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Compartment fire risk analysis by advanced Monte Carlo simulation

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Abstract

Quantitative fire risk analysis aims at providing an assessment of fire safety on a scientific basis and taking relevant uncertainties into account in a rational quantitative manner. Under a probabilistic approach, performance measures are formulated as multi-dimensional probability integrals, whose efficient computation is pivotal for practical implementation. Direct Monte Carlo method is a well-known technique, but it is not efficient for investigating rare failure events which are commonly encountered in engineering applications. A recently developed stochastic simulation approach called Subset Simulation is presented for quantitative fire risk analysis with a focus on the critical temperature in a compartment fire event. In the method, random samples leading to progressive failure are generated efficiently and they are used for computing probabilistic performance measures by statistical averaging. The random samples can also be used for probabilistic failure analysis, which yields information conditional on the occurrence of the failure event. A global approach is adopted for incorporating the uncertainties in the functionality of active fire measures into the fire risk analysis, where the failure probabilities can be obtained by a single simulation run rather than by multiple runs exhausting the possibilities in the associated event tree.

Keywords: Fire risk; Monte Carlo method; Reliability; Subset Simulation; Uncertainty

1. Introduction

Structural-fire risk analysis has been highly reliant on prescriptive rules in traditional building codes, which, despite their relatively easy implementation, are inflexible and usually lead to expensive designs. It has been a worldwide trend to develop performance-based codes for engineering designs. A probabilistic approach provides a rational framework for addressing the effects of uncertainties in engineering designs and it has been gradually incorporated in performance-based design guidelines [1–3].

In the quantitative structural-fire risk assessment of compartments, studies have been devoted to the development of stochastic models, experimental investigations and statistical characterization of parameter, i.e. statistical or “state-of knowledge”, uncertainties. Ho and co-workers [4–6] developed a fire hazard model called COMPBRN, which was originally used for nuclear power plants. The model focuses on the uncertainty of coefficients associated with burning rate, air entrainment, plume and wall heat transfer processes and predicts the fire growth in a compartment for fire risk analysis. Brandyberry and Apostolakis [7,8] studied the ignition risk of a consumer product in a building based on heat transfer mechanisms. The study accounted for uncertainties in the ignition source (e.g., surface area, amount of radiated heat) and in the target scenario (e.g., density, specific heat of furniture substrates). The probability of ignition of a target object for a given exposure was obtained using a direct Monte Carlo method. The results were combined with exposure frequency data obtained from a statistical database to yield the probability of ignition and other risk-related measures. The need for simulation models for quantitative fire risk assessment was discussed in Phillips [9], who adopted a direct Monte Carlo method in a simulation model that incorporated (to different levels of sophistication) the evacuation of occupants and the physical/chemical processes of fire growth. Magnussen and co-workers [10] studied egress reliability by assessment of the evacuation “marginal time”

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of a fire compartment using traditional reliability techniques, including the First Order Second Moment Method (FOSM), the direct Monte Carlo method and Latin Hypercube sampling. They adopted, for simplicity, response surface functions for predicting the durations governing egress failure but commented that the results can be significantly influenced by model uncertainty. Frantzich [11] presented a study of the societal risk of evacuation during a fire event. An event tree approach augmented with a direct Monte Carlo method was followed to treat the different possibilities of events distinguished by the functioning state of the alarm, sprinklers and emergency doors. The results were presented in the form of FN (Frequency–Number) curves describing the exceedance probability of the number of fatalities. Jonsson and Lundin [12] carried out a case study in high rise buildings to simulate the fire consequence and movement of people by using different design methods, including prescriptive regulations, FOSM [10], quantitative risk analysis [11] and commercial computational packages. Holborn et al. [13] conducted a statistical characterization on uncertainties of fire size, fire growth rate and event time based on real compartment fire reports from the London Fire Brigade's real fire library. The lognormal distribution function was recommended to characterize compartment fire statistics and verified against the real fire data. Siu and co-workers [14,15] discussed in detail the definition of both statistical and state-of-knowledge uncertainties. Stochastic models were applied to evaluate fire risk in large compartment fires in nuclear plants. In compartment fire risk analysis, numerous computer programs, using zone or computational fluid dynamics (CFD) modelling, exist for simulating and visualizing the movement history of smoke growth and heat transfer, e.g., OZone, CFAST, FDS, etc. In this paper, CFAST [16,17] is employed to compute the fire development and temperature history in a prescribed compartment. Besides, the natural fire safety concept (NFSC) in OZone [18] is used to design the fire load inside the compartment.

The current state-of-the-art is that when complex models are used for response prediction, a direct Monte Carlo method is always used for its general applicability. Traditional variance reduction techniques are used when the model has lower complexity, e.g., when it is simplified using response surface functions, which nevertheless is vulnerable to model error. They have bottleneck problems with complex simulation models, such as in finding design points or when the number of uncertain parameters is large [19].

This paper presents a stochastic analysis of the compartment fire temperature using an advanced simulation algorithm called Subset Simulation. In addition to reliability analysis, the method also allows efficient system analysis using samples conditional on failure. The importance of individual uncertain parameters shall be investigated through the conditional samples generated by Subset Simulation. Discrete-event type uncertainties are also considered in the analysis, which are incorporated in Subset Simulation by means of augmented random variables representing their probabilistic occurrence. This has reduced the computational effort required in reliability analyses of individual events of the event-tree, which in practical applications can be quite extensive.

2. Stochastic analysis by advanced Monte Carlo simulation

Let $\underline{\Theta} \in R^n$ denote the vector of random variables for which a probability model is available, say, in terms of the joint probability density function (PDF) $p(\underline{\theta})$. Many failure events in engineering risk analysis can be formulated as the exceedance of a critical response variable $Y(\underline{\Theta}) \geq 0$ over some specified threshold level y, i.e.,

$$P(F) = P(Y > y) = \int_F p(\underline{\theta}) \mathrm{d}\underline{\theta}. \tag{1}$$

Complementary to the failure probability is the performance margin that corresponds to the percentile of a given risk tolerance, say $\bar{p}$, through which the risk tolerance of a decision-maker manifests. For example, the 90th, 99th and 99.9th percentiles might provide a decision-maker with low-, medium- and high-confidence estimates in the upper-bound value of response, corresponding to a risk-tolerant, risk-neutral or risk-averse decision-maker, respectively.

Monte Carlo simulation (MCS) [20] is the most established sampling technique and the benchmark for comparison by other techniques. In MCS, N_T random samples of the random variables are generated according to their specified probability distributions. The corresponding values of the response Y are then evaluated and analyzed statistically. A simple estimator for the upper $\bar{p}$-percentile value can be obtained as the $\bar{p}N_T$th largest value of Y among the N_T samples, i.e., the $\bar{p}N_T$th order statistics. This estimator is asymptotically unbiased, although the highest percentile value that can be legitimately estimated can be significantly biased for finite N_T. Complementarily, the failure probability $P(F) = P(Y > y)$ for a given y can be estimated simply as the fraction of samples with $Y > y$ among the N_T MCS samples. The coefficient of variation (c.o.v.) of this failure probability estimate is given by

$$\delta = \sqrt{[1 - P(F)]/P(F)N_T} \sim 1/\sqrt{P(F)N_T} \quad \text{for small } P(F). \tag{2}$$

While MCS is applicable to all types of reliability problems, its computational efficiency is a practical concern when estimating small failure probabilities because information must be gained from samples that correspond to failure but these are rarely simulated. A rule of thumb is that one must generate at least 10 failure samples to get a reasonably accurate estimate of $P(F)$, so if $P(F) = 0.001$, at least 10,000 system analyses must be performed. This has motivated recent research to develop more efficient reliability algorithms. Over the past few decades, a number of reliability methods have been developed that are effective when the number of variables n is not too large or when the failure boundary has limited complexity. A common feature of most stochastic simulation methods is that they estimate the integral for $P(F)$ by gaining information about the system behavior and then using such information to account for the failure probability. Excellent reviews can be found at