels. Ferson and Ginzburg (1996) argued that the two types of uncertainty should be propagated through mathematical expressions with different calculation methods, i.e. interval analysis based on fuzzy set theory could be used to propagate imprecision and probability theory could be applied in propagating variability. In 2006, Baudrit et al. proposed a pioneering hybrid study based on the evidence theory to combine the propagation process of aleatory uncertainty represented by probabilistic random variables and epistemic uncertainty represented by fuzzy numbers. Similarly, Baraldi and Zio (2008) presented an approach applying a combined Monte Carlo and possibilistic approach to propagate parameter uncertainty in event tree analysis. The frequencies of various scenarios (outputs of the uncertainty propagation procedure) are considered as a set of fuzzy numbers in the above-mentioned approaches. However, as mentioned by Baudrit et al. (2006), the hybrid propagation scheme presented in their paper does not so much account for dependence among probabilistic parameters or possibilistic variables. The similar assumption of independence is also made by Baraldi and Zio (2008). In addition, the above-mentioned models aim to address the uncertainty in event tree analysis, which is only one component to estimate frequency in a QRA model. In reality, parameter uncertainty is involved in not only event tree analysis but also consequence estimation models, which is the other component of calculating the consequences of scenarios in a QRA model. Therefore, both the frequency and number of fatalities (consequence) of a scenario should be considered as a set of fuzzy numbers based on the approach. Accordingly, the IR (combination of frequencies and consequences) generated by a QRA model with parameter uncertainty may no longer be a crisp number and the SR calculated by the model could not be represented by a single F/N curve. Consequently, new approaches should be proposed to estimate the IR and SR in order to support tunnel risk evaluators.

On the basis of the QRAM-I, this chapter proposes a further study on developing a QRA model for fire in a road tunnel section which takes into consideration the two types of uncertainty. In this model, all the input parameters are categorized into three types: constants, parameters with aleatory uncertainty, and parameters with epistemic uncertainty. The two types of uncertainty are formulated by probability distribution functions and fuzzy numbers. Accordingly, a Monte Carlo based estimation approach is applied to propagate parameter uncertainty in QRA models including not only event tree analysis but also consequence estimation models. The dependencies or interrelations among parameters with epistemic uncertainty are taken into account by using optimization models based on extension principle of fuzzy set theory. Based on definitions of individual risk and societal risk, percentile-based individual risks and α-cut-based societal risks are proposed and the risk indices provide a whole picture of risks to assess the safety level of a road tunnel.

The contributions of this chapter are summarized as follows. Firstly, a QRA model for a road tunnel section with parameter uncertainty (QRAM-II) is proposed and a hybrid Monte Carlo simulation based estimation procedure is applied to calculate the frequencies and consequences of various scenarios. Second, interrelations among parameters with epistemic uncertainty are taken into consideration in the proposed estimation procedure. Thirdly, different from the previous studies, uncertainty propagation for not only event tree analysis but also consequences estimation model are addressed in this study. Fourthly, percentile-based individual risks and α-cut-based societal risks are initially proposed to support decision makers with distinct risk attitudes. Lastly, a case study utilizing actual data collected from Singapore KPE road tunnel is carried out to compare the results generated by the previous QRAM-I model and the proposed QRA model for demonstrating the necessity of the uncertainty propagation procedure.

The remainder of the chapter is organized as follows. In Section 2, a QRA model for a road tunnel section with parameter uncertainty is proposed. Section 3 presented a Monte Carlo simulation based approach to estimate the frequencies and consequences of various accidental scenarios. In Section 4, the percentile-based individual risks and α-cut-based societal risks are defined and the application of this model to Singapore KPE road tunnel is carried out in Section 5. Conclusions are discussed in the last section.

6.2 QRA Model for A Road Tunnel Section with Parameter Uncertainty

6.2.1 Parameters with Aleatory and Epistemic Uncertainty

Ferson and Ginzburg (1996) recognized two basic types of uncertainty that were considered as fundamentally different from each other: aleatory uncertainty and epistemic uncertainty. The former arises from variability or randomness due to inherent stochasticy or heterogeneity. The latter refers to imprecision due to lack of knowledge or information on the system. In the previous QRA models for road tunnels, both types of uncertainty are formulated by crisp values (PIARC, 2008; Meng et al., 2009). Some researchers began to formulate the aleatory and epistemic uncertainty by means of probability distribution functions (Labaieniec et al., 1997; Meng et al., 2010). In reality, probabilistic representation of aleatory uncertainty is appropriate because sufficiently informative data are usually available for aleatory uncertainty with inherent stochasticy (Baraldi and Zio, 2008; Huang et al., 2001). However, it may not be appropriate to formulate to formulate epistemic uncertainty by using the same representation because sufficiently informative data are often not available for statistical analysis to derive a probability distribution function. Indeed, an expert may not have sufficiently refined knowledge to characterize the uncertainty in terms of probability distributions. The epistemic uncertainty may be more adequately captured by fuzzy numbers based on possibility theory (Huang et al., 2001; Baudrit et al., 2006)[4].

[4] According to the review paper by Möller and Beer (2008), subjective uncertainty (or epistemic uncertainty used by some other researchers) could be represented by interval, fuzzy numbers, rough sets, etc. However, a limitation of the interval modelling is its binary treatment of information – an element either belongs to or not belongs to the interval. By contrast, fuzzy set theory is a direct generalization and enhancement of the interval method: the intervals could be assessed or weighted with the aid of different types of membership functions. Thus fuzzy numbers are more appropriate in this study.

Input parameters which have relatively less uncertainty are considered as constants in a QRA model for fire in road tunnels. These parameters are represented by crisp numbers in this study. Peak hour fraction, normal period fraction, night period fraction, various vehicles composition, distance between two consecutive exits, tunnel user profiles, average lengths of various vehicles, vehicle driver profiles, total length of the tunnel, and air velocities are identified as constants in the proposed model. The input parameters and their notations are illustrated in Table 6-1.

Table 6-1: Input parameters (constant).

Input Parameters	Notation	Input Parameters	Notation
Fraction of Peak Hour	u_1	Average Length-Motorcycle	u_{14}
Fraction of Normal Period	u_2	Average Length-HGV	u_{15}
Fraction of Night Period	u_3	Average Length-Hazmat	u_{16}
Car Proportion	u_4	Average Persons Per Bus	u_{17}
Bus Proportion	u_5	Average Persons Per Car	u_{18}
Heavy Goods Vehicle Proportion	u_6	Average Persons Per Motorcycle	u_{19}
Hazardous Materials Vehicle Proportion	u_7	Average Persons Per HGV	u_{20}
Motorcycle Proportion	u_8	Average Persons Per Hazmat	u_{21}
Distance Between Two Consecutive Exits	u_9	Fraction of Experienced Driver	u_{22}
Proportion of the Elderly	u_{10}	Fraction of Inexperienced	u_{23}

Tunnel Users		Driver	
Proportion of the Young Tunnel Users	u_{11}	Air Velocity (Tunnel Ventilation Success)	u_{24}
Average Length-Bus	u_{12}	Air Velocity (Tunnel Ventilation Failure)	u_{25}
Average Length-Car	u_{13}	Length of the tunnel section	u_{26}

There are enough daily traffic data collected by Operation Control Center of road tunnels. Therefore, it is more appropriate to use random variables to formulate the uncertainty of traffic volume. Based on the collected data, the distribution types and parameters can be derived by using statistical methods. The HFD events could be formulated by lognormal probability distributions and sufficient experimental data are available to derive probability distributions of these events (Huang et al., 2001; Baraldi and Zio, 2008). Therefore, the traffic volume and tunnel safety provisions failure rate are represented by random variables in this study, which are shown in Table 6-2. The likelihoods of tunnel safety provisions success can be calculated accordingly.

Table 6-2: Input parameters with aleatory uncertainty.

Input Parameters	Notation
Traffic Volume in Peak Hour	x_1
Traffic Volume in Normal Period	x_2
Traffic Volume of Night Period	x_3

Probability of Tunnel Ventilation System Failure	x_4
Probability of Tunnel Detection System Failure	x_5
Probability of Tunnel Communication System Failure	x_6

The frequency of fire in road tunnels, the reaction time of drivers, and delay time of the systems should be estimated by expert judgments due to limited information. The fuzzy input parameters are illustrated in Table 6-3. Note that the fuzzy input parameters could be calibrated by using fault tree technique (most probable value) and expert judgment (lower and upper bounds).

Table 6-3: Input parameters with epistemic uncertainty.

Input Parameters	Notation
Frequency of Fire in Tunnel	y_1
Reaction Time of the Inexperienced Driver	y_2
Reaction Time of the Experienced Driver	y_3
Delay Time when Fire Communication System Failing to work	y_4
Delay Time if Tunnel Communication System Working Normally	y_5
Delay Time when Fire Detection System Failing to Work	y_6
Delay Time when Fire Detection System Working Normally	y_7

Consequently, the outputs of the proposed model are determined by a number of constants, random variables, and fuzzy numbers. If the distributions of the random variables and the membership functions of the fuzzy numbers are available, it is possible to calculate the results (consequences and frequencies of various scenarios of the event tree) by using probability theory and fuzzy arithmetic principle. However, due to the complexity of the QRA model, it is straightforward that the problem does not have a closed form. Therefore, a Monte Carlo based approach is proposed to estimate the frequency and number of fatalities of each scenario (See Chapter 6.3).

6.2.2 The Dependencies between Uncertain Parameters

The dependency among parameters with aleatory uncertainty (random variables) can be conveniently accounted for with the Monte Carlo technique in this study. However, the dependency or interrelations among parameters with epistemic uncertainty is not easy to deal with. To date, there is no approach to deal with the relationships or dependencies in the QRA framework (Meng et al., 2009; PIARC, 2008; Baudrit et al., 2006; Baraldi and Zio, 2008). However, dependencies or relationships among fuzzy numbers should not be neglected in risk assessment for road tunnels.

The membership functions of fuzzy input parameters are based on expert judgments. However, the judgments from various experts may not be consistent and this may result in irrational or contradictory results. For example, the membership functions with respect to the delay times with different working conditions in Singapore KPE road tunnel are shown in Figure 6-1. From the figure, we can see the two membership functions have overlaps. In reality, it is improbable that the delay time with tunnel E&M systems failure is less than that with success conditions of the systems. Similarly, the average reaction time of experienced drivers should be less than that of inexperienced drivers. In this regard, interrelations among the fuzzy numbers may significantly influence the rationality of the results. Therefore, the interrelations have to be taken into account in the estimation procedure.

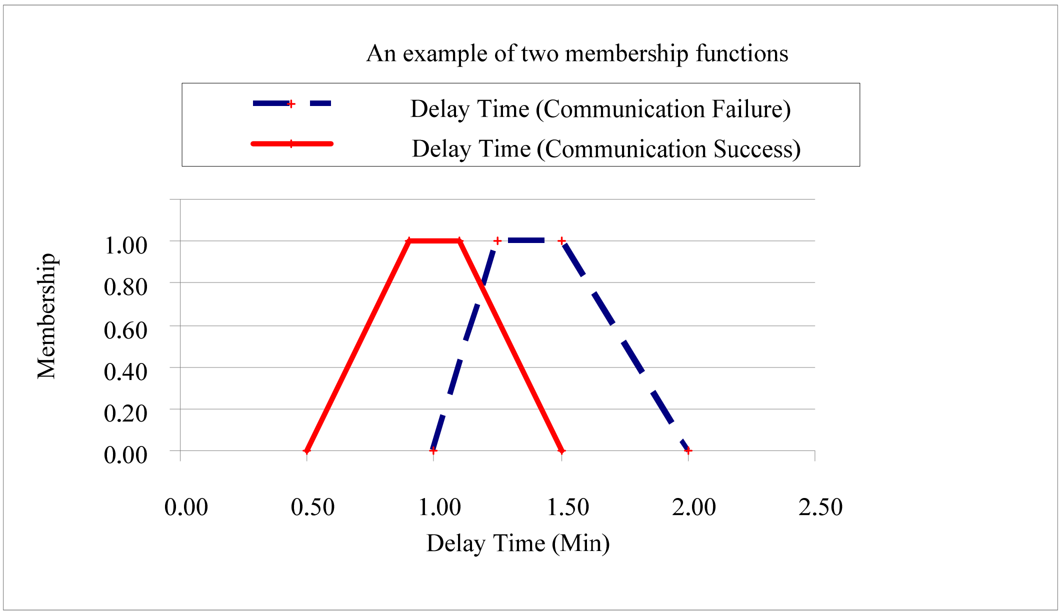


Figure 6-1: An example of two membership functions.

6.3 A Monte Carlo Simulation Based Estimation Approach

In this section, a Monte Carlo simulation based approach is proposed to estimate the frequencies and numbers of fatalities of various accidental scenarios (leaf nodes of the event tree) in a QRA model. The interrelations among input parameters with epistemic uncertainty are also addressed in the simulation process.

6.3.1 Propagation Procedure

The uncertainty propagation process involves two main steps. It combines a Monte Carlo technique (random sampling) with the extension principle of fuzzy set theory. Let us consider a model which output, consequence or frequency of a particular scenario, is a function of $f\left(u_1, u_2, \cdots, u_I, x_1, x_2, \cdots, x_J, y_1, y_2, \cdots, y_K\right)$. The first I input parameters are considered as constants $\left(u_1, u_1, \cdots, u_I\right)$, the following J parameters are characterized as parameters with aleatory uncertainty which are represented by random variables $\left(X_1, X_2, \cdots, X_J\right)$, and the last K parameters are considered as parameters with epistemic uncertainty represented by fuzzy numbers $\left(Y_1, Y_2, \cdots, Y_K\right)$. The hybrid uncertainty propagation procedure is summarized as follows:

Step 0: Initialize the values for deterministic parameters $\left(u_1, u_2, \cdots, u_I\right)$;

Step 1: Generate the rth realization of J random numbers $(x_1^r, x_2^r, \cdots, x_J^r)$ from the multivariate probability distribution $\left(X_1, X_2, \cdots, X_J\right)$ taking into account dependencies (if known);

Step 2: Select a possibility value $\alpha \in (0:\sigma:1]$ (σ is the step size, e.g. 0.05) and the corresponding α cuts $\left(\underline{y_1^{r\alpha}}, \overline{y_1^{r\alpha}}\right), \left(\underline{y_2^{r\alpha}}, \overline{y_2^{r\alpha}}\right), \cdots, \left(\underline{y_K^{r\alpha}}, \overline{y_K^{r\alpha}}\right)$ of fuzzy numbers $Y_1, Y_2, \cdots, Y_K$;

Step 3: Interval calculation: calculate the *Inf* (or minimum) and *Sup* (or maximum) values of $f\left(u_1, u_2, \cdots, u_I, x_1^r, x_2^r, \cdots, x_J^r, y_1^{r\alpha}, y_2^{r\alpha}, \cdots, y_K^{r\alpha}\right)$, considering all values located within the α-cut interval for each fuzzy number taking into account the mate-dependency between fuzzy numbers (see Section 3.2);

Step 4: Assign these *Inf* and *Sup* values ($\underline{f^{r\alpha}}$ and $\overline{f^{r\alpha}}$) to the lower and upper bounds of the α -cut of the fuzzy output f^r (fuzzy output with respect to the *r*th realization);

Step 5: Return to step 2 and repeat steps 3 and 4 for another α -cut. The fuzzy output $f\left(u_1, u_2, \cdots, u_I, x_1^r, x_2^r, \cdots, x_J^r, y_1^{r\alpha}, y_2^{r\alpha}, \cdots, y_K^{r\alpha}\right)$ can be obtained from the *Inf* and *Sup* values of various α -cuts. Thus the membership function of fuzzy output f^r can be derived accordingly;

Step 6: Return to step 1 to generate a new realization of the random variables. A family of fuzzy outputs $\left(f^1, f^2, \cdots, f^M\right)$ is obtained, where M is the number of realizations for random vector $\left(X_1, X_2, \cdots, X_J\right)$.

Step 7: Calculate possibility measures $\left(\Pi_{f^1}, \Pi_{f^2}, \cdots, \Pi_{f^M}\right)$ and necessity measures $\left(N_{f^1}, N_{f^2}, \cdots, N_{f^M}\right)$ for various fuzzy numbers $f^1, f^2, \cdots,$ and f^M.

Step 8: Combine these *M* possibility and necessity measures to obtain the believe *Bel* and the plausibility *Pl* for $f\left(u_1, u_2, \cdots, u_I, x_1, x_2, \cdots, x_J, y_1, y_2, \cdots, y_K\right)$ according to the following eqns. (6.1) and (6.2).

$$Bel = \sum_m \frac{1}{M} N_{f^m} \tag{6.1}$$

$$Pl = \sum_m \frac{1}{M} \Pi_{f^m} \tag{6.2}$$

6.3.2 The Dependency between Parameters with Epistemic uncertainty

As mentioned above, the dependency among parameters with epistemic uncertainty should not be neglected. In this sub-section, an approach based on extension principle is proposed.

Let us consider a QRA model $f\left(u_1,u_2,\cdots,u_I,x_1^r,x_2^r,\cdots,x_J^r,Y_1,Y_2,\cdots,Y_K\right)$, where $u_1,u_2,\cdots,u_I$ are crisp numbers, $x_1^r,x_2^r,\cdots,x_J^r$ are the *r*th realization of random vector $\left(X_1,X_2,\cdots,X_J\right)$, and $Y_1,Y_2,\cdots,Y_K$ are fuzzy numbers with some types of interdependencies. In the present study, two types of dependencies are discussed in view of the actual condition of risk assessment for road tunnels: equation relationship and inequality relationship, e.g. one parameter is consistently greater than another one. As mentioned in last section, we use interval calculation (Step 3) to estimate the membership function of fuzzy number f^r. Assume that the α -cut intervals for $Y_1,Y_2,\cdots,Y_K$ are intervals $\left(\underline{y_1^\alpha},\overline{y_1^\alpha}\right),\left(\underline{y_2^\alpha},\overline{y_2^\alpha}\right),\cdots,\left(\underline{y_K^\alpha},\overline{y_K^\alpha}\right)$, respectively. Based on the definition of extension principle of fuzzy arithmetic, the *Inf* and *Sup* values of $f\left(u_1,u_2,\cdots,u_I,x_1^r,x_2^r,\cdots,x_J^r,Y_1,Y_2,\cdots,Y_K\right)$ are considered as the lower bound and upper bound of the α -cut of f^r. After obtaining all α -cuts ($\alpha\in(0,1]$) of f^r, the membership function of f^r can be estimated. Hence, the critical procedure of the membership function estimation is to derive the *Inf* and *Sup* values of the fuzzy output in the feasible intervals (α -cuts intervals) subjected to the interrelationships between variables. Based on the analysis above, an optimization model is developed to calculate the α -cuts of f^r, namely, the *Inf* and *Sup* values of f^r.

The model can be formulated as follows:

$$\min(or\ \max)\ f = f\left(u_1, u_2, \cdots, u_I, x_1^r, x_2^r, \cdots, x_J^r, y_1^\alpha, y_2^\alpha, \cdots, y_K^\alpha\right) \tag{6.3}$$

subject to:

$$g\left(y_1^\alpha, y_2^\alpha, \cdots, y_K^\alpha\right) \ge 0 \tag{6.4}$$

$$h\left(y_1^\alpha, y_2^\alpha, \cdots, y_K^\alpha\right) = 0 \tag{6.5}$$

$$\underline{y_k^\alpha} \le y_k^\alpha \le \overline{y_k^\alpha}, \forall k \in 1, \cdots, K \tag{6.6}$$

The minimum and maximum values of the objective function are considered as the lower and upper bounds of the α -cut for the fuzzy number f^r .

6.4 Risk Indices

Individual risk and societal risk are well recognized risk indices for risk assessment of road tunnels. According to the previous definitions, the risk indices are combinations of frequencies and consequences of various scenarios. However, the frequency and consequence derived by the proposed model are fuzzy numbers rather than crisp numbers. Therefore, new methods to calculate IR and SR are proposed in this section.

6.4.1 Individual Risk

According to the individual risk defined in eqn. (4.1), n_k , L_k , Q_{ki} , and λ_i are crisp numbers and F_{jk} and x_{jk} are sets of fuzzy numbers. Therefore, an IR should be a set of fuzzy numbers based on the fuzzy arithmetic and extension principle since that it is a function of fuzzy input parameters F_{jk} and x_{jk} . The plausibility and belief curve could be drawn accordingly. The plausibility and belief curves are considered as the upper and lower bound of the IR, respectively. The index will be further discussed in Chapter 6.5.1.

6.4.2 Societal Risk

As introduced earlier, the societal risk (F/N curve) reflects the relationship between the frequencies and the number of fatalities of all these possible scenarios on a double logarithmic scale. $F(N)$ represents the cumulative frequencies of all the scenarios with N or more fatalities, mathematically:

$$F(N)=\sum_{i=1}^{n}\left[F_i \times \delta(x_i, N)\right] \tag{6.7}$$

where F_i is the yearly frequency that scenario i occurs; x_i is the number of fatalities caused by scenario i; indicator function $\delta(x_i, N)$ is defined by

$$\delta(x_i, N)=\begin{cases}1, & \text{if } x_i \geq N \\ 0, & \text{otherwise}\end{cases} \tag{6.8}$$

However, eqns. (6.7) and (6.8) are inapplicable since the frequency and the number of fatalities (consequence) are both considered as fuzzy numbers in this approach. In order to visualize the societal risk in an F-N axis to be better understood by the decision makers, let $F_k(N)$ denote the cumulative frequencies of all the accident scenarios occurred at tunnel section k with N or more fatalities, where a scenario with N or more fatalities is defined as the scenario when the core, namely, 1.0 cut of fuzzy number (the number of fatalities of scenario i) x_i lies completely by the right of crisp number N. We thus have:

$$F(N)=\sum_{i=1}^{n}\left[F_i \times \delta(x_i, N)\right] \tag{6.9}$$

where F_i is the yearly fuzzy frequency that scenario i occurs; x_i is the fuzzy number of fatalities caused by scenario i; indicator function $\delta(x_i, N)$ is defined by

$$\delta(x_i, N)=\begin{cases} 1, \text{ the core of } x_i \text{ lies completely by the right of } N \\ 0, \text{ otherwise} \end{cases} \tag{6.10}$$

Then N is a crisp number and F is the weighted summation of corresponding fuzzy numbers F_i $(i \in [1,n])$. Accordingly, a fuzzy F/N curve can be expressed in two-dimension axis as shown in Figure 6-2. However, this expression is not straightforward for tunnel managers or decision makers to use. Eventually, two alternative measures are proposed to derive the *F/N* curve to better represent societal risk. The first one is to use cores of fuzzy numbers to represent F_i. The second method is to use α cuts of fuzzy numbers F_i to express the fuzzy number series. The risk indices will be further discussed in Section 6.5.

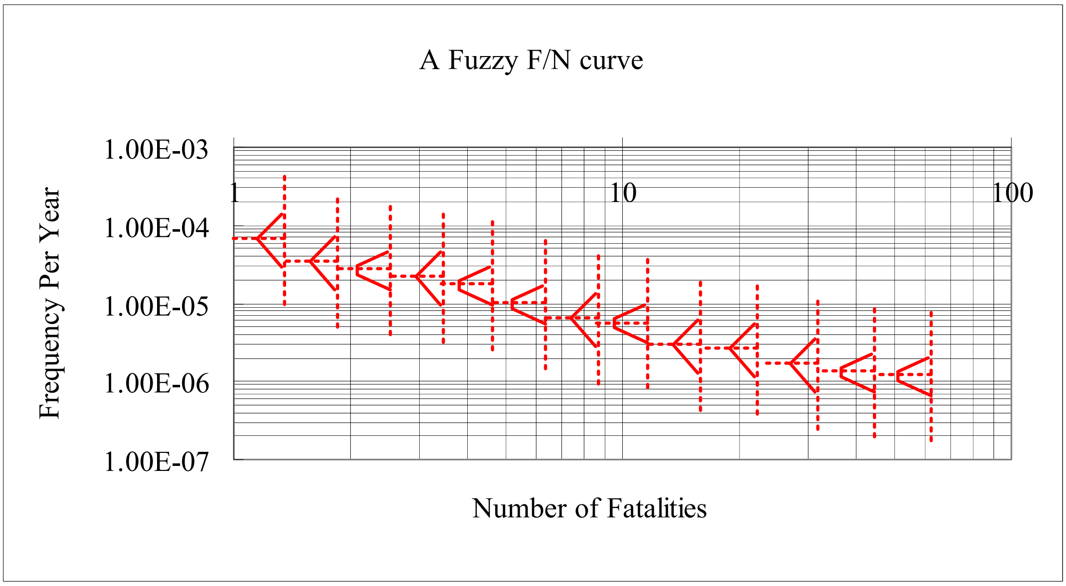


Figure 6-2: A fuzzy F/N curve.

6.5 A Numerical Study

In order to illustrate the proposed model, a numerical study is carried out to assess risks for one road tunnel section of KPE (shown in Figure 6-3). The section is an 1.8-long main tunnel section. The data for this study are provided by LTA of Singapore.

Figure 6-3: KPE road tunnel in Singapore.

6.5.1 Input Parameters

6.5.1.1 Input parameters (constant)

Table 6-4 shows the input parameters without uncertainty. Peak hour refers to the time intervals 7:00 am – 9:30 am and 5:00 pm – 8:00 pm and night period refers to the time interval 12:00 am – 6:00 am in Singapore. The vehicle proportions are obtained from the 24-hrs manned Operation Control Centre (OCC). Note that vehicles carrying hazardous materials are not allowed to pass through the KPE road tunnel. These parameters have relatively less uncertainty and are considered as constants which are represented by crisp numbers in this study.

Table 6-4: Input parameters for KPE road tunnel (constant).

Notation	Value	Notation	Value
u_1	0.23	u_{14}	2m
u_2	0.52	u_{15}	20m
u_3	0.25	u_{16}	20m
u_4	0.644	u_{17}	30
u_5	0.021	u_{18}	2
u_6	0.164	u_{19}	1.2
u_7	0	u_{20}	1
u_8	0.171	u_{21}	1
u_9	100m	u_{22}	0.98
u_{10}	0.3	u_{23}	0.02

u_{11}	0.7	u_{24}	1.2 m/s
u_{12}	20m	u_{25}	4.5 m/s
u_{13}	3.5m	u_{26}	1.8 km

6.5.1.2 Input parameters with aleatory uncertainty

The distributions of input parameters with aleatory uncertainty are summarized as Table 6-5 and Table 6-6. Figure 6-4 depicts the probability distributions of traffic volumes and the probabilities of tunnel safety provisions failure. This study assumes that there is no interdependency among those parameters, which are reasonable in reality. Note that we assume the fire fighting system is always available to work.

Table 6-5: Traffic volumes of KPE road tunnel and their distributions.

Input Parameters	Notation	Distribution	Sample Mean	Sample Variance
Traffic Volume in Peak Hour	x_1	Poisson	1412	1685
Traffic Volume in Normal Period	x_2	Poisson	707	852
Traffic Volume of Night Period	x_3	Poisson	195	201

Table 6-6: Tunnel safety provisions failure probability distributions.

Input Parameters	Notation	Distribution	Assumed Location	Assumed Scale

Prob. of Tunnel Ventilation System Failure	x_4	Lognormal	-8	1
Prob. of Fire Detection System Failure	x_5	Lognormal	-7.5	1
Prob. of Tunnel Communication System Failure	x_6	Lognormal	-8	0.5

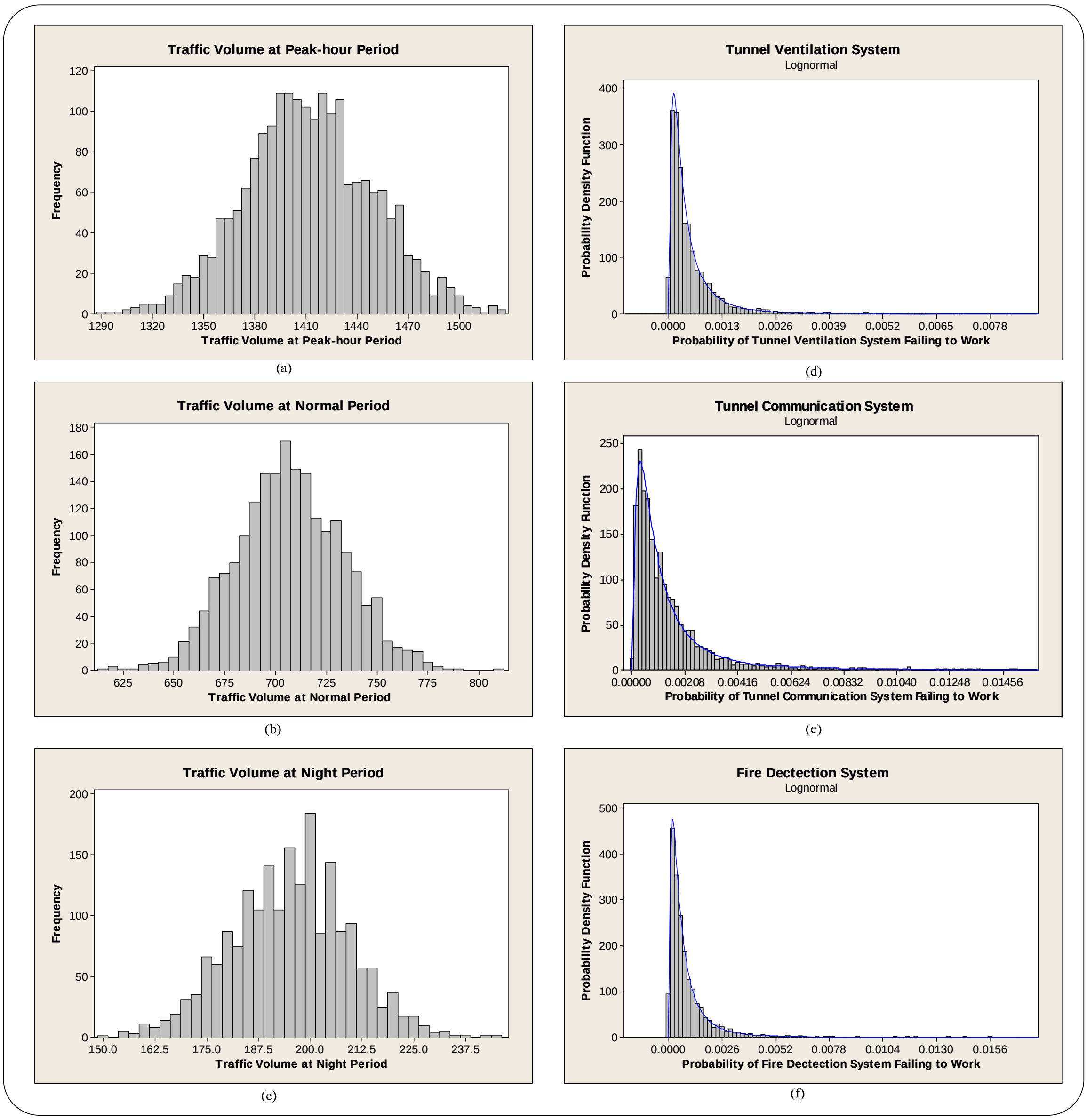


Figure 6-4: Probability distributions of input parameters with objective uncertainty

6.5.1.3 Input parameters with epistemic uncertainty

Table 6-7 shows the input parameters with epistemic uncertainty and their membership functions. The membership functions are obtained in a simple way as follows. We requested 9 LTA tunnel risk evaluators to indicate two ranges for a parameter with epistemic uncertainty (the possible range $\left(\underline{L},\overline{U}\right)$ and most probable range $\left(\overline{L},\underline{U}\right)$) according to their expert judgment. Then 9 triangular or trapezoidal membership functions could be derived for the parameter. Accordingly, crisp weighting approach proposed by Bardossy et al. (1993) has been applied to combine the fuzzy numbers representing expert opinions[5].

Table 6-7: Input parameters with epistemic uncertainty for KPE road tunnel.

Input Parameters	Notation	Membership Function
Frequency of Fire in Tunnel	y_1	Triangular (0.05, 0.21, 0.5)
Reaction Time of the Inexperienced Driver	y_2	Triangular (1.8, 2.5, 3)
Reaction Time of the Experienced Driver	y_3	Triangular (1, 1.5, 2)
Delay Time when Fire Communication System Failing to work	y_4	Trapezoidal (1, 1.25, 1.5, 2)
Delay Time if Tunnel Communication System Working Normally	y_5	Trapezoidal (0.5, 0.9, 1.1, 1.5)
Delay Time when Fire Detection System Failing to Work	y_6	Triangular (2, 3, 4)

[5] There are three interpretations in literature for member functions (Beer, 2009; Möller and Beer, 2008; Dubois and Prade, 1997): degree of similarity (similarity with weight), degree of preference, and degree of possibility. In this study, we adopted the first interpretation.

Delay Time when Fire Detection System Working Normally	y_7	Triangular (1, 1.5, 2)

As can be seen from these membership functions, there are overlaps between reaction time, delay time, and air velocities with respect to different working conditions of various tunnel safety provisions. This is because the imprecise information due to lack of information. The interrelations among the fuzzy numbers are formulated as eqns. (6.12)-(6.14). These interrelations are considered as constraints when calculating the upper and lower bounds of α -cuts for fuzzy numbers (See Chapter 6.3.2).

$$y_2 \geq y_3 \tag{6.11}$$

$$y_4 \geq y_5 \tag{6.12}$$

$$y_6 \geq y_7 \tag{6.13}$$

6.5.2 Uncertainty Propagation

The estimation approach described in Section 4 has been applied for the uncertainty propagation in the risk assessment of KPE road tunnels. With respect to the input parameters with aleatory uncertainty $\left(x_1, x_2, \cdots, x_9\right)$, based on an empirical trial-and-error test, the sampling realization size is determined to be 1000.

6.5.2.1 Individual risk

Figure 6-5 depicts a set of fuzzy individual risks with respect to various realizations. For each realization, the individual risk is a fuzzy number. The proposed QRA model utilizes the evidence theory to integrate these fuzzy individual risks for all the realizations which is shown in Figure 6-6. The separation between plausibility and belief measure is caused by the fuzzy input parameters with epistemic uncertainty. In reality, if the sufficient data with respect to the fuzzy parameters are available, the individual risk should be represented by a single probability cumulative distribution function, namely, the belief measure and plausibility measure should converge to the probability curve. However, due to limited information of those parameters, it is not possible to obtain the probability distribution of the individual risk. The plausibility measure gathers the imprecise evidence that asserts the judgment and it is the minimal amount of probability that supports the judgment. On the contrary, the belief function provides the maximal amount of probability that supports the judgment. Hence, the actual probability curve of individual risk should lie in between the plausibility measure curve and belief measure curve. Accordingly, the upper bound and lower bound of percentile-based individual risk can be shown in Figure 6-6. For example, the 80% percentile individual risk is between 1.6236×10^{-8} and 6.1787×10^{-8}. Hence, different from individual risk generated by previous QRA models, not a crisp individual risk value but the lower and upper bounds of all the percentile-based individual risk can be derived from the proposed model. The percentile-based individual risk is thus more useful than a crisp most probable individual risk value for decision makers.

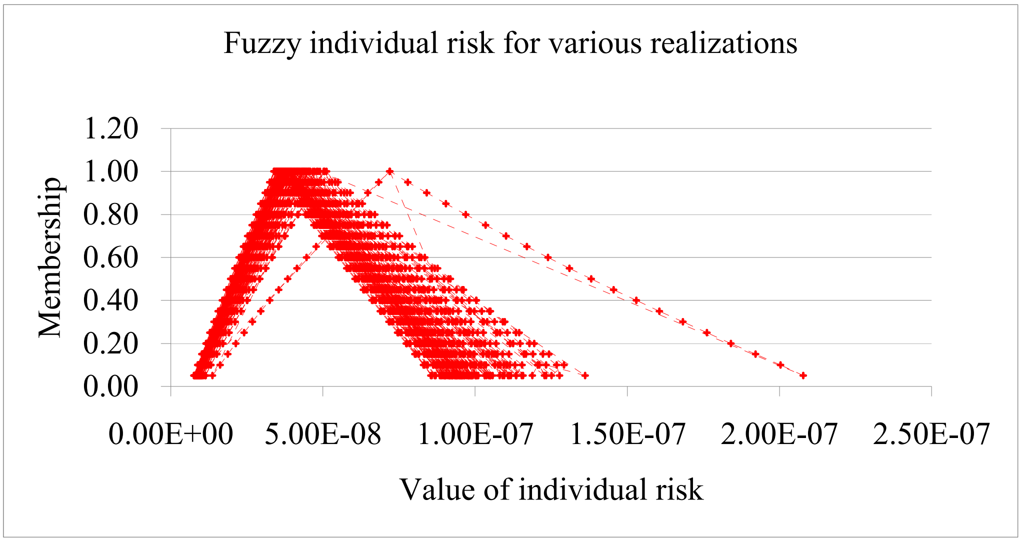


Figure 6-5: Fuzzy individual risk for various realizations.

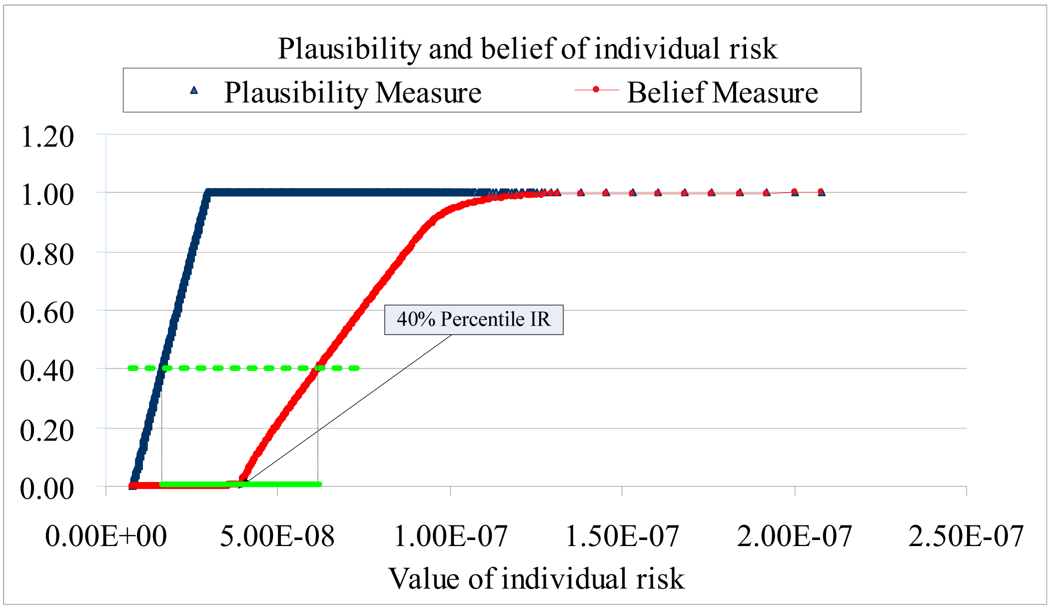


Figure 6-6: Plausibility and belief measures of individual risk.

6.5.2.1 Societal risk

Societal risk refers to the relationship between frequency and number of fatalities of various scenarios. According to eqns. (10) and (11), the core value (1.0

cut) based F/N curve and 0.90 cut based F/N curve are depicted in Figure 6-7 and Figure 6-8. Similarly, fuzzy F/N curves based on other cuts can also be plotted.

As can be seen in Figure 6-8, the F/N curve based on core values have similar trend with F/N curve derived from the previous QRAFT model with crisp input parameters. However, the former has more high-consequence-events (more than 10 fatalities) circled by Ellipse *A* in Figure 6-7. This is because the Monte Carlo sampling procedure generates some high-consequence scenarios with extremely low frequencies (less than 10^{-10} time per year). It seems that the F/N curve generated by QRAFT model is consistently lower than the F/N curve based on core values for those scenarios with less than 10 fatalities from the figure. Consequently, we may draw the conclusion that the previous evaluation is underestimated. As for the comparison between 0.9 cut based F/N curve and F/N generated by QRAM-I, the latter is generally in between the upper bound and lower bound of the former for those scenarios with less than 10 fatalities. The α-cut based F/N provides lower and upper bounds of the actual F/N curve with different levels of confidence. It thus provides more information to decision makers to support them to make decisions.

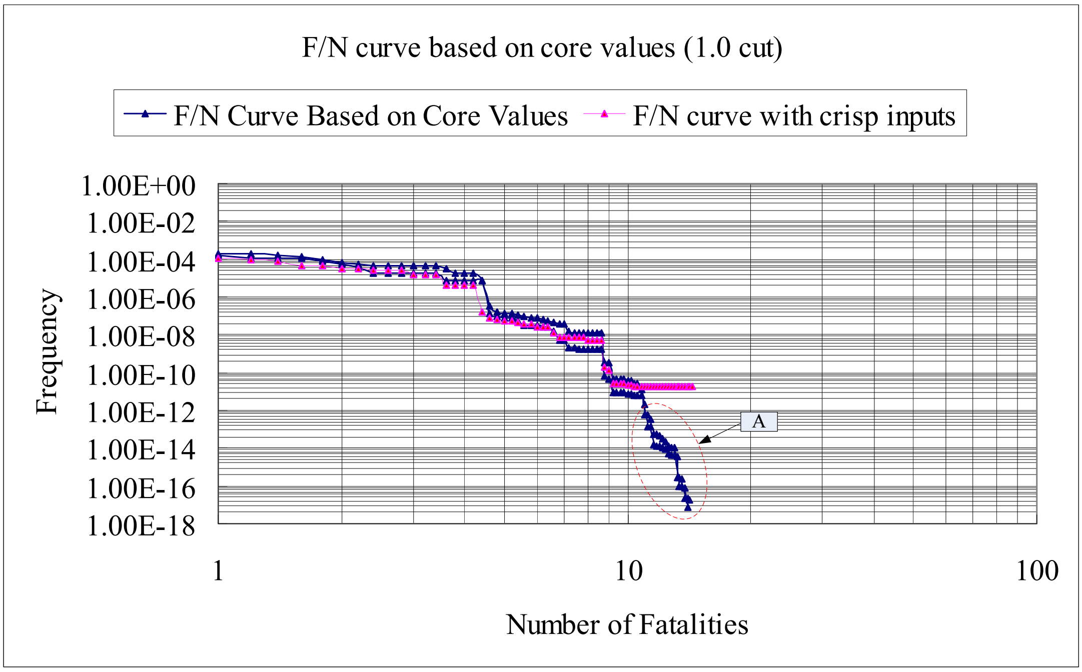


Figure 6-7: F/N curve based on core values (1.0 cut).

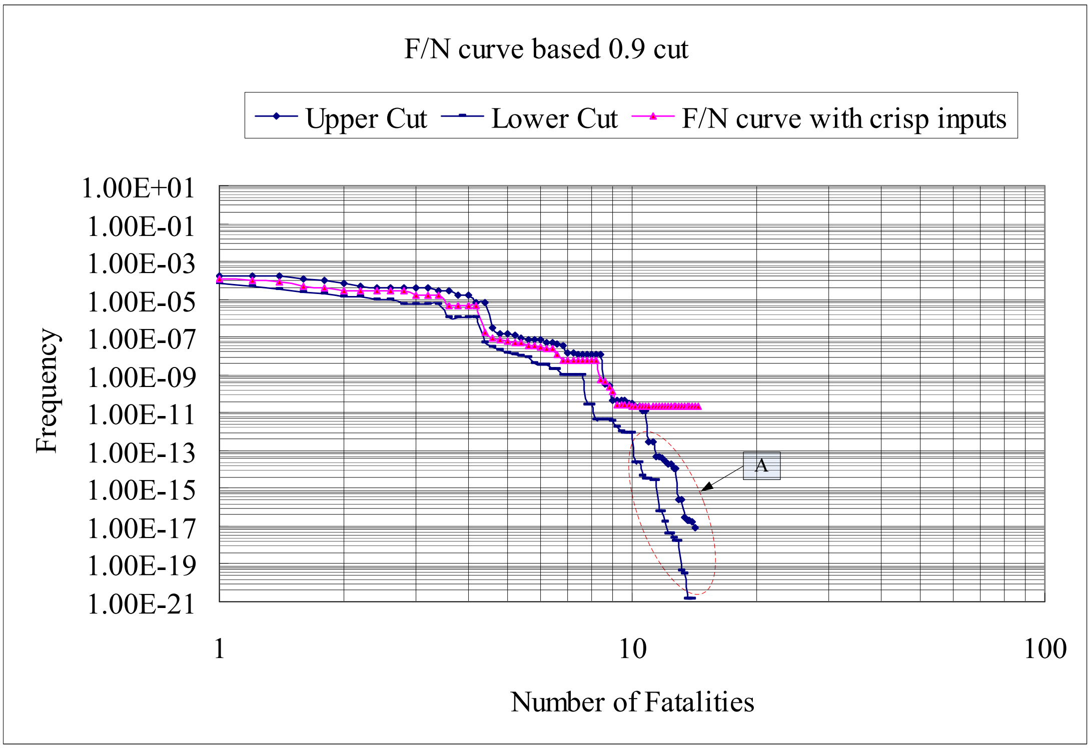


Figure 6-8: F/N curve based on 0.9 cut.

If the subjective uncertainty is neglected, that is, we use the core values to represent the fuzzy numbers; the percentile-based F/N curves can be derived. Figure 6-9 depicts the F/N curve with crisp inputs (crisp F/N curve in short), the 95% and 5% percentile-based F/N curves with objective uncertainty only (percentile based F/N curves in short), and lower and upper bound by taking into consideration two kinds of uncertainty (lower and upper cut in short). As can be seen from the Figure, the percentile-based F/N curves are in between the lower and upper cut and the crisp F/N curve are further in between the percentile-based F/N curves. The α-cut based F/N provides lower and upper bounds of the actual F/N curve with different levels of confidence. It thus provides more information to decision makers.

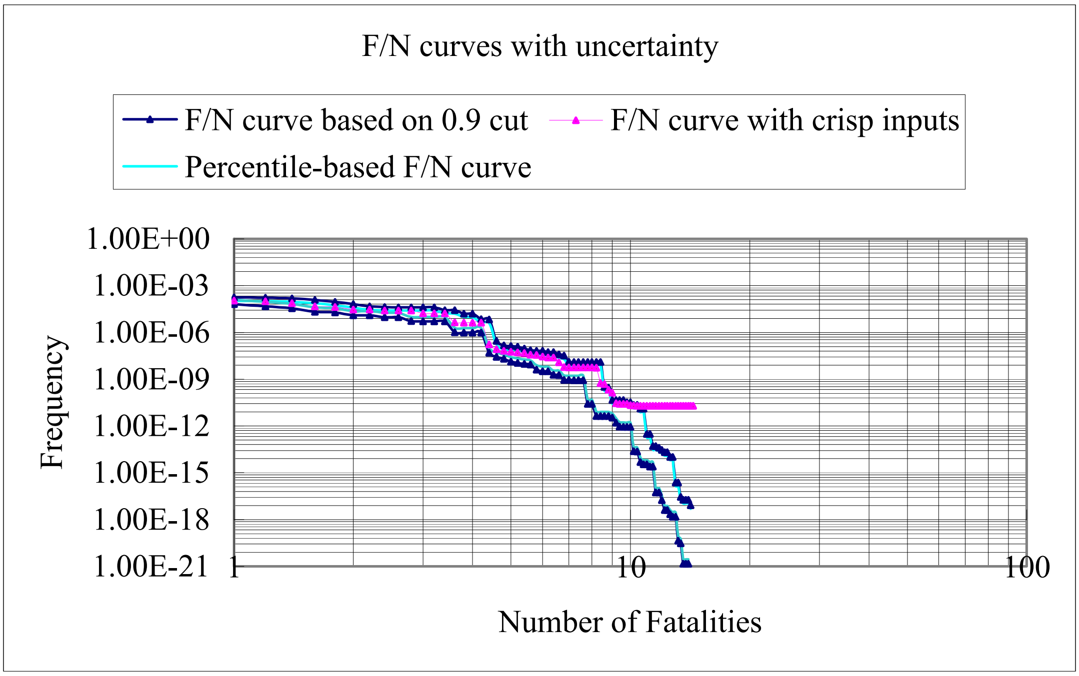


Figure 6-9: F/N curve based on 0.9 cut and percentile based F/N curve

6.6 Conclusions

In a QRA model for fire in road tunnels, a number of input parameters possess epistemic or aleatory uncertainty. It would be inappropriate to neglect the influence of parameter uncertainty, which may result in unreliable evaluation. This chapter presents a study on the representation and propagation of parameter uncertainty in a QRA model including event tree analysis as well as consequence estimation models. Aleatory uncertainty is formulated by probability distribution functions and parameters with epistemic uncertainty are represented by fuzzy numbers. It should be pointed out that the dependencies and relationships among variables are addressed by using Monte Carlo technique and extension principle of fuzzy set theory. A numerical study utilizing Singapore KPE tunnel data is carried out to compare the risk indices generated by the present study and the previous QRA model. Eventually, percentile-based individual risk and α-cut based F/N curve are considered as better indices for QRA models of road tunnels.

The QRAM-I focuses on providing overall risk indices to decision-makers and diagnosing the most risky tunnel sections. Indeed, the tunnel managers would prefer a simplistic number (individual risk) or a straightforward figure (societal risk) to get an idea of the risk level of a road tunnel. However, the tunnel operators may want to look into a particular tunnel section (they concerned) to obtain more information about the risks (e.g. lower and upper bounds, percentile based values, etc.) by taking into account the parameter uncertainty (QRAM-II). In fact, through the discussions with LTA engineers, they are more concerned of the uncertainty of several particular input parameters. In sum, QRAM-I provides straightforward risk indices for tunnel managers and QRAM-II depicts more information about the risks for tunnel operators with concerns of parameter uncertainty.

CHAPTER 7 OPTIMAL SELECTION OF TUNNEL SAFETY PROVISIONS

7.1 Introduction

In order to control the loss caused by a certain accident, tunnel safety provisions are required to be installed in urban road tunnels. These provisions include tunnel detection system, tunnel verification system, tunnel ventilation system, fire fighting system, etc. Every system has various types with different functional parameters. For example, there are two types of tunnel ventilation systems – transverse ventilation and longitudinal ventilation. The former is to protect the tunnel users by keeping the smoke stratified in a hot layer underneath the ceiling of the tunnel and extracting it at the ceiling, while the latter is to prevent backlayering (Beard, 2009; Beard and Carvel, 2005). In practice, the selection of tunnel safety provisions is on the basis of expert judgment by taking the risk assessment results into account. In reality, the tunnel safety provisions are designed at the planning stage. Once the tunnel is open to traffic, these parameters are considered to be un-adjustable - it would be difficult, if not impossible, to adjust these parameters to reduce the risks. Therefore, it is of great importance to assess the risks when selecting tunnel safety provisions at the planning stage by assuming possible traffic conditions.

7.2 Life Cycle Cost Analysis for Tunnel Safety Provisions

It is now a common practice to apply engineering economics principles in the evaluation of transportation projects, such as highways, bridges, pavements, etc (Fwa and Sinha, 1991). Life cycle cost analysis (LCCA) is considered as an effective assessment tool for analyzing the performance of complex systems (Mitropoulou, et al., 2011). It was introduced in the fields of infrastructures in early 1980s as an appraisal tool for the total cost of ownership over the lifespan of an asset (Arditi and Messiha, 1996; Asiedu and Gu, 1998).

The total costs with respect to tunnel safety provisions include purchase cost, maintenance cost, and operating cost. The purchase cost refers to the price at which one tunnel safety provision is actually purchased and implemented. The maintenance cost is the money used to upkeep the tunnel safety provision. The operating cost includes the electrical cost of the tunnel safety provision and the salaries of operators for the provision. The salvage cost is usually assumed to be zero in the analysis of tunnel safety provisions. The different types of tunnel safety provisions with distinct cost compositions and life spans could be evaluated in the LCCA framework.

Henceforth, the following notations apply.

V_p^i: the purchase cost of the tunnel ventilation system with type *i*;

V_m^i: the maintenance cost of the tunnel ventilation system with type *i*;

V_o^i: the operating cost (the electrical cost and salaries of operators) of the tunnel ventilation system with type *i*;

D_p^j: the purchase cost of the fire detection system with type *j*;

D_m^j: the maintenance cost of the fire detection system with type *j*;

D_o^j: the operating cost (the electrical cost and salaries of operators) of the fire detection system with type *j*;

F_p^k: the purchase cost of the fire verification system with type *k*;

F_m^k: the maintenance cost of the fire verification system with type *k*;

F_o^k : the operating cost (the electrical cost and salaries of operators) of the fire verification system with type *k*;

V^i : the annual worth of the tunnel ventilation system with type *i*;

D^j : the annual worth of the fire detection system with type *j*;

F^k : the annual worth of the fire verification system with type *k*;

n_v^i, n_d^j, and n_f^k : the study period for tunnel ventilation system with type *i*, fire detection system with type *j*, and fire verification system with type *k*, respectively;

The purchase costs and maintenance costs of various types of tunnel safety provisions are obtainable from the conceptual design of the tunnel project. The operating costs could be estimated by the experienced tunnel operators. By using LCCA, we can estimate the annual worth for each combination of candidate tunnel safety provisions.

7.3 QRA II Model Based Optimal Selection of Tunnel Safety Provisions

7.3.1 Model Formulation

As mentioned earlier, it would be difficult, if not impossible, to change or upgrade the tunnel safety provisions to reduce the risks as soon as a tunnel is open to traffic. Consequently, on the one hand, the tunnel risks in the life span of the tunnel should be managed to be within the safety targets; on the other hand, the decisions makers (e.g. LTA of Singapore) may want to minimize the total costs. In this chapter, a QRAM-II based optimal selection approach is proposed to support decision makers.

Sherali et al. (2008) proposed a risk reduction optimization (RRO) model to optimally allocate the available resources on the basis of a QRA model for gasline rupture situation related to an offshore oil and gas production platform. Their RRO model is to minimize risks (in terms of expected loss), subject to the budget and resources constraints. However, the formulation cannot be applied to the current study. Since the safety targets are compulsory by regulations to be fulfilled in road tunnel risk assessment, we should put the risks as the constraints rather than the object to be minimized.

Let *AW* denote the annual worth of the total costs of various types of tunnel safety provisions. We further define binary variables x^i, y^j, and z^k as follows.

$$x^i = \begin{cases} 1, \text{if the tunnel ventilation system with type } i \text{ is selected;} \\ 0, \text{otherwise} \end{cases} \tag{7.1}$$

$$y^j = \begin{cases} 1, \text{if the fire detection system with type } j \text{ is selected;} \\ 0, \text{otherwise} \end{cases} \tag{7.2}$$

$$z^k = \begin{cases} 1, \text{if the fire verification system with type } k \text{ is selected;} \\ 0, \text{otherwise} \end{cases} \tag{7.3}$$

Thus, we have the objective function as follows.

$$\min AW = \sum_{i=1}^{I} x^i V^i + \sum_{j=1}^{J} y^j D^j + \sum_{k=1}^{K} z^k F^k \tag{7.4}$$

Subject to:

$$\sum_{i=1}^{I} x^i \geq 1 \tag{7.5}$$

$$\sum_{j=1}^{J} y^j \geq 1 \tag{7.6}$$

$$\sum_{k=1}^{K} z^k \geq 1 \tag{7.7}$$

$$SR_\alpha\left(\vec{x}, \vec{y}, \vec{z}\right) \leq SR_{\text{criterion}} \tag{7.8}$$

$$IR_\beta\left(\vec{x}, \vec{y}, \vec{z}\right) \leq IR_{\text{criterion}} \tag{7.9}$$

$$EV_\beta\left(\vec{x}, \vec{y}, \vec{z}\right) \leq EV_{\text{criterion}} \tag{7.10}$$

$$x^i, y^j, \text{ and, } z^k = 0, 1. \tag{7.11}$$

In this formulation, the objective function (7.4) seeks to minimize the total costs; constraints (7.5) to (7.7) implies that tunnel ventilation systems, fire detection systems, and fire verification systems are compulsory components, i.e. at least one type should be chosen, for urban road tunnels in Singapore according to the Project Safety Review Manual for roads in Singapore; constraint (7.8) indicates that the α cut based societal risk should not beyond a predetermined safety target ($SR_{\text{criterion}}$); constraints (7.9) and (7.10) represent that the β percentile based individual risk and expected value of fatalities should be less than or equal to the corresponding predetermined safety targets ($IR_{\text{criterion}}$ and $EV_{\text{criterion}}$), respectively.

7.3.2 Algorithm

The optimization model formulated in Section 7.3.1 is a typical integer non-linear programming model. Thanks to the Constraints (7.5) to (7.7), there would be only limited number of feasible combinations of tunnel safety provisions. Theoretically, the numbers of solutions satisfying Constraint (7.5), Constraint (7.6), and Constraint (7.7) are $2^I - 1$, $2^J - 1$, and $2^K - 1$, respectively. If the numbers of candidate tunnel safety provisions raise up, the computational complexity of the optimization model would be dramatically increased. In practice, the experts from land transport authorities may only provide a few candidate tunnel safety provisions (usually $I \leq 3, J \leq 4,$ and $K \leq 4$). If the *I* is equal to 3, *J* and *K* are both equal to 4, the number of solutions satisfying Constraints (7.5) to (7.7) is 1575. Under such circumstance, it would be very time-consuming (although it is possible) to enumerate all solutions satisfying Constraints (7.5) to (7.7) and check whether or not they fulfil the safety targets (Constraints (7.8) to (7.10)).

Based on the QRAM-II, addition of a new tunnel safety provisions will at least not increase (most probably reduce) the tunnel risks, i.e. any additional investments on tunnel safety provisions will not increase the tunnel risks. For example, assume we have a solution (Solution 1), represented by

$$\vec{x} = (1,0,0), I = 3 \tag{7.12}$$

$$\vec{y} = (0,1,1,0), J = 4 \tag{7.13}$$

$$\vec{z} = (0,0,0,1), K = 4 \tag{7.14}$$

The solution suggests that the type 1 of ventilation system, types 2 and 3 of fire detection system, and type 4 of fire verification system are implemented in the road tunnel. Evidently, if the solution satisfies Constraints (7.8) to (7.10), additions of any other tunnel safety provisions (e.g. $\vec{x} = (1,1,0), \vec{y} = (0,1,1,0), \vec{z} = (0,0,0,1)$) will definitely be within the safety targets. On the contrary, if the solution does not satisfy the Constraints (7.8) to (7.10), any combinations with deductions of any tunnel safety provisions (e.g. $\vec{x}=(1,0,0)$, $\vec{y}=(0,0,1,0)$, $\vec{z}=(0,0,0,1)$) will also be unacceptable according to the safety target. Therefore, two domination rules are illustrated as follows.

Rule 1: if a combination of candidate tunnel safety provisions does not satisfy Constraints (7.8) to (7.10), all the other combinations with deductions of tunnel safety provisions will also not be acceptable according to the safety targets.

Rule 2: if a combination of candidate tunnel safety provisions fulfils Constraints (7.8) to (7.10), all the other combinations with higher AW value (objective function eqn. (7.4)) are not the optimal solution.

By taking advantage of the special structure of the problem, we design a Bi-Section Search and Bound Algorithm (BSSBA) to solve the problem. The BSSBA is presented as follows.

Step 0: calculate the AW values (the objective function (7.4)) for all the possible combinations satisfying Constraints (7.5) to (7.7);

Step 1: rank the combinations in terms of AW values: $AW^{(0)}, AW^{(1)}, \cdots, AW^{(N-1)}$, where N is the number of available combinations;

Step 2: check whether or not the combination with median AW value satisfies the Constraints (7.8) to (7.10): if yes, remove all the combinations with higher AW values (due to domination rule No. 2); otherwise, remove the combination itself and all the combinations with deductions of tunnel safety provisions (due to domination rule No. 1).

Step 3: re-rank the remainder combinations in terms of AW values and go to Step 2.

Step 4: stop when optimal solution is found.

7.4 A Numerical Study

In this section, we use a numerical study to illustrate the model and algorithm proposed in Section 7.3. We assume that there are two types of tunnel ventilation systems: longitudinal ventilation system and transverse ventilation system; three types of fire detection system: line-type heat-sensing cable, smoke detectors, the automatic incident detectors; and two types of fire verification system: Closed-Circuit Television (CCTV) and emergency telephones. The purchase costs, maintenance costs, and operating costs are presented in Table 7-1. Note that the cost summary is provided by the tunnel operators from Land Transport Authority of Singapore. The life spans of the safety provisions are assumed to be 30 years. The Minimum Attractive Rate of Return (MARR) is assumed to be 8%. We use the 0.9 cut based societal risk and 0.9 percentile based individual risk and expected number of fatalities as the risk indices. The safety targets for societal risk, individual risk, and expected number of fatalities are ${10^{-3}}/{N^2}$, 10^{-8}, and 0.5, respectively.

Table 7-1: The purchase costs, maintenance costs, and operating costs for various types of tunnel safety provisions

Tunnel safety provisions	Types	Purchase costs (million SD)	Maintenance costs (million SD per year)	Operating costs (million SD per year)
Tunnel ventilation system	Longitudinal	50	5	0.8
	Transverse	80	8	1.8
Fire detection system	Heat	4	0.4	0.1
	Smoke	8	0.8	0.1
	AID	4	0.4	0.1
Fire verification system	CCTV	25	2.5	0.4
	Emergency telephone	20	2	0.1

According to life-cycle cost analysis (LCCA), the annual worth for various types of tunnel safety provisions can be estimated by

$$V^i = V_p^i \times (A/P, 8\%, 30) + V_m^i + V_o^i \tag{7.15}$$

$$D^i = D_p^i \times (A/P, 8\%, 30) + D_m^i + D_o^i \tag{7.16}$$

$$F^i = F_p^i \times (A/P, 8\%, 30) + F_m^i + F_o^i \tag{7.17}$$

Table 7-2 illustrates the estimation results for annual worth of tunnel safety provisions.

Table 7-2: The annual worth of the candidate tunnel safety provisions

Tunnel safety provisions	Types	Annual Worth (Million SD)
Tunnel ventilation system	Longitudinal	10.24
	Transverse	16.904
Fire detection system	Heat	0.8552
	Smoke	1.6104
	AID	0.8552
Fire verification system	CCTV	5.12
	Emergency telephone	3.876

The problem can be efficiently solved by the proposed BSSBA algorithm in 9 iterations (as detailed in Table 7-3).

Table 7-3: Iterations for solving the problem

Combinations		Number of remainder combinations	Annual worth (AW) (Million SD)	Safety evaluation		
				Societal risk	Individual risk	EV value
Iteration 1	$\bar{x}=(0,1)$, $\bar{y}=(1,1,0)$, $\bar{z}=(1,0)$	32	24.4896	Safe	Safe	Safe
Iteration 2	$\bar{x}=(1,0)$, $\bar{y}=(1,0,0)$, $\bar{z}=(1,1)$	16	20.0912	Safe	Safe	Safe
Iteration 3	$\bar{x}=(1,0)$, $\bar{y}=(0,2,3)$, $\bar{z}=(0,1)$	14	16.5816	Risky	Safe	Safe
Iteration 4	$\bar{x}=(1,0)$, $\bar{y}=(1,1,0)$, $\bar{z}=(1,0)$	7	16.9704	Safe	Safe	Safe
Iteration 5	$\bar{x}=(1,0)$, $\bar{y}=(1,0,1)$, $\bar{z}=(0,1)$	6	15.8264	Risky	Safe	Safe
Iteration 6	$\bar{x}=(1,0)$, $\bar{y}=(0,1,0)$, $\bar{z}=(0,1)$	5	15.7264	Risky	Safe	Safe
Iteration 7*	$\bar{x}=(1,0)$, $\bar{y}=(1,0,0)$, $\bar{z}=(1,0)$	3	16.2152	Safe	Safe	Safe
Iteration 8	$\bar{x}=(1,0)$, $\bar{y}=(0,0,1)$, $\bar{z}=(0,1)$	2	14.9712	Risky	Safe	Safe
Iteration 9	$\bar{x}=(1,0)$, $\bar{y}=(1,0,0)$, $\bar{z}=(0,1)$	1	14.9712	Risky	Safe	Safe

* indicates the optimal solution.

As can be seen in Table 7-3, the optimal combination of tunnel safety provisions is 16.2152 million Singapore dollars. The longitudinal ventilation system, heat detector based fire detection system, and CCTV based fire verification system are chosen. The societal risk, individual risk, and expected number of fatalities of the combination are presented in Figure 7-1 to Figure 7-3.

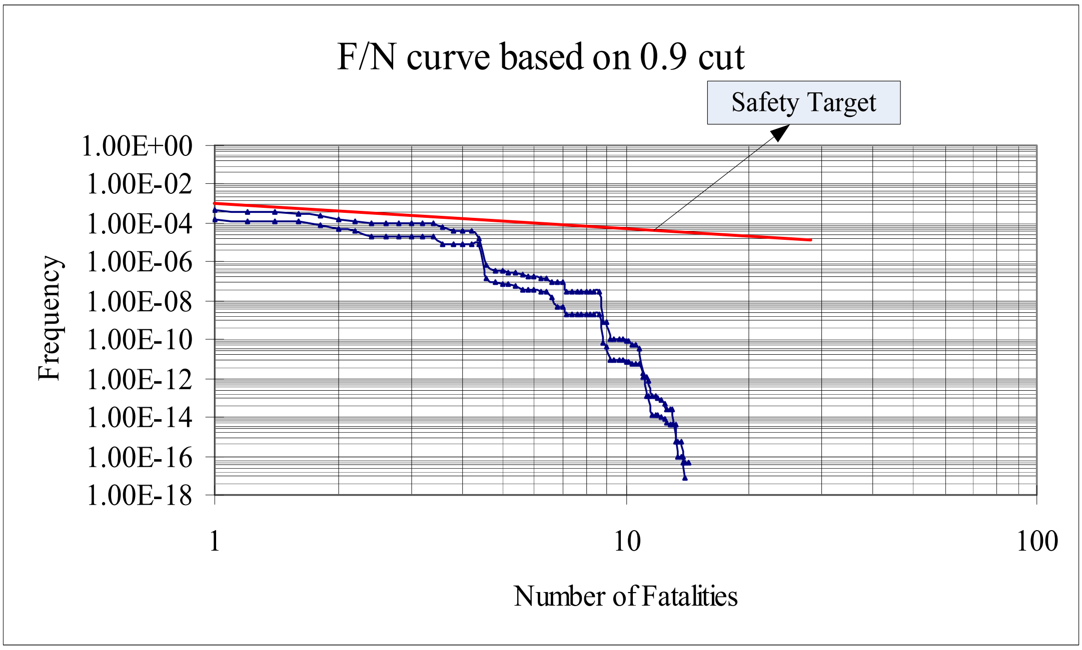


Figure 7-1: Societal risk of the optimal combination

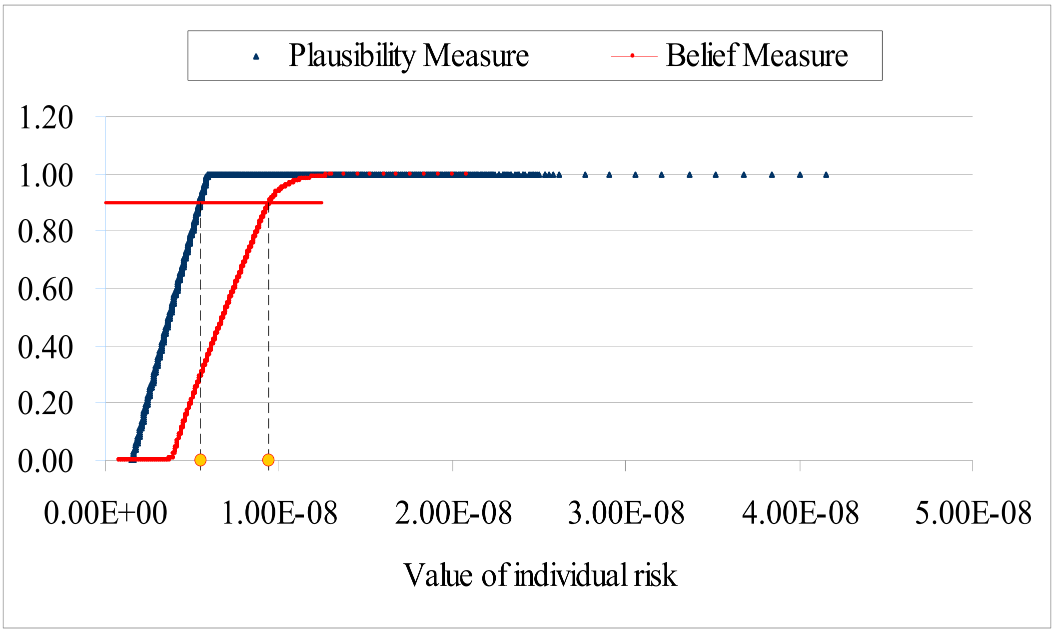


Figure 7-2: Individual risk of the optimal combination

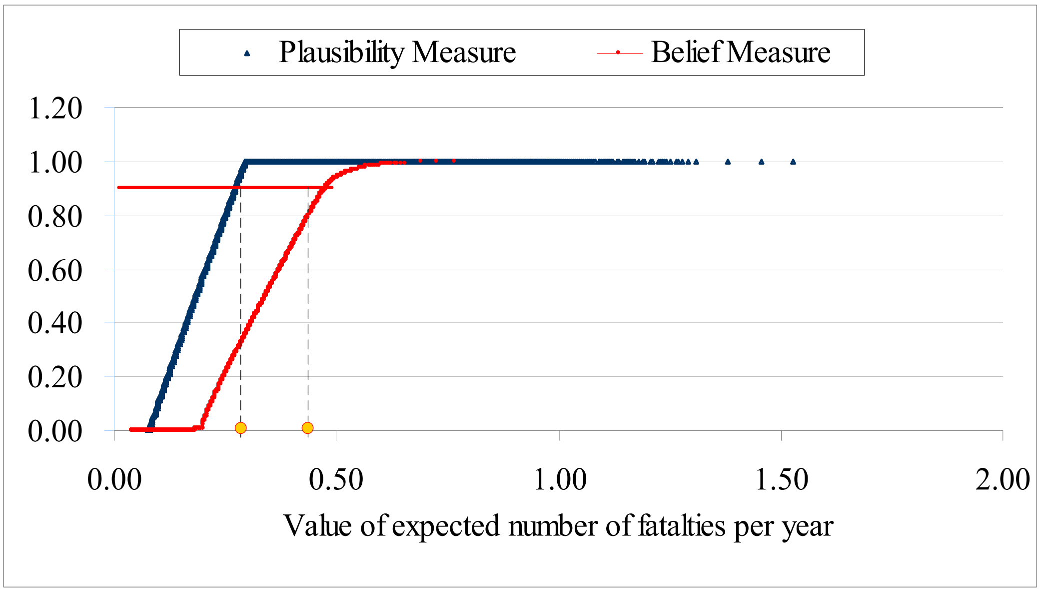


Figure 7-3: Expected number of fatalities per year of the optimal combination

7.5 Conclusions and Discussions

In this chapter, an optimization model is developed to optimally select the tunnel safety provisions on the basis of QRAM-II described in Chapter 6. Tunnel safety provisions are the assets of urban road tunnels which are installed and implemented to reduce the tunnel risks, which are basically selected by expert judgment in practice. In this study, an optimization model is proposed to obtain the optimal solution for the selection of tunnel safety provisions. The objective function is to minimize the life cycle costs of tunnel safety provisions, which subjects to the requirements for tunnel safety provisions and the safety targets. Finally, by taking advantage of the special structure of the optimization model, a Bi-Section Search and Bound Algorithm (BSSBA) is designed to efficiently solve the problem.

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

8.1 Overview and Contributions of the Work

This work was performed with regard to two important components in the QRA framework: risk assessment and risk control/management. The risk control/management strategies are suggested based on the proposed risk assessment models (QRAM-I and QRAM-II).

8.1.1 Risk Assessment Models

In view of the limitations of the existing QRA models for road tunnels, QRAM-I was developed to evaluate the risks in non-homogeneous urban road tunnels. A new frequency estimation model is proposed and applied in QRAM-I, and a fire simulation model and fractional effective dose methodology are initially applied in the QRA modelling framework. In addition, IR for urban road tunnels is proposed, to better reflect the risks to individual tunnel users with distinct travel profiles. The model has been computerized into software, to help tunnel operators evaluate tunnel risks. The software has been applied by the Land Transport Authority of Singapore to assess the risks of urban road tunnels in the country.

During discussions with tunnel operators at the Land Transport Authority of Singapore, we found that a number of model parameters include uncertainties from two distinct origins: inherent variability and a lack of information. Accordingly, QRAM-II was developed to address the issue of parameter uncertainty. A hybrid Monte Carlo simulation-based approach was designed to propagate the parameter uncertainty in the framework of the QRA model, by taking into account the dependencies among these uncertain parameters. Finally, percentile-based individual risk and α-cut based societal risk were proposed as the most appropriate indices for tunnel operators with distinct risk attitudes.

8.1.2 Risk Control/Management Strategies

If tunnels do not pass a predetermined safety target, risk control/management strategies should be implemented. In reality, risk control/management is another component of QRA. However, in most existing studies, researchers have focused only on the quantitative risk assessment itself and little work has been done on risk control/management strategies. Accordingly, in this study, strategies are suggested based on QRAM-I and QRAM-II.

Once a tunnel is open to traffic, the only adjustable parameters by which tunnel operators can control/manage the risks are traffic volumes and the proportion of HGVs. A QRAM-I based risk impact analysis methodology is proposed. An excess risk index is defined to quantify the severities of unacceptable scenarios, which place road tunnel operations above a predetermined safety target. A contour chart, based on the excess risk index, could be used to help tunnel operators implement suitable risk control/management solutions.

In the planning stage, a critical step that influences tunnel risk is the choice of tunnel safety provisions. These are basically selected by expert judgement in practice. On the basis of QRAM-II, an optimization model is proposed to obtain the optimal solution for the selection of tunnel safety provisions. The objective function is defined to minimize the life cycle costs of tunnel safety provisions, subject to the requirements for the tunnel safety provisions and the safety targets. Finally, by taking advantage of the special structure of the optimization model, a BSSBA is designed to efficiently solve the problem.

8.2 Limitations of the thesis

The limitations of this thesis are summarized as follows. First, tunnel geometric parameters are not taken into consideration in the crash frequency estimation model. In reality, tunnel geometric parameters, including curvature, gradient, lane width, etc. are also important contributing factors to the vehicle crash. TTC alone is not enough to predict collisions. Second, the lane changing and weaving are not taken into account in this study. In the Singapore's road tunnels, the HGVs are required to keep in lane and cars are allowed to change lanes. Lane changing and weaving could also result in crashes. Thus the crash frequency estimated by the proposed model in Chapter 3 is just an approximation for the actual crash count. Third, the risk assessment by QRAM-I does not deal with entire problem of risk prediction. The risk level in the merging area among slip road and main tunnel bore (tunnel intersection area) should be specially addressed. This is because the connection area between two tunnel sections would be with higher risks since the traffic conditions vary. The overall risk indices calculated by weighted summation principle and pessimistic principle may only provide partial information to tunnel risk evaluators.

8.3 Recommendations for Future studies

In future research, it would be of high value to address the following recommended research topics, based on the work accomplished in this study:

(1) The tunnel geometric parameters should be taken into account in the crash frequency estimation models. In addition, the crash frequency estimation model proposed in Chapter 3 may be applied to estimate crash frequencies on highways. However, the distribution types and causation factors should be calibrated using actual data collected on the target highway. Further, the lane changing and weaving behavior for vehicles in road tunnels would be a very interesting research topic.

(2) The connection area among two tunnel sections should be paid more attention to. New risk integration principles (and new risk indices) proposed in QRAM-I should be proposed to provide more information for tunnel risk evaluators.

(3) The approach used to build QRAM-I (as detailed in Figure 4-8) could be generalized to other critical transportation infrastructures, such as shipping channels. In fact, the author of this research has already carried out some preliminary studies, applying the same modeling principle (Qu et al., 2011; Qu and Meng, 2011). The consequence model validation for QRAM-I will also be an interesting topic for future study.

(4) Dependencies among random numbers or fuzzy numbers could be taken into account in the hybrid Monte Carlo simulation-based approach. However, the simulation approach cannot address a dependency between a random number and a fuzzy number. Accordingly, we assume there are no such dependencies in our problem (which is realistic in practice). Further studies could be conducted to design a new simulation procedure to address this kind of dependency.

(5) The model uncertainty may also result in variation in the risk assessment procedure. Therefore, future studies could also be focused on the model uncertainty analysis in the QRA framework.

APPENDIX A: Fault Trees for Tunnel Safety Provisions

(See Section 4.3.1)

A.1. Fault Tree for Fire detection Systems

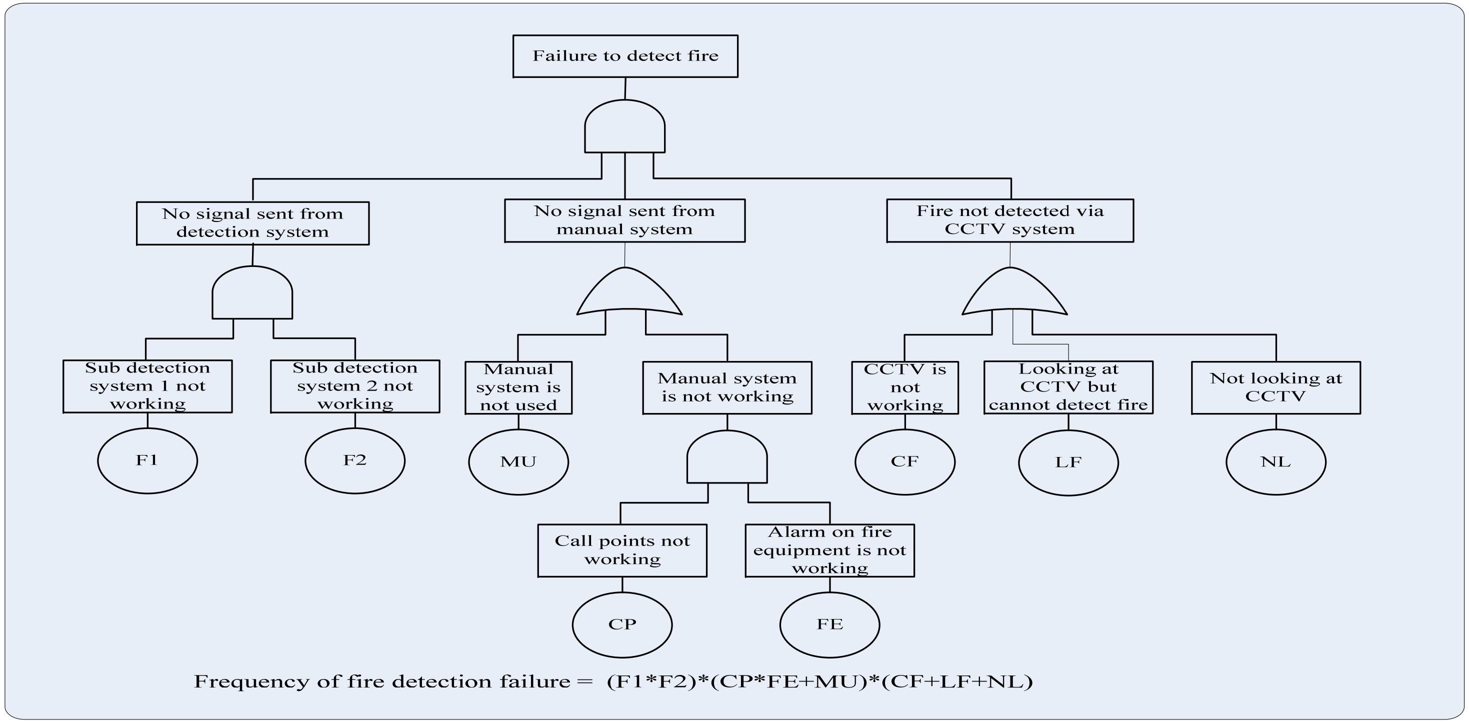


Figure A-1: Fault tree for fire detection systems

A.2. Fault Tree for Tunnel Ventilation Systems

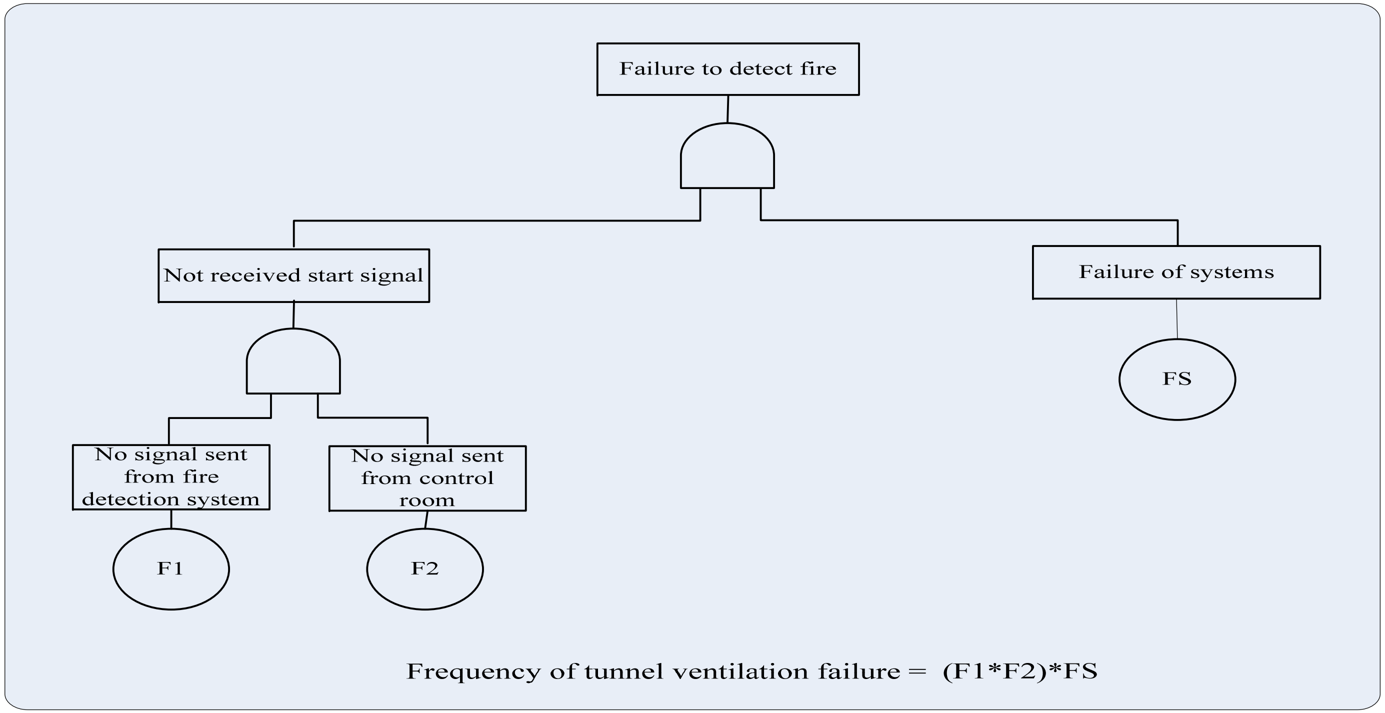


Figure A-2: Fault tree for tunnel ventilation systems

Appendix B: An example of FDS code

Tunnel-Case Study.fds

```
&HEAD CHID='tunnel-case/
&TIME T_END=500.0/
&DUMP RENDER_FILE='tunnel-case.ge1', DT_RESTART=300.0/
&MISC CO_PRODUCTION=.TRUE./
&MESH ID='KPE', FYI='KPE', IJK=7,50,4, XB=0.0,15.0,0.0,100.0,0.0,8.0/
&SPEC ID='CARBON DIOXIDE', MASS_FRACTION_0=0.03/
&SPEC ID='CARBON MONOXIDE'/
&SPEC ID='OXYGEN', MASS_FRACTION_0=0.21/
&PART ID='Fuel',
    FYI='Ethanol',
    FUEL=.TRUE.,
    AGE=60.0,
    DENSITY=789.0,
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    MELTING_TEMPERATURE=-114.3,
    VAPORIZATION_TEMPERATURE=78.4,
    HEAT_OF_VAPORIZATION=841.0,
    HEAT_OF_COMBUSTION=2.98E4/
&REAC ID='REAC',
    C=3.0,
    H=8.0,
    O=2.0,
    N=1.0/
&PROP ID='Default', QUANTITY='LINK TEMPERATURE',
ACTIVATION_TEMPERATURE=74.0/
&PROP ID='Cleary Ionization I1',
    QUANTITY='CHAMBER OBSCURATION',
    ALPHA_E=2.5,
    BETA_E=-0.7,
    ALPHA_C=0.8,
    BETA_C=-0.9/
&DEVC ID='HD', PROP_ID='Default', XYZ=0.0,0.0,0.0,
INITIAL_STATE=.TRUE./
&DEVC ID='SD', PROP_ID='Cleary Ionization I1', XYZ=0.0,0.0,0.0/
&MATL ID='XLP',
    FYI='NISTIR 1013-1 - NIST NRC Validation',
    SPECIFIC_HEAT_RAMP='XLP_SPECIFIC_HEAT_RAMP',
    CONDUCTIVITY_RAMP='XLP_CONDUCTIVITY_RAMP',
    DENSITY=1374.0,
    EMISSIVITY=0.95/
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    VEL=-4.0,
    POROUS=.TRUE./
&SURF ID='Pine',
    RGB=146,202,166,
    HRRPUA=5.0E4,
    MATL_ID(1,1)='XLP',
    MATL_MASS_FRACTION(1,1)=1.0,
    THICKNESS(1)=0.5,
    PART_ID='Fuel'/
&VENT SURF_ID='Blow', XB=0.0,15.0,0.0,0.0,0.0,8.0/ Vent
&VENT SURF_ID='Pine', XB=5.0,9.0,5.0,9.0,0.0,0.0/ Vent
&VENT SURF_ID='OPEN', XB=0.0,15.0,100.0,100.0,0.0,8.0/ Vent
&BNDF QUANTITY='MASS FLUX', SPEC_ID='carbon dioxide'/
&BNDF QUANTITY='MASS FLUX', SPEC_ID='carbon monoxide'/
&SLCF QUANTITY='TEMPERATURE', PBZ=0.0/
&SLCF QUANTITY='DENSITY', SPEC_ID='carbon dioxide', PBZ=2.0/
&SLCF QUANTITY='DENSITY', SPEC_ID='carbon monoxide', PBZ=2.0/
&SLCF QUANTITY='DENSITY', SPEC_ID='oxygen', PBZ=2.0/
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&SLCF QUANTITY='TEMPERATURE', PBZ=4.0/
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&TAIL /

Appendix C: QRA Software Introduction

(See Section 4.3.3)

The QRAM-I is computerized in order to facilitate the tunnel engineers from LTA of Singapore to evaluate the risks. Currently, the software is applied by the Division of System Integration and Assurance of LTA to assess and audit the risks for Singapore's road tunnels.

C.1 Development Platform

The object-oriented programming (OOP) has unique features including encapsulation, inheritance, polymorphism, pointers, operator overloading. In reality, OOP is an appropriate method for modeling complex situations. OOP concepts are more flexible and powerful than traditional methods. There are several advantages of the object-oriented programming. First, OOP allows users to decompose a problem into a number of entities called objects and builds data and functions around these entities. Second, OOP treats data as a critical element in the program development and does not allow it to flow freely around the entire program. Third, Object-Oriented Programs can be assembled from pre-written software components, which can be used in different applications. Fourth, new software components in OOP can be written or developed from the existing ones without affecting the original components. Last but not least, in OOP, the program units mirror the real world entities effectively and therefore are particularly reusable.

The typical object oriented programming languages like C++, C# and Java, are designed to provide major advantages in the professional software development and engineering application. C# is a simple, modern and object oriented language derived from C and C++. C# code looks like C++ and Java codes. C# compiler was designed by a team led by Microsoft, to create code for the .NET (dot net) Framework. Microsoft .NET Framework is a development platform using the Microsoft Windows operating system. With the high-level language platform (Microsoft .NET) it is much easier to develop software than in any of the other low level programming languages. The C# language was designed to create code on visual studio.NET and it uses the libraries defined by the .NET Framework. The C# language provides the features that are most important to programmers, such as object oriented programming, strings, properties and events, graphics, graphical-user interface components, exception handling, multithreading, ASP.NET dynamic web pages, XML, web services, file processing, data base processing. We develop the QRA software tool by using.NET Framework because it is a good environment that supports the development and execution of highly distributed component based applications.

C.2 Database

XML file is used to manage the tree structures and MS access is adopted to manage all the input data and parameters needed by the proposed QRA model. XML files have a hierarchical structure and can conceptually be interpreted as a tree structures which is called XML tree. In addition, the parameters attached to each node in the tree structures of the proposed QRA model can be saved as the node attribute. Therefore, the XML file is well recognized as an efficient and effective tool to deal with the tree structures including event trees and fault trees. Figure C-1 shows the MS access structure of important tables.

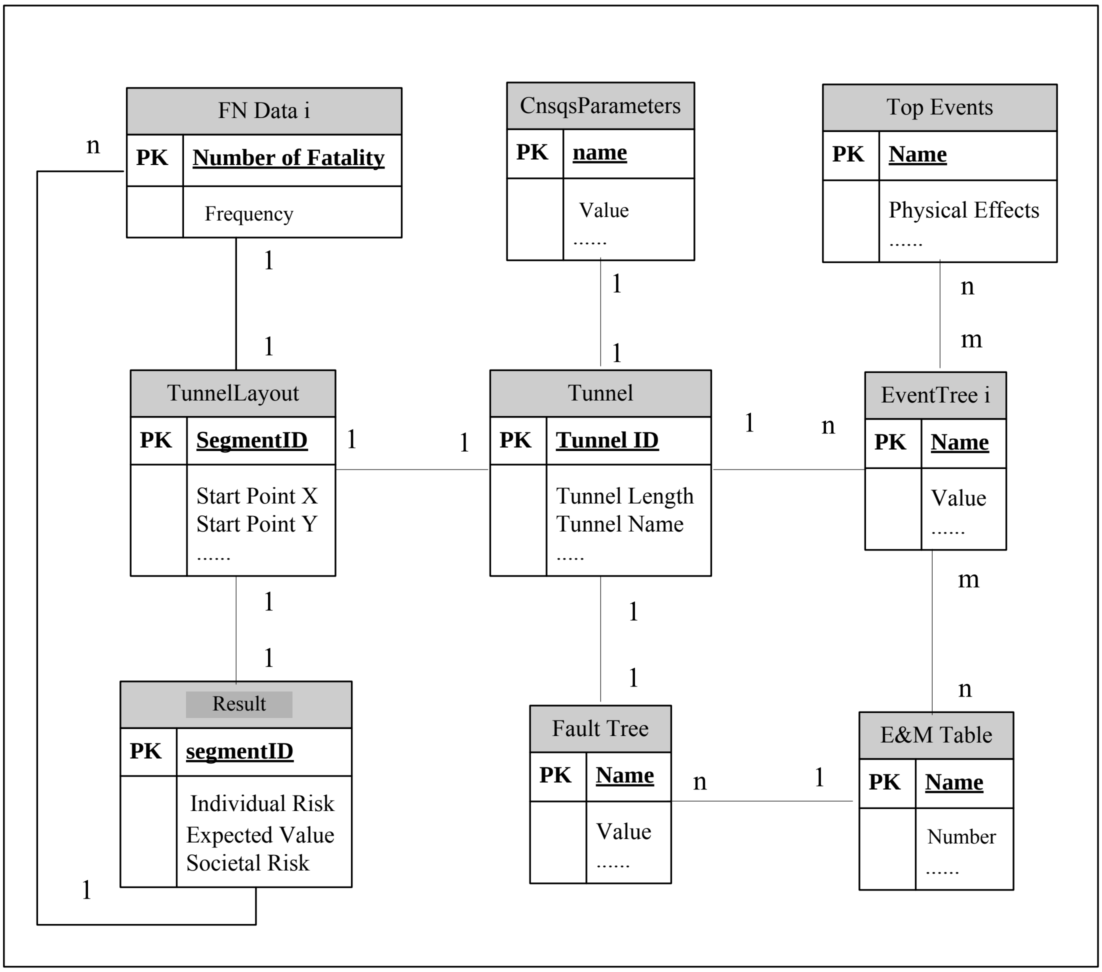

Figure C-1: Database design

C.3 Business Logic

Three-layer system structure is employed – Graphical User Interface (GUI), functional modules, and databases, and their relations are shown in Figure C-2. The basic business logic is as follows: first, all the parameters are inputted and stored in databases by GUI. Second, the functional module retrieves data from databases to perform their function. There are five main functional modules: event tree edit, fault tree edit, GIS (Geographic Information System) module, risk calculation module, and risk evaluation module. Among the five modules, calculation module is the most important one. The consequence parameters from database, event tree parameters from event tree XML file, and fault tree parameters from fault tree XML file are retrieved in this module. Our QRA model will be performed in C#.net environment by using this module. The output of this module is the frequency and number of fatalities of each scenario.

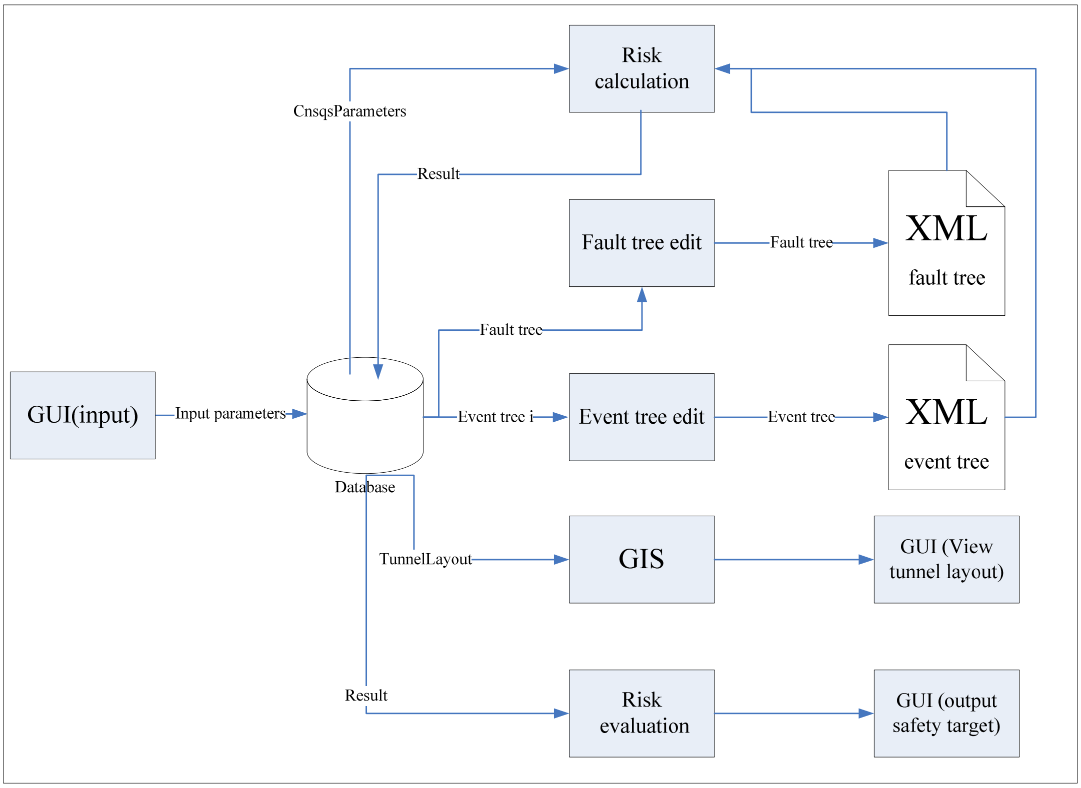

Figure C-2: Business logic

C.4 Snapshots of the QRA Software Tool

Figure C-3 shows the main interface of the QRA software tool, and each menu corresponds to a functional module. Figure C-4 depicts traffic and vehicle inputting interface. Similarly, other event tree parameters and fault tree parameters can also be inputted to database by GUI. Figure C-5 shows the deterministic safety analysis (DSA) module of the software tool. Once scenarios are selected, consequences and frequencies of the related scenarios can be presented in GUI.

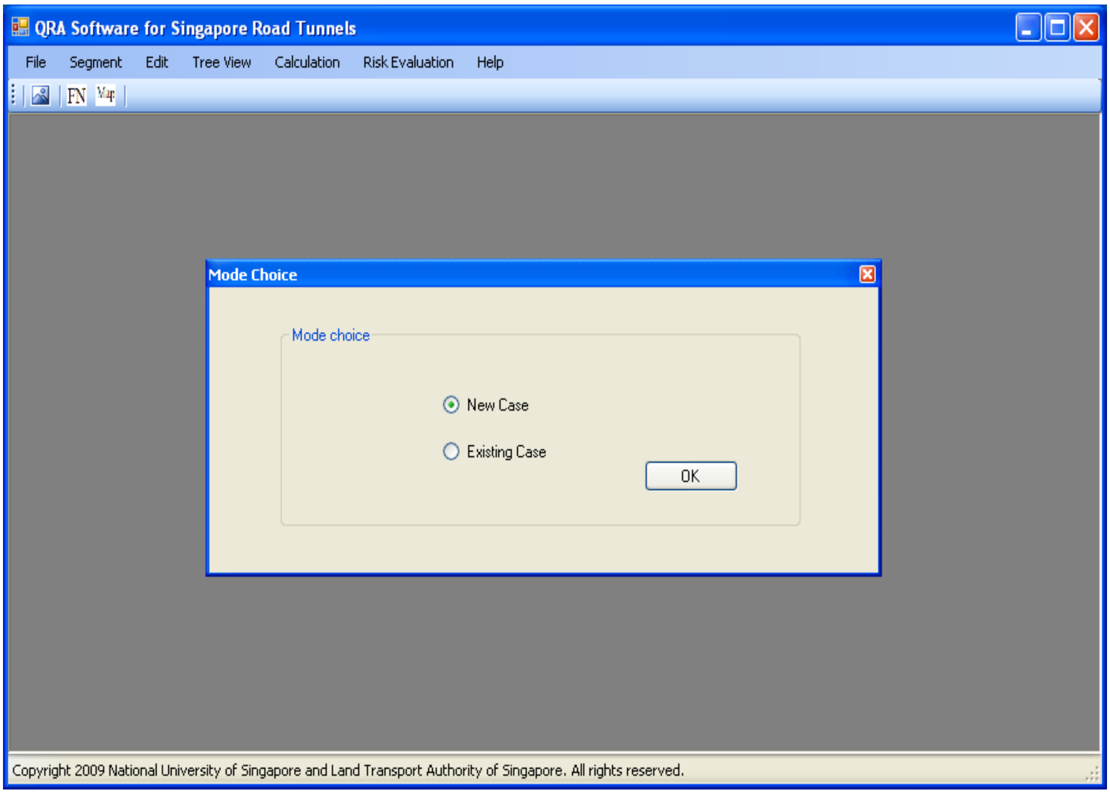

Figure C-3: Main interface of the QRA software tool

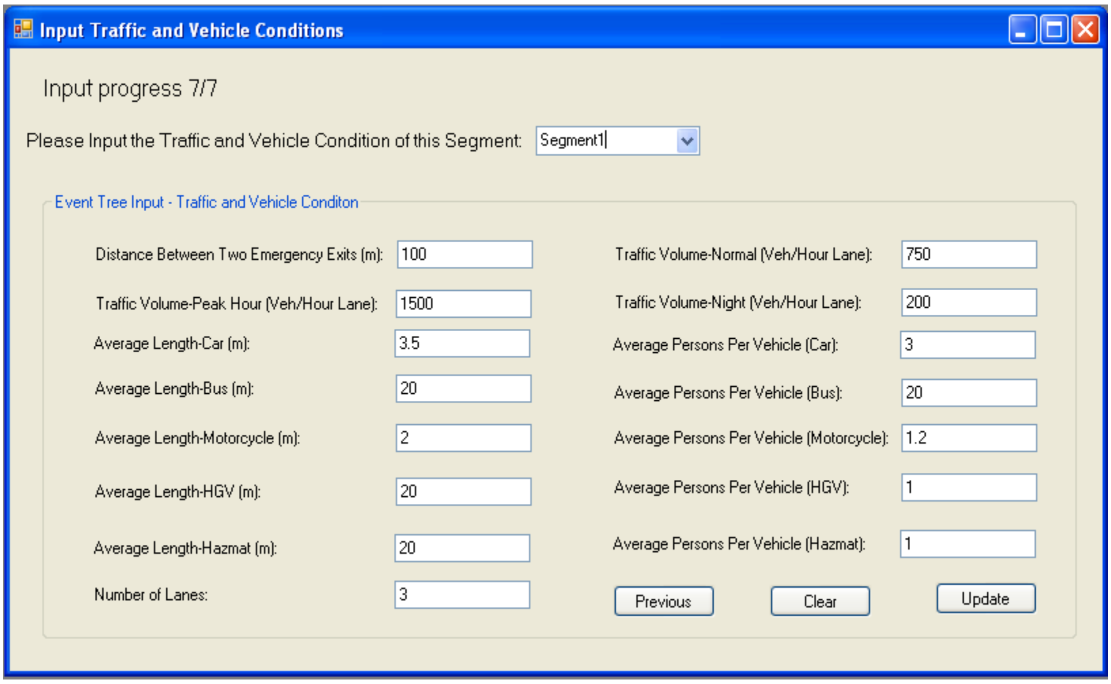

Figure C-4: Interface for the event tree module

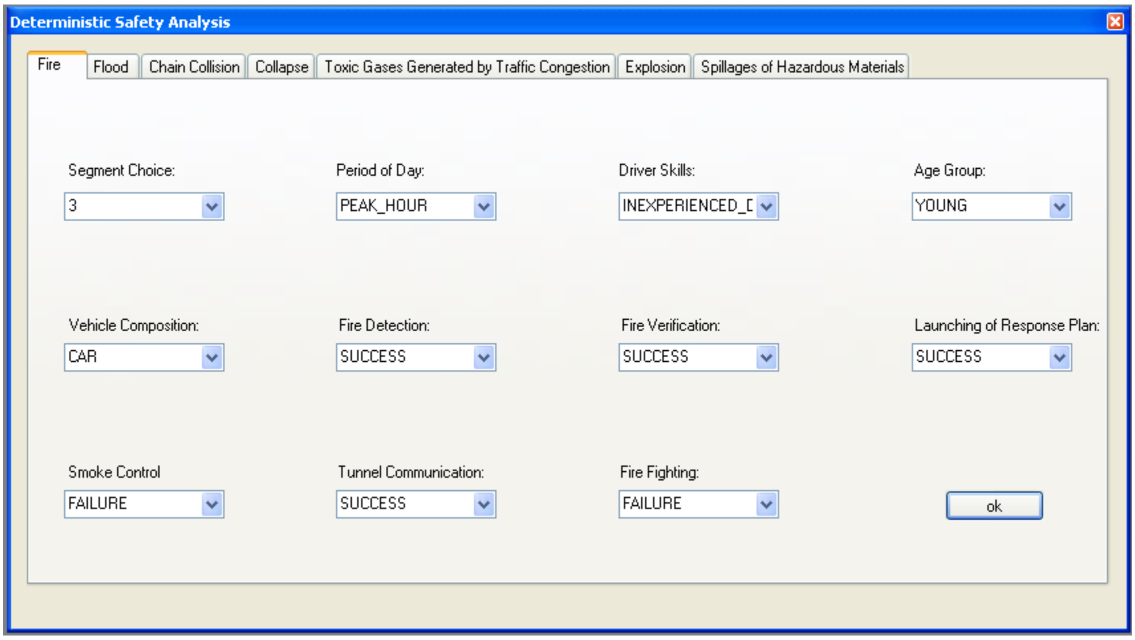

Figure C-5: Interface for the deterministic safety analysis

C.5 Merits

Object Oriented Design method is adopted in this software due to its flexibility and robustness. According to OOD method, database and functional modules can be easily maintained and updated. Therefore, our software possesses advantage of strong portability. Without any major changes, it can be applied to estimate risks for road tunnels in other countries. Meanwhile, the consequence models can be updated according to the development of related researches if necessary. In this case, the software can be conveniently upgraded by programmer.

The QRA Software employs XML files to access the tree structures of event trees and fault trees, instead of adjacency list or adjacency matrix. Each sequential event can be represented by a set of XML tree nodes. Therefore, it is effortless for programmer to edit, add, or delete sequential events. Once the tunnel is equipped with new tunnel mitigation facilities, trees structure can be rebuilt by making minor revisions.

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ACCOMPLISHMENTS DURING PHD STUDY

Awards and Honours

1 Awardee: President's Graduate Fellowship of NUS

The President's Graduate Fellowship (PGF) is awarded to candidates who show outstanding promise or accomplishment in research and coursework.

2 Awardee: Ministry of Transport Minister's Innovation Award

My thesis is on the basis of the research project "Quantitative Risk Analysis (QRA) of Road Tunnels" collaborated between Land Transport Authority of Singapore and National University of Singapore (NUS). The research team was conferred the Ministry of Transport Minister's Innovation Award by the Ministry of Transport of Singapore to recognize the excellent work.

3 Nominee: Land Transport Excellence Award

As a key member for the research project "Quantitative Risk Analysis (QRA) of Road Tunnels", I was nominated the Land Transport Youth Excellence Award in 2010.

<u>Publications related to the thesis</u>

Journal Papers

1. Q Meng, and ***X Qu***, 2011. Estimation of rear-end vehicle crash frequencies in road tunnels. ***Accident Analysis and Prevention***. Article in Press. (***Chapter 3***)
2. Q Meng, ***X Qu***, X Wang, V Yuanita, and SC Wong, 2011. Quantitative risk assessment modeling for non-homogeneous urban road tunnels. ***Risk Analysis***. 31(3): 382-403. (***Chapter 4***)
3. Q Meng, ***X Qu***, KT Yong, and YH Wong, 2011. QRA model based risk impact analysis of traffic flow in urban road tunnels. ***Risk Analysis***. 31(12): 1872-82. (***Chapter 5***)
4. Q Meng, and ***X Qu***, 2011. A probabilistic quantitative risk assessment model for fire in road tunnels with parameter uncertainty. ***International Journal of Reliability and Safety***. 5(3-4): 285-98. (***Chapter 6***)
5. Q Meng, and ***X Qu***, 2011. Uncertainty Propagation in Quantitative Risk Assessment Modeling for Fire in Road Tunnels. ***IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews***. Article in Press (***Chapter 6***)
6. ***X Qu***, Q Meng, YH Wong, and Y Vivi, 2011. Design and implementation of a quantitative risk assessment software tool for Singapore's road tunnels. ***Expert Systems with Applications***. 38(11): 13827-34. (***Appendix C***)
7. ***X Qu***, Q Meng, and S Li, 2011. Ship collision risk assessment for the Singapore Strait. ***Accident Analysis and Prevention***. 43(6): 2030-6. (***Chapter 8***)
8. ***X Qu***, and Q Meng, 2011. The economic importance of the Straits of Malacca and Singapore: a hypothesis scenario analysis. ***Transportation Research Part E: Logistics and Transportation Review***. 48(1): 258-65. (***Chapter 8***)

Conference Papers

9. ***X Qu***, and Q Meng, 2011. Optimal resources allocation for risk reduction in non-homogeneous road tunnels. In *Proceedings of the 90th Transportation Research Board Annual Meeting*, Washington DC, 23-27 Jan 2011. (***Chapter 7***)