Quantitative Risk Assessment Model for Fire in Road Tunnels with Parameter Uncertainty

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Abstract: Quantitative Risk Assessment (QRA) models have already been developed and used to assess various risks of road tunnels, including the societal risk and expected number of fatalities (ENF). Fire in a road tunnel is considered as the most severe disaster in that road tunnel is an enclosed space. The risk assessment for fire in road tunnels involves a number of parameters. Some of these parameters possess uncertainties in reality and they cannot be formulated as a crisp number. In this paper, these uncertain parameters are assumed to be random variables with given probability distribution functions. A novel QRA model is thus proposed to address the uncertainties in risk assessment caused by fire in road tunnel. In addition, the societal risk and ENF with distinct characteristics could be used to facilitate tunnel managers to make decisions. A case study is illustrated and the new characteristics of the risk indices are also discussed.

Keywords: QRA, road tunnel, societal risk, uncertainty

1. Introduction

Road tunnels are the vital transport infrastructures. They not only provide underground vehicular passageways but also enhance traffic network capacity and accessibility. However, safe operation of a road tunnel is of utmost concern due to its relatively heavy traffic volume and in case of any accident or emergency, it will be possible to result in catastrophic consequences. Therefore, risk assessment of road tunnels has become one of the requirements under the EU directive (2004/54/EC) and Netherlands legislation on road tunnel.

Fire disaster is the most catastrophic hazard in road tunnels. According to Meng et al. (2008), fire in tunnel contributes more than fifty percent out of all the fatalities in tunnel. Tunnel is an enclosed environment. Therefore, once fire takes place, the concentration of oxygen will be sharply decreased; at the same time, the concentration of toxic gases such as CO and CO_2 are increased dramatically. Furthermore, enclosed and confined space limits tunnel users to evacuate. Fatal fire accidents occurred in Europe in 1999 (Mont Blanc Mountain, 39 dead; Tauern, 12 dead) and 2001 (Gleinalm, 8 dead; Saint Gotard, 11 dead) brought about concerns on safety issues of road tunnels against fire (Leitner, 2001; Vuilleumier et al., 2002). From then, researchers have concerned on the risk assessment for road tunnels. Quantitative risk assessment (QRA) models, including event trees, fault trees, and consequence estimation models, have been proven to be an effective methodology to evaluate and quantify various risks of road tunnels; for example, TuRisMo model of Austria, TUNPRIM model of Dutch, OECD/PIARC DG QRA model, and NUS-LTA

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QRA model (Brussaard et al., 2001; Knoflacher, 2002; PIARC, 2008; Meng et al., 2009). These QRA models consider all the possible hazards, magnitude (severity) of the possible adverse consequence, and likelihood (probability) of occurrence of each scenario. It is widely regarded as a systematic and comprehensive methodology to evaluate risks associated with a complex hazardous installation (PIARC, 2008; Meng et al., 2009).

The road safety criterion in terms of societal risk is expressed by frequency vs number of fatalities (F/N) curve and expected number of fatalities (ENF). Both indices are based on the As Low As Reasonably Practicable *(*ALARP*)* principle (Jonkman et al., 2003). Most countries have chosen the upper bound of the F/N curve as a safety target of the road tunnels (Stallen et al., 1996; Botterlberghs, 2000; Vrouwenvelder et al., 2001). If the F/N curve generated by the QRA model is below the chosen safety target, the road tunnel is regarded as safe. Otherwise, risk reduction measures such as traffic volume control needs to be implemented.

There are a considerable number of parameters in a QRA model. For example, the key input parameters required by the NUS-LTA model have 4 categories: traffic parameters, tunnel user characteristics, tunnel geometries, and parameters associated with tunnel Electrical & Mechanical (E & M) systems. Traffic parameters include traffic volume, accident frequencies, vehicle composition (different proportions of various types of vehicles), theadway distance, fraction of peak / off-peak hours, and etc. Tunnel user characteristics refer to the reaction time of tunnel users, movement speeds of tunnel users, proportion of aged tunnel users, proportion of experienced drivers, and etc. Tunnel geometries relate to the distance between two consecutive emergency exits, number of lanes, tunnel sectional area, tunnel height etc. These parameters are usually fraught with some degree of uncertainty. The accurate values of some parameters could be obtained such as the tunnel sectional area and tunnel height, while others may vary in one particular range or follow some distribution such as evacuate time for tunnel users and probability of tunnel E & M system working normally. Uncertainty of these parameters may origin from randomness due to variability resulting from stochasticity. Hence, we cannot formulate all these input parameters by the crisp numbers. It is of great importance to model the appropriate propagation of uncertainty. However, to date, few studies addressed uncertainty of the parameters involved in a QRA model. Braldi and Zio (2008) attempted to use probabilistic and possibilistic method to examine uncertainty of parameters in an event tree analysis. In reality, uncertainty of these parameters has significant impact on the consequence estimation models of a QRA model and there is no QRA model that can deal with uncertainty of its input parameters.

In this paper, probability distribution is employ to characterize uncertainty of input parameters with uncertainties. More specifically, the lognormal distribution is adopted to represent the probabilities of tunnel E & M system failing to work and the normal distribution is applied to represent the air velocities with different ventilation status as well as the evacuate times for different people. Having had the probability density functions of those uncertain parameters, Monte Carlo sampling method is used to perform the event tree analysis and consequence estimation. For each realization generated by Monte Carlo sampling approach, the F/N (Frequency vs. number of fatalities) curve and expected number of fatalities are calculated. The risk indices associated with uncertainties are also analyzed accordingly.

2. Risk Indices and Safety Target

Societal risk is defined as the relationship between frequency and the number of people suffering from a specified level of harm in a given population from the realization of specified hazard (PIARC, 2008; Meng et al., 2009). It can be represented graphically in the form of an F/N curve. The societal risk (F/N curve) has also been accepted in the quantitative risk assessment of road tunnels (PIARC, 2008). A QRA model consists of event trees, fault trees and consequence estimations. A top event may trigger a number of possible scenarios associated with their frequencies and number of fatalities. The F/N curve reflects the relationship between the frequencies and the number of fatalities of all these possible scenarios on a double logarithmic scale. Let $F(N)$ denoted the cumulative frequencies of all the scenarios with N or more fatalities. We thus have:

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

where F_i is the yearly frequency of scenario i occurred per year; x_i is the number of fatalities caused by scenario i; indicator function $\delta(x_i - N)$ is defined by

$$\delta(x_i - N) = \begin{cases} 1, & \text{if } x_i \geq N \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

With the frequency shown by eqn. (1), the expected value for the number of fatalities per year (ENF) can be calculated by

$$ENF = \sum_{i=1}^{n} (F_i \times x_i) \tag{3}$$

An upper bound curve of $F(N)$ is usually adopted as the safety target (Jonkman et al., 2003):

$$F(N) \leq \frac{C}{N^k} \tag{4}$$

where k and C specified the steepness and intercept point. Alternatively, eqn. (4) can also be written as follows:

$$k \log(N) + \log(F(N)) \leq \log(C) \tag{5}$$

It should be noted that k represents a slope, i.e. gradient of the safety target, and C denotes an intercept, i.e. constant value that determines the position of the target. Different combinations of k and C express various strictness degrees of the safety targets. As a result, different countries may propose their own safety targets. For example, the k and C values adopted by Netherlands are $C=10^{-3}$ and k=2, while Switzerland adopts $C=10^{-4}$ and k=1 (Jonkman et al., 2003).

3. QRA Models for Fire in Road Tunnels

As described by Jonkman et al. (2003) and Vrouwenvelder et al. (2001), a QRA model building procedure comprises the following steps. Firstly, all possible hazards such as fire and flood are identified as top events. After that, fault tree and event tree for each top event are built. Event tree consists of a number of particular scenarios triggered by the top event and fault tree is used to estimate frequency of a top event that could occur. Finally, consequence estimation models are required to calculate number of fatalities for various scenarios involved in an event tree. After obtaining frequency and fatality of each scenario, the societal risk and expected value can be calculated.

3.1 FAULT TREE AND EVENT TREE

The initiating event (top event) in this model is identified as fire in road tunnel. Fault tree is constructed to estimate the frequency of fire in tunnel. Fire in tunnel top event triggers a sequence of events. In this section, fault tree and event tree for fire in tunnel top event are described.

Fault tree, which is regarded as a good tool to estimate the frequencies, are several photographical diagrams showing how the undesired states of system are analyzed by using Boolean logic to combine series of low-level sub-events. The fault tree of the "Fire in tunnel" is shown in Figure 1. The leaf circles, such as PI and VD in Figure 1, are the input parameters of the fault tree. The uncertainties of fault tree input parameters will not be discussed in this paper.

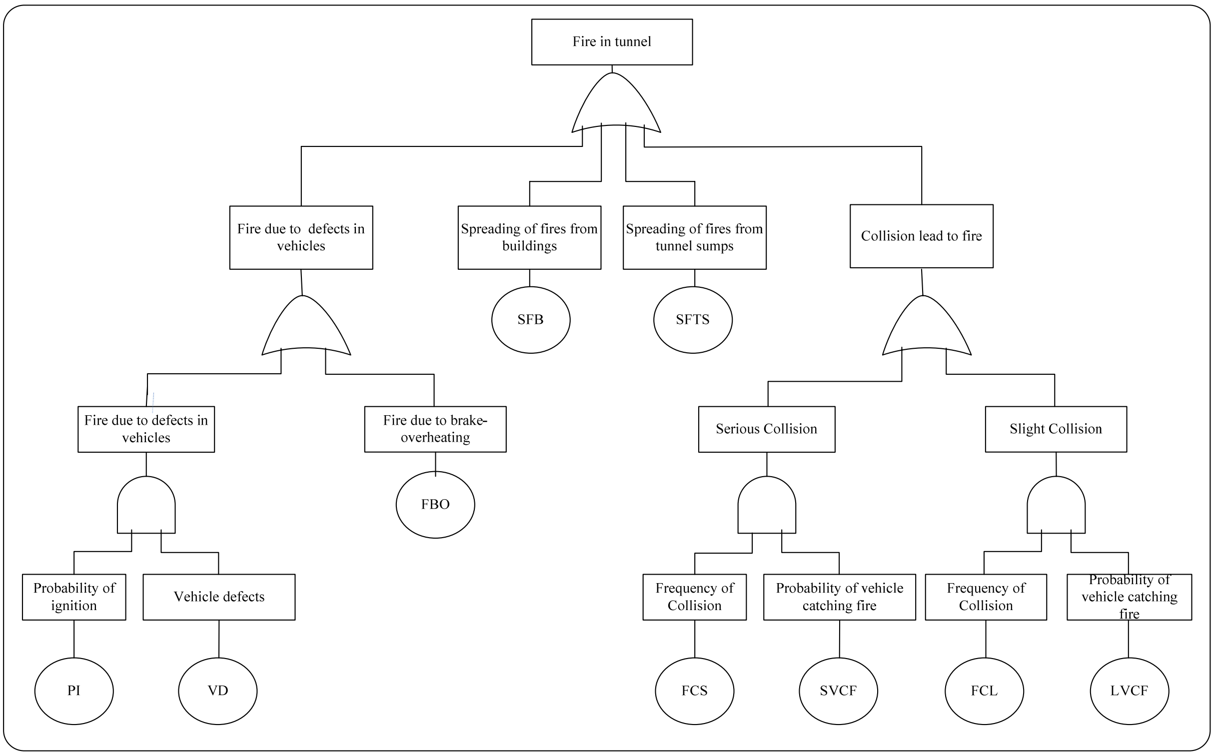

***Figure 1** Fault tree for fire in tunnel top event*

Event tree is a tree diagram that refers to complex events that can be discretized in terms of their possible outcomes and possibly in terms of their distinction by sequential events into a series of simple scenarios. Such diagram has been used in describing the possible outcome of events occurring sequentially in time as in sampling sequences, a collection of decisions and chance events in decision trees or in taxonomies of various items in classes. The event tree for fire in tunnel top event is shown in Figure 2.

Frequency and consequence are associated with scenarios of event tree. Frequencies can be calculated by multiplying the frequency of top event and frequencies / proportions / probabilities of sequential events, while consequences of various scenarios could be estimated by consequence estimation model

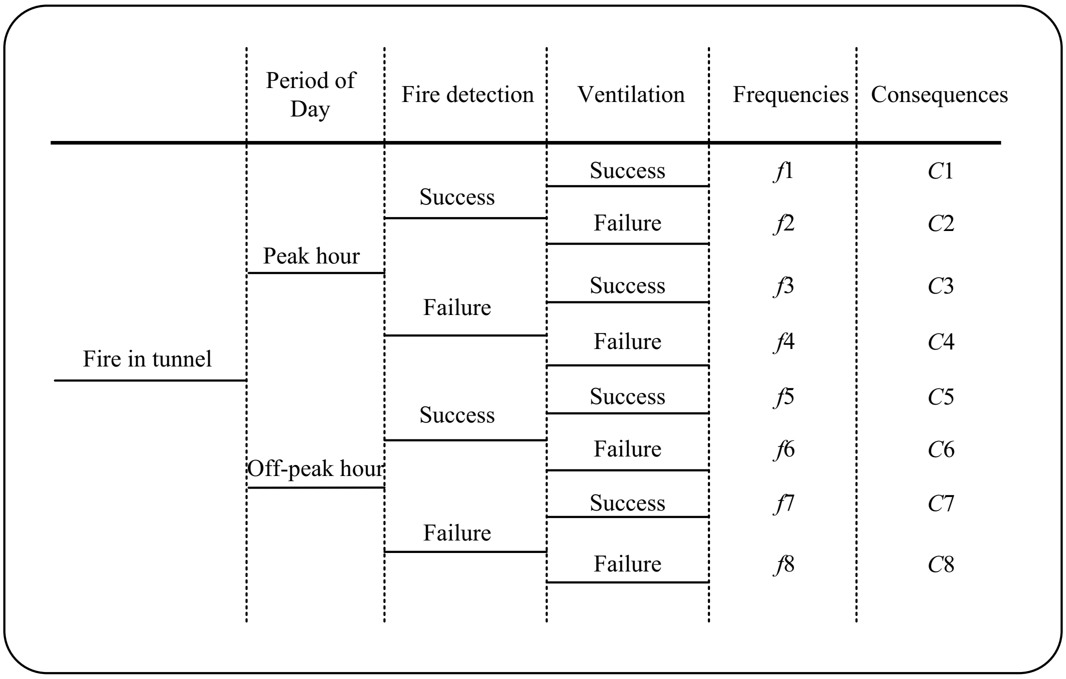

Figure 2 *Event tree for fire in tunnel top event*

3.2 CONSEQUENCE ESTIMATION MODELS

3.2.1 Branch-based generic consequence estimation method

Since there are a number of particular scenarios for each event tree, the consequence estimation model is established for each scenario, referred to as the scenario-based consequence estimation model. The models for various scenarios are the same for different scenarios. However, the input parameters may differ according to the choice of sequential events (failure or success). For example, if the tunnel ventilation system fails to work, the air velocity will take different value from that of the system working normally.

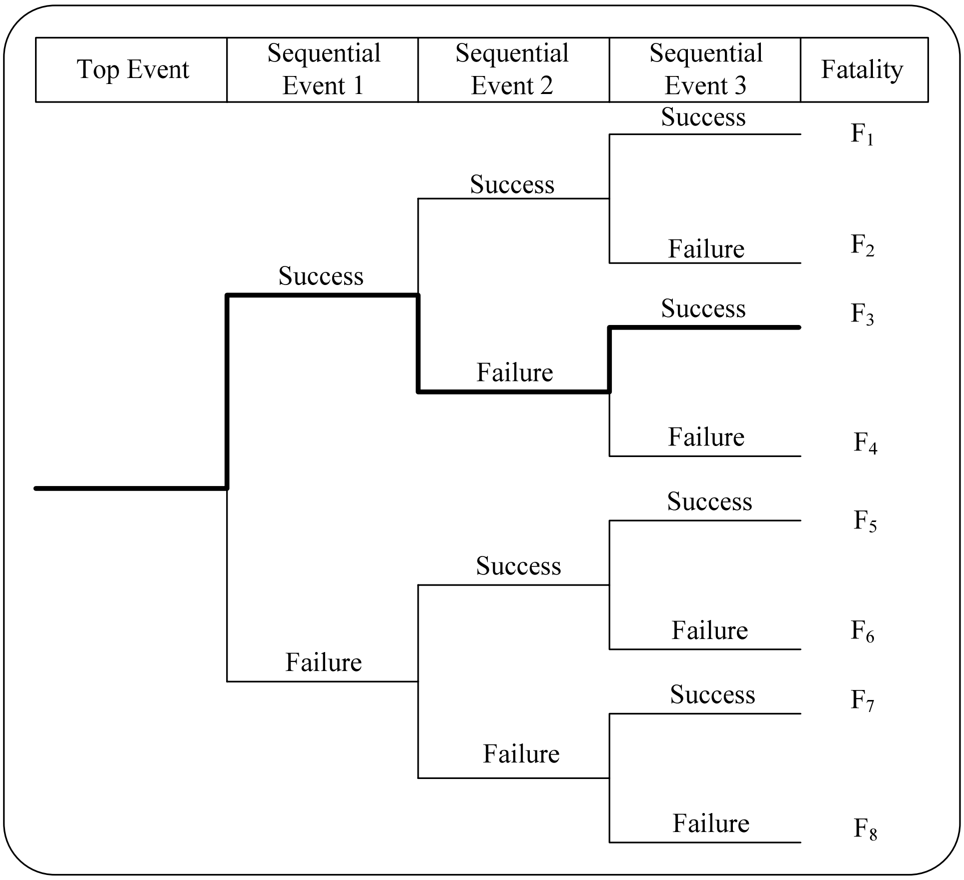

Figure 3 *Example of Branch-based generic consequence estimation method*

Assuming that the number of fatalities for various branches in the event tree sample can be calculated by formula

$$F = f(u_1, u_2, u_3) \tag{6}$$

where u_1, u_2, and u_3 are the input parameters which are influenced by the choice of sequential events, namely, they will take different values for different choice (success or failure). For example, if we want to calculate F_3, u_1, u_2, and u_3 should adopt the corresponding value of sequential event 1 working normally, sequential event 2 failing to work, and sequential event 3 working normally, respectively.

3.2.2 Consequence estimation model for fire in tunnel

Purser (1988) proposed a formula to estimate the fatality rate function due to heat

$$F_D = F_D(t, T) = t / e^{(5.1849 - 0.0273T)} \tag{7}$$

where T stands for the temperature (*°C*) and t is the exposure time (*min*). Bergqvist (2001) contributed the following formula to calculate the temperature due to heat at a certain time.

$$T_{em}(t) = T_0 + \frac{0.7Q(t)}{\mu\rho_0 A c_p} \tag{8}$$

Temperature will descend with the distance x away from the fire and time according to the following equation:

$$T_g(x,t) = T_0 + \left[T_{em}(\lambda) - T_0\right] e^{\frac{-hP_x}{\rho_0 \mu A c_p}} \tag{9}$$

where the parameter $\lambda = t - x/u$ is defined as the time delay for transporting the smoke a distance x (m) with a air velocity of u (m/s); h is the lumped heat loss coefficient for the tunnel surface = 0.03$kW/m^3 \cdot °C$; P_x is the perimeter of the tunnel (m), and A is the sectional area of tunnel (m^2); the parameters T_0 is initial temperature in the tunnel ($°C$); ρ_0 is the air density in the tunnel (kg/m^3); c_p is 1$kJ/°C$ for air. $Q(t)$ is the heat release rate. The results can be used as an input variable for calculating the fatality rate due to heat using the equation (7).

The toxic gases generated by fire include carbon monoxide (CO), carbon dioxide (CO_2), and oxygen (O_2). The following equations can be adopted to calculate the concentratio□s of CO, CO_2, and O_2 (Bergqvist, 2001).

$$X_{O_2}(t) = \left[X_\infty - \frac{Q(t) M_a (X_\infty \frac{M_{o_2}}{M_a} + r_0)}{\Delta H M_{o_2} \rho_0 \mu A c_p} \right] \times 100 \tag{10}$$

$$X_{CO_2}(t) = \left[\frac{Q(t)(1 + r_0)}{\Delta H \rho_0 \mu A c_p} \right] \times 100 \tag{11}$$

$$X_{CO}(t) = \left[Y_{co} \frac{Q(t) M_a}{\Delta H M_{co} \rho_0 \mu A c_p} \right] \times 10^6 \tag{12}$$

where X stands for the concentration of different gases and $Q(t)$ is determined by each scenario and the time period. Molecular mass of each gas is as follows: $M_{o_2} = 32$ *grams/mole*, $M_{CO} = 28$ *grams/mole* and $M_a = 29$ *grams/mole*. Parameter r_0 is stoichiometric heat coefficient (*0.3 - 0.5*), Y_{CO} is the fraction CO per *gram* burnt fuel that is involved in the fire (*0.01 - 0.05*) and ΔH is effective heat of release (30 *MJ/Kg* fuel); u is the wind velocity in the tunnel (m/s); X_∞ is the concentration of related gas in normal environment; ρ_0 is the air density in the tunnel (kg/m^3); c_p is a constant which takes value of 1$kJ/°C$; A is the sectional area of tunnel (m^2).

The dose response function can thus be calculated by the following formula (Persson 2002):

$$F_{CO} = \frac{K\left(X_{CO}^{1.036}\right)t}{D} \tag{13}$$

where parameter D is %COHb at incapacitation (30%); X_{CO} is CO concentration; and $K = 8.2925 \times 10^{-4}$.

The fatality rate due to low concentration of O_2 can be calculated according to the formula below (Persson, 2002).

$$F_{o_2} = \frac{t}{e^{8.13-0.54(20.9-X_{o_2})}} \tag{14}$$

where the parameter *t* is the exposure time (*min*) and X_{o_2} is the oxygen concentration.

The fatality rate due to CO_2 can be calculated using the formula (Persson 2002):

$$F_{co_2} = \frac{t}{e^{6.1523-0.5189X_{co_2}}} \tag{15}$$

where t is the exposure time (min) and X_{co_2} is the carbon dioxide concentration.

4. Parameter Uncertainty Analysis

4.1 INPUT PARAMETERS WITH UNCERTAINTIES

In this paper, the uncertainties of fault tree parameters will not be discussed. Tunnel E & M systems, air velocities in tunnel, evacuation time of tunnel users are considered as uncertain parameters. Adopting the same assumptions of Huang et al. (2001), sufficient experimental data are available to build lognormal probability distribution representing the uncertainty in the event probability of tunnel E & M systems failing to work, which is called hardware-failure-dominated (HFD) events. Air velocities are assumed to distribute normally. A reasonable assumption is that tunnel ventilation system affects the mean of air velocity and doesn't have effects on the standard deviation of the parameter. The evacuation time is also assumed to follow normal distribution.

4.2 MONTE CARLO SAMPLING METHOD

As mentioned above, the frequency of one particular scenario can be calculated by multiplying frequency of top events and the frequencies / proportions / probabilities of corresponding sequential events, denoted by:

$$f_j = \sum_{k=1}^{K} P\left(E_k \middle| S_j \right) \tag{16}$$

where f_j is the frequency of scenario, *K* is number of corresponding top and sequential events, S_j stands for the scenario *j*, E_k stands for the sequential event *k*, $P(E_k|S_j)$ is the conditional probability of E_k given the occurrence of S_j. With respect to the consequence estimation, eqns (6) -(15) can be resorted to calculate the number of fatalities and frequencies associated with each particular scenario.

If the probability density functions of those probabilistic parameters are obtained, the probability distribution functions of the consequences and frequencies with respected to each scenario can be calculated. However, due to the complexity of the system, those variables do not have closed form. Therefore, Mento Carlo sampling method is used to address the problems.

Let us consider a model whose output is a function $g(u_1, u_1, \cdots, u_n)$ of *n* input parameters $(u_1, u_1, \cdots, u_n)$. The first *k* input parameters are considered as constants $(u_1, u_1, \cdots, u_k)$, whereas the other *n-k* parameters are characterized by random variables $\left(U_{k+1}, U_{k+2}, \cdots, U_n\right)$. For the propagation of such mixed deterministic and uncertain information, in view of their independency, the Monte Carlo technique (Kalos & Whitlock, 1986) can be combined with the probability theory by means of the following steps.

Step 0: given the values of deterministic parameters $\left(u_1, u_1, \cdots, u_k\right)$

Step 1: determine the probability distribution function of probabilistic parameters $\left(U_{k+1}, U_{k+2}, \cdots, U_n\right)$;

Step 2: determine the sampling number of Monte Carlo sampling *m*;

Step 3: Sample the *ith* realization $\left(u_{k+1}, u_{k+2}, \cdots, u_n\right)$ of the probabilistic variable vector $\left(U_{k+1}, U_{k+2}, \cdots, U_n\right)$;

Step 4: if *i =m*, then stop. Otherwise, go to step 5;

Step 5: Compute the results of each scenario for the *ith* realization $g\left(u_1^{(i)}, u_2^{(i)}, \cdots, u_n^{(i)}\right)$, then *i=i+1*;

The QRA model can generate the frequencies and fatalities with respect to various scenarios for each realization. Accordingly, the ENF of probabilistic QRA model is also considered as a random variable. Similarly, the societal risk generated by the QRA model is a set of F/N curves (one F/N Curve for a realization).

It should be pointed out that the ENF is a random variable in this process. In order to examine the degree of uncertainties of ENF, the uncertainty index is defined as the ratio between 5% percentile ENF and 95% percentile ENF.

$$\gamma = \frac{ENF_{0.05}}{ENF_{0.95}} \tag{17}$$

where γ is the degree of uncertainty, $ENF_{0.05}$ is the 5% percentile ENF and $ENF_{0.95}$ is the 95% percentile ENF. Evidently, the index is between 0 and 1. If there is no uncertainty involving in the QRA model, it will take value of 1. A smaller value of the index stands for larger degree o uncertainties in the model.

5. Case Study

The Kallang / Paya Lebar Expressway (KPE) of Singapore, shown in Figure 3, is 12km in total length and 9km is built underground as a road tunnel, which was built to serve the grow ing traffic demands of the north-eastern sector of Singapore. It is also the longest road tunnel in the South East Asia. The KPE road tunnel is a dual 3-lane, 9*km* underground passageway and has nine entry slip roads, eight exit slip roads and six ventilation buildings. The accident frequency of the road tunnel is 560 per year according to the historical records. The distance between two emergency exits is 100 meters. The tunnel air velocity when tunnel ventilation works normally is 4 m/s. There is a 24-hrs manned Operation Control Centre (OCC) at one ventilation building and an unmanned hot standby OCC located in another ventilation building. The functionality and working profiles of the E & M systems can be obtained from their instruction manuals. The values of the vehicle profiles are obtainable from the OCC. The deterministic parameters of the case study are collected from operational data in KPE road tunnel.

Figure 4 *KPE road tunnels in Singapore*

5.1 INPUT PARAMETERS

Probabilities with respect to fire detection system (failure, P_{de}) and tunnel ventilation system (failure, P_{ve}) are accounted for by lognormal distribution. Accordingly, the probabilities associated with the two E & M system working normally can be represented by $(1-P_{de})$ and $(1-P_{de})$, respectively. The evacuation time (fire detection system failure, T_f), evacuation time (fire detection system success, T_s), air velocity (ventilation system failure, V_f), and air velocity (ventilation system success, V_s) are represented by normal distribution. Figure 4 depicts the probability density function of those probabilistic parameters.

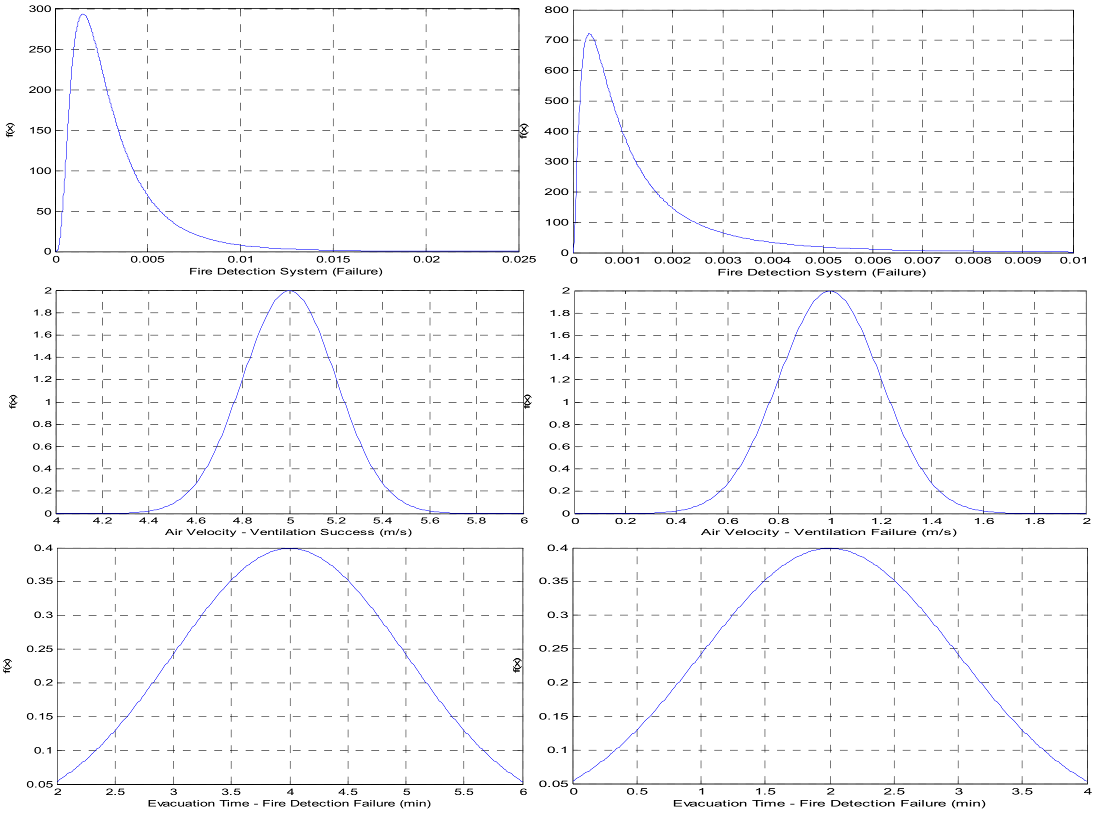

***Figure 5** Probability distribution functions of probabilistic parameters*

5.2 CALCULATION RESULTS

Figure 6(a) is the frequency of the occurrence of scenario 1. From the figure, we can easily get the percentile based frequencies. For example, the frequency of 85% percentile is 0.5 per year, which means that the probability of 0.5 or more per year is only 15%. Figure 6(b) is the consequence with respect to scenario 1. It can be seen that the probability of consequences within the interval of (4, 6) is more than 70%. Figure 6(c) shows the expected number of fatalities in this road tunnel. The maximum ENF value is 0.22, however 90% of the ENF is smaller than 0.14. Those curves provide a good tool for decision makers with different preferences.

Figure 6(d) is a set of FN curves with respect to various realizations of Monte Carlo Sampling method. Those curves show the possible results of the input parameters. The green and red curve is considered as the upper bound and lower bound of the set of FN curves. Note that the bounds are not compact bound in that all the FN curves are in between those bounds.

The degree of uncertainty for this case is calculated as follows:

$$\gamma = \frac{EV_{0.05}}{EV_{0.95}} = \frac{0.087}{0.152} = 0.57 \tag{18}$$

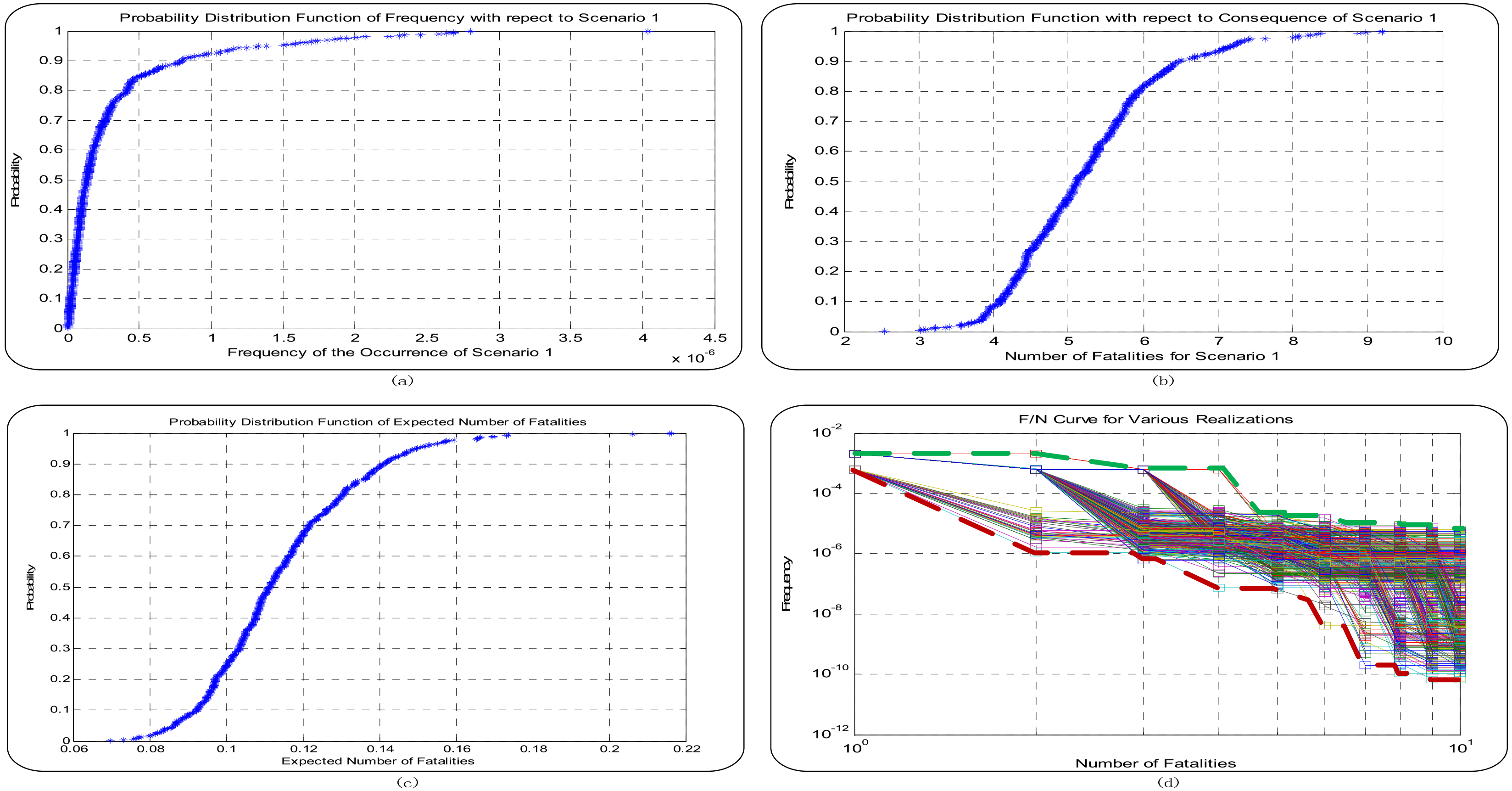

Figure 6 *Calculation results (frequency, number of fatality, ENF, F/N curve)*

6. Conclusions

Fire is the most severe disaster in road tunnels in that tunnel is an enclosed space. Risk assessment for fire in road tunnel becomes a significant concern in past decades. The existing QRA studies for road tunnels neglect randomness of input parameters with different degree of uncertainties. This paper proposed a QRA model to evaluate the risks caused by fire in road tunnel by taking into account uncertainty of input papers.

From the expert judgment and / or sufficient experiments, the probabilities of tunnel ventilation system and fire detection system are formulated by the lognormal distributions. In addition, the evacuation time and air velocities in road tunnel are assumed to be distributed normally. Monte Carlo Sampling method is employed to generate various possible realizations of those uncertain input parameters. Therefore, the frequencies, consequences, and expected number of fatalities (ENF) of the proposed model become random variables instead of fixed number. Moreover, the F/N curves with respect to various realizations can be depicted in one Frequency – Number of fatalities coordinators. The risk indices with different characteristics could be used to support the decision makers (tunnel managers). KPE road tunnel in Singapore is used to illustrate the proposed model.

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