for fire in road tunnels with parameter uncertainty

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Abstract: Fire in road tunnels can lead to catastrophic consequences in combination with tunnel safety provision failures, thus necessitating a need for a reliable and robust approach to assess tunnel risks caused by fire. In a quantitative risk assessment (QRA) model for road tunnels, uncertainty is an unavoidable component because input parameters of the model possess different levels of uncertainties which are inappropriate to be formulated by crisp numbers. In this paper, a Monte Carlo sampling-based QRA model is proposed to address parameter uncertainty of a QRA model. The tunnel risks are assessed in terms of percentile-based societal risk as well as expected number of fatalities (ENF) curve, which would facilitate tunnel managers to make decisions. A case study is carried out to demonstrate the approach.

Keywords: QRA; quantitative risk assessment; road tunnel; societal risk; uncertainty.

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1 Introduction

Road tunnels are increasingly considered as cost-effective infrastructures which provide underground vehicular passageways for commuters and motorists. They contribute to the transportation systems from the viewpoints of economics and practicality since they

improve transportation system capacity as well as accessibility. However, safe operation of a road tunnel is of utmost concern due to its relatively heavy traffic volume as any accident or emergency could 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 tunnels (PIARC, 2008).

Fire disaster is the most catastrophic hazard for road tunnels. Once fire takes place, the concentration of oxygen decreases dramatically because tunnels are enclosed space; at the same time, the concentration of toxic gases such as carbon monoxide (CO) and carbon dioxide (CO_2) also increases. Furthermore, the enclosed and confined space limits the number of tunnel users who can evacuate. Accordingly, fire in road tunnels may result in loss of lives as well as other damages like blockade of tunnels. Fatality is considered as the most severe consequence of fire in tunnels. Indeed, vehicles still have the option to transit from other alternative routes if a tunnel is blocked. Fatal fire accidents, which occurred in Europe in 1999 (Mont Blanc Mountain, 39 dead; Tauern, 12 dead) and 2001 (Gleinalm, 8 dead; St. Gotthard Road Tunnel, 11 dead), brought about concerns on safety issues of road tunnels against fire (Leitner, 2001; Vuilleumier et al., 2002). Since then, various researchers have contributed their efforts to the risk assessment of road tunnels in terms of number of fatalities. 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 in terms of fatalities, for example, TuRisMo model of Austria, TUNPRIM model of Netherlands, OECD/PIARC DG QRA model and NUS-LTA QRA model (Brussaard et al., 2001; Knoflacher, 2002; 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 for 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 need to be implemented.

Based on the well-recognised QRA models mentioned above, 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, safety provisions (electrical and mechanical (E&M) systems), distance between two evacuation exits, etc. It is universally acknowledged that uncertainty is an unavoidable component in the risk assessment procedure (Nilsen and Aven, 2003; Baudrit et al., 2006). Some parameters possess uncertainties resulting from random variability and they are not suited to be formulated by crisp numbers. However, the aforementioned QRA models for road tunnels do not take random uncertainty with respect to input parameters into consideration. Mean values or most probable values of input parameters are used to represent them, which are unrealistic and could result in erroneous and unreliable assessment.

In this paper, a QRA model with parameter uncertainty is proposed for fire in road tunnels. Probability distributions are employed to characterise uncertainty of input parameters. More specifically, the lognormal distribution is adopted to represent the probabilities of tunnel E&M systems failing to work, and normal distribution is applied to represent the air velocities with different ventilation status as well as the evacuation times for different people. The Monte Carlo sampling approach is applied to formulate

the random input parameters. Accordingly, the societal risk and ENF generated by the proposed model may no longer be a single *F/N* curve or a crisp number. Consequently, there is a need to analyse the new features of societal risk and ENF.

The features of the present study are summarised as follows. Firstly, a probabilistic QRA model for fire in road tunnels is developed, and a Monte Carlo sampling procedure is proposed to solve the QRA model. Secondly, new features of societal risk and ENF are discussed, and the risk indices are considered as better solutions for evaluating the safety level of a road tunnel. Thirdly, a case study is carried out to compare the results generated by the deterministic QRA model and the proposed probabilistic QRA model for highlighting the necessity of the uncertainty propagation procedure.

The remainder of the paper is organised as follows. Risk indices and safety target are introduced in Section 2. Section 3 recalls the deterministic QRA model for fire in road tunnels. The probabilistic QRA model is proposed in Section 4, and a case study is carried out in Section 5. The last section concludes this paper.

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 realisation 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 QRA 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 $F(N)$ denote 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 frequency that scenario i occurs per year and 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 equation (1), the expected value for the number of fatalities per year (ENF) can be calculated by:

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

An upper bound curve of $F(N)$ is usually adopted as the safety target (Jonkman et al., 2003; PIARC, 2008):

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

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

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

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 C and k 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, is composed of several photographical diagrams showing how the undesired states of system are analysed by using Boolean logic to combine series of low-level sub-events. The fault tree of the fire in tunnel top event is shown in Figure 1. The leaf circles, such as probability of ignition (PI) and vehicle defects (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.

Event tree is a tree diagram that refers to complex events that can be discretised 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 in terms of number of fatalities could be estimated by consequence estimation model (see Section 3.2). After obtaining the frequency and consequence of each scenario (leaf node of event tree), societal risk and ENF can be calculated according to equations (1–3).

Figure 1 Fault tree for fire in tunnel top event
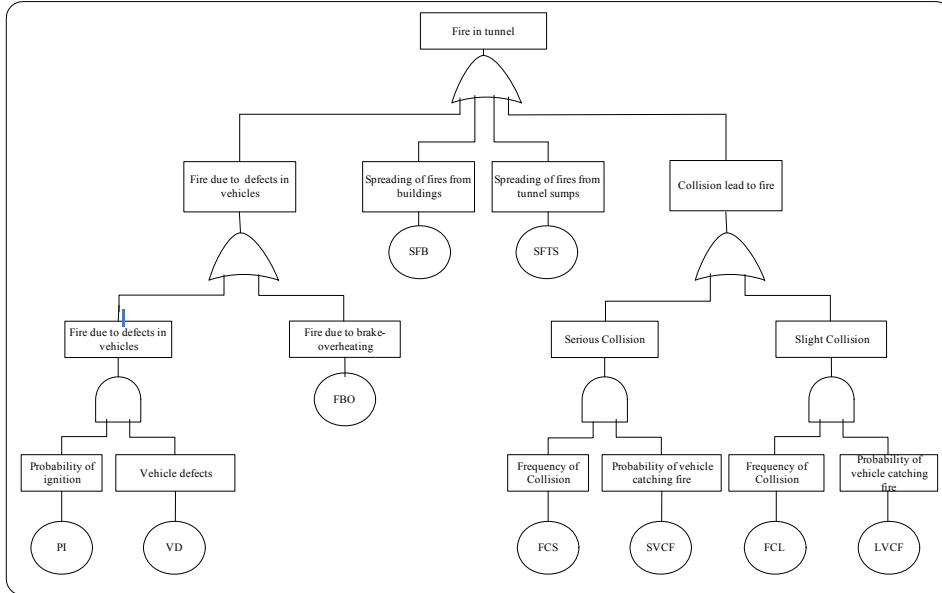
Figure 2 Event tree for fire in tunnel top event

3.2 Consequence estimation models

The procedure for estimating the number of fatalities is as follows. Firstly, the number of people at risk area (N_{par}) needs to be estimated. Secondly, part of tunnel users may evacuate from risk area to safe location, thus we need to calculate the probability of people who have evacuated successfully (P_{ev}), so as to estimate the people exposed to

fire. After that, the fatality rate (*f*) for the people exposed to fire should be calculated. The product of N_{par}, $(1-P_{ev})$ and *f* is the number of fatalities. N_{par} can be roughly estimated once obtaining the traffic volume and vehicle occupation. P_{ev} can be derived from the statistics associated with response time of people at risk and the distances from the emergency exit. The most important part of the procedure is the estimation of fatality rate, which will be elaborated in this section. For the exposed people, heat and toxic gases are major threats caused by fire.

3.2.1 Fatality due to heat

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

$$F_D = F_D(t,T) = t / e^{(5.1849-0.0273T)} \tag{6}$$

where *T* stands for the temperature (°C) and *t* is the exposure time (min). It should be noted that the temperature calculation is a transient heat transfer problem which leads to time-dependent fields from an engineering point of view. In this paper, we apply the following formula to calculate the temperature due to heat at a certain time.

$$T_{em}(t) = T_0 + \frac{0.7Q(t)}{\mu \rho_0 A c_p} \tag{7}$$

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

$$T_g(x,t) = T_0 + \left[T_{em}(\lambda) - T_0\right] e^{\frac{-hP_x}{\rho_0 \mu A c_p}} \tag{8}$$

where the parameter $\lambda = t - x/u$ is defined as the time delay for transporting the heat at distance *x* (m) with an air velocity of *u* (m/s), *h* is the lumped heat loss coefficient for the tunnel surface = 0.03 kW/m^3°C, P_x is the perimeter of the tunnel (m), *A* is the cross-sectional area of tunnel (m^2), the parameter T_0 is initial temperature in the tunnel (°C), ρ_0 is the air density in the tunnel (kg/m^3) and c_p is 1 kJ/°C for air. $Q(t)$ is the heat release rate (HRR). It should be pointed out that the HRR is dependent on the type of vehicle causing the fire, namely car fire, fire involved in HGV and/or fire involved in Hazmat vehicles. The HRR calculation formulas for these scenarios are obtainable from PIARC (1999). The results can be used as an input variable for calculating the fatality rate due to heat using equation (6). Note that the result of equation (7) is an input parameter $T_{em}(\lambda)$ in equation (8), and the result of equation (8) is an input parameter *T* in equation (6).

3.2.2 Fatality due to toxic gases

The toxic gases generated by fire include CO and CO_2. Additionally, the shortage of Oxygen (O_2) could also cause fatalities. The following equations can be adopted to calculate the concentrations of CO, CO_2 and O_2 (Persson, 2002).

$$X_{O_2}(t) = \left[X_\infty - \frac{Q(t)M_a \left(X_\infty \frac{M_{O_2}}{M_a} + r_0 \right)}{\Delta H M_{O_2} \rho_0 \mu A c_p} \right] \times 100 \tag{9}$$

$$X_{CO_2}(t) = \left[\frac{Q(t)(1+r_0)}{\Delta H \rho_0 \mu A c_p} \right] \times 100 \tag{10}$$

$$X_{CO}(t) = \left[Y_{CO} \frac{Q(t)M_a}{\Delta H M_{CO} \rho_0 \mu A c_p} \right] \times 10^6 \tag{11}$$

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), 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/m³), c_p is a constant which takes value of 1 kJ/°C and A is the sectional area of tunnel (m²).

The fatality rate function can thus be calculated by the following formula (Persson, 2002):

$$F_{CO} = \frac{K\left(X_{CO}^{1.036}\right)t}{D} \tag{12}$$

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):

$$F_{O_2} = \frac{t}{e^{8.13-0.54(20.9-X_{O_2})}} \tag{13}$$

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):

$$F_{CO_2} = \frac{t}{e^{6.1523-0.5189X_{CO_2}}} \tag{14}$$

where t is the exposure time (min) and X_{CO_2} is the carbon dioxide concentration.

3.2.3 Fatality rate due to fire

Based on Sections 3.2.1 and 3.2.2, the fatality rates due to heat and toxic gases are calculated. We assume that fatalities due to heat and toxic gases are independent. Accordingly, fatality rate due to fire is obtained as follows:

$$F_{fire} = 1 - \left[(1-F_D) \times (1-F_{CO}) \times (1-F_{O_2}) \times (1-F_{CO_2}) \right] \tag{15}$$

4 Parameter uncertainty analysis

4.1 Input parameter with random variability

In this paper, the uncertainty with fault tree parameters will not be taken into consideration. As suggested by Huang et al. (2001), Hardware Failure Dominated (HFD) events such as the failure of tunnel E&M systems could be formulated by lognormal probability distributions, and sufficient experimental data are available to derive the probability distributions. Furthermore, air velocities are assumed to be normally distributed according to data collected from tunnels. In addition, the evacuation time is also assumed to follow normal distribution.

4.2 Monte Carlo sampling procedure

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:

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

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 and $P(E_k|S_j)$ is the conditional probability of E_k given the occurrence of S_j. With respect to the consequence estimation, equations (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 respect to each scenario can be calculated. However, due to the complexity of the system, those variables do not have closed forms. Therefore, Monte Carlo sampling method is used to address the problems.

Let us consider a model whose output is a function $g\left(u_1, u_1, \cdots, u_n\right)$ of n input parameters $\left(u_1, u_1, \cdots, u_n\right)$. The first k input parameters are considered as constants $\left(u_1, u_1, \cdots, u_k\right)$, whereas the other n–k parameters are characterised 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 and Whitlock, 1986) can be combined with the probability theory by means of the following steps:

Step 0: Give 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 *i*-th realisation $\left(u_{k+1}, u_{k+2}, \cdots, u_n\right)$ 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 *i*-th realisation $g\left(u_1^{(i)}, u_2^{(i)}, \cdots, u_n^{(i)}\right)$,

then $i = i + 1$.

The QRA model can generate the frequencies and fatalities with respect to various scenarios for each realisation. Accordingly, frequency and consequence of each scenario will have *m* results as well. Similarly, the societal risk generated by the QRA model is a set of *F/N* curves (one *F/N* curve for each realisation).

Figure 3 ENF generated by the proposed QRA model (see online version for colours)
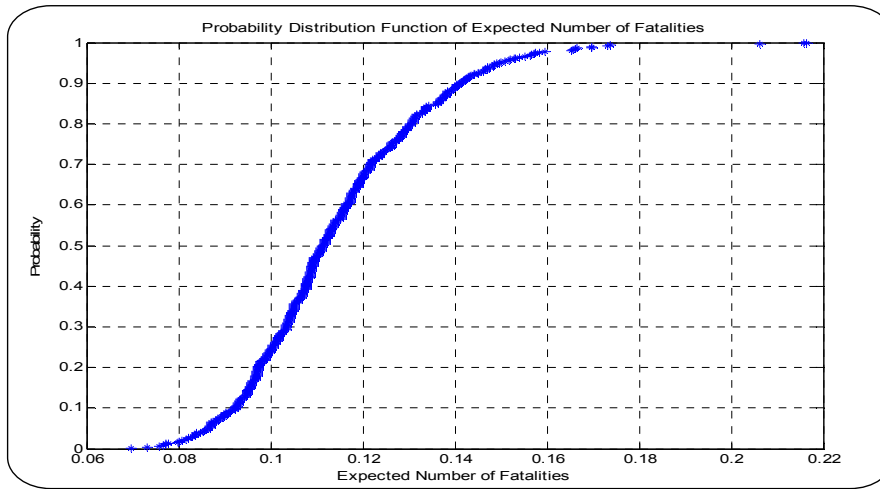
4.3 New features of risk indices

As mentioned above, the ENF is no longer a crisp number but a set of samples, and societal risk is no longer a single curve but a set of *F/N* curves in this study. ENF can be considered as a random variable, and its distribution can be estimated using its samples (*m* realisations). After obtaining the ENF generated by the proposed model, we can easily find the values of ENF with different percentiles, which provide tunnel evaluators more information about the tunnel risk. As for societal risk, percentile-based *F/N* curve is proposed to visualise the tunnel risks. The frequency and the number of fatalities are both considered as random variables in the proposed approach. In order to visualise the societal risk in an *F–N* axis to be better understood by tunnel evaluators, a scenario with *N* or more fatalities is defined as the scenario when its expected number of fatalities (mean value) x_i is greater than a crisp number *N*. Then, *N* is a crisp number and *F* is a random variable in an *F/N* curve. The *F/N* curve can be drawn like what is shown in Figure 4. However, this probabilistic *F/N* curve is not straightforward for tunnel evaluators or decision-makers to use. Eventually, a percentile-based measure is proposed to derive the *F/N* curve to better represent societal risk. We use various percentile values to represent the random variable calculated by equation (16). This risk index is further discussed in Section 5.

Figure 4   An example of probabilistic *F*/*N* curve (see online version for colours)
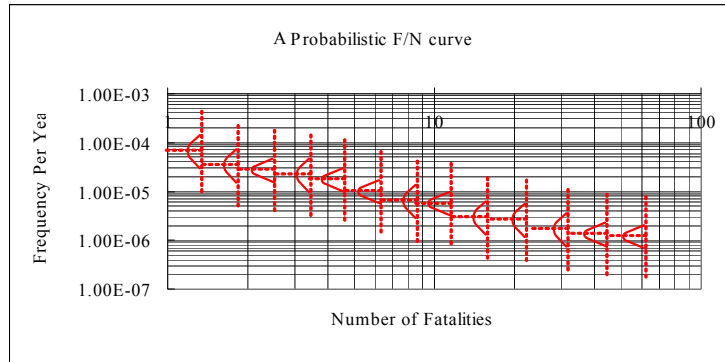
5   A case study

The Kallang/Paya Lebar Expressway (KPE) of Singapore, shown in Figure 5, is 12 km in total length and 9 km is built underground as a road tunnel, which was built to serve the growing 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 three-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 m. The tunnel air velocity when tunnel ventilation works is normally 4 m/s, and the initial temperature is assumed to be 30°C. There is a 24 hr 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 5   KPE road tunnel in Singapore (see online version for colours)

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 systems working normally can be represented by $(1 - P_{de})$ and $(1 - P_{ve})$, 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 6 depicts the probability density function of those probabilistic parameters.

Figure 6 Probability distribution functions of probabilistic parameters (see online version for colours)
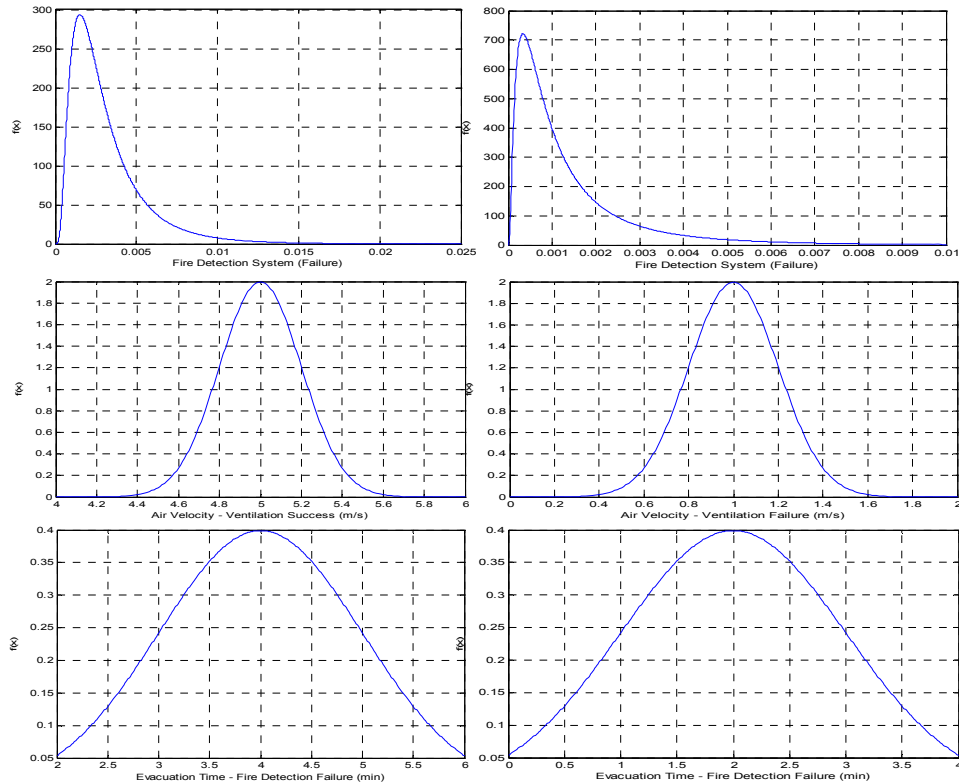
5.2 Calculation of results

Figure 7 shows the probability distribution function of ENF generated by the proposed model. From the figure, we can see that 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. The ENF result calculated by deterministic QRA model which is using mean values of random input parameters (air velocities, evacuation times, etc.) to represent the inputs is 0.137, which is corresponding to the 85 percentile ENF value in the probabilistic QRA model.

Figure 7   Probability distribution function of ENF for KPE road tunnel (see online version for colours)
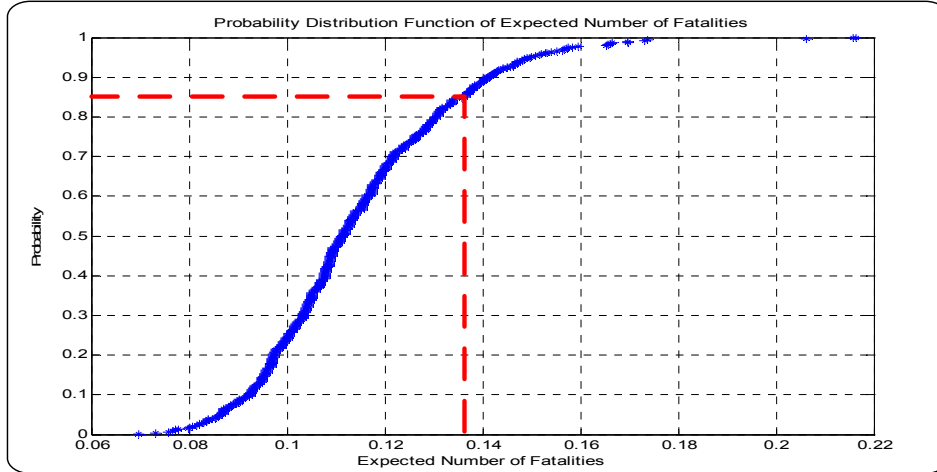

Figure 8 illustrates the 95- and 5-percentile-based *F/N* curves. From the figure, we can find that the *F/N* curve generated by the deterministic QRA model is approximately in between the two percentile-based curves. The percentile-based approach provides the *F/N* curves for tunnel evaluators with different risk attitudes, thus provides better solutions for decision-makers. The 95 percentile *F/N* curve could be considered as an upper bound of *F/N* curve of the road tunnel. Similarly, 5 percentile *F/N* curve could be regarded as a lower bound of the societal risk. Note that the bounds are not compact bound.

Figure 8   Percentile-based *F/N* curve for KPE road tunnel (see online version for colours)
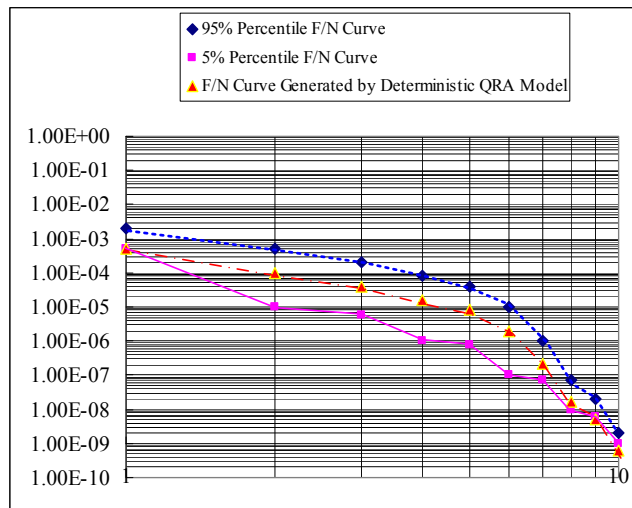
6 Conclusions

Fire is the most severe disaster in road tunnels in that tunnel is an enclosed space. Accordingly, risk assessment of fire in road tunnels has become a significant concern in past decades. Aiming at demerits of the existing QRA models for road tunnels, this paper proposed a probabilistic QRA model to evaluate the risks caused by fire in road tunnel by taking into account uncertainty of input parameters. The case study demonstrates that the percentile-based societal risk and ENF curve would facilitate tunnel managers to make decisions.

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