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Efficient functional reliability estimation for a passive residual heat removal system with subset simulation based on importance sampling

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ABSTRACT

An innovative reliability analysis approach known as "Subset Simulation based on Importance Sampling" is developed for the efficient estimation of the small functional failure probability of a passive safety system. This approach is based on the idea that a small failure probability can be expressed as a product of larger conditional failure probabilities by introducing a proper choice of intermediate failure events. Importance sampling simulation is carried out to generate conditional samples for each intermediate failure region. This application is illustrated for the functional reliability analysis of a passive residual heat removal system due to epistemic uncertainty parameters. The numerical results demonstrate the high level of computational efficiency and excellent computational accuracy by comparison with direct Monte Carlo simulation, Importance Sampling simulation and Subset Simulation based on Markov Chain Monte Carlo. The sensitivity, defined as the partial derivative of the failure probability with respect to the distribution parameter is also discussed, which can help to identify the contribution of each parameter and guide the optimization model.

1. Introduction

The expanded consideration of severe accidents, the increased safety requirements, and the aim of introducing effective – yet transparent – safety functions lead to growing interest in passive safety systems for future nuclear reactors. As a result, innovative reactor designs incorporate passive safety features with active safety or operational functions (Marquès et al., 2005). According to an IAEA definition, a passive safety system is either a system which is composed entirely of passive components and structures or a system which uses active components in a limited way to initiate subsequent passive operation. Most often, a passive system does not need any external input (especially energy) to operate (IAEA, 1991). This is why passive safety systems are simple and robust.

Many passive safety systems are based on natural circulations, which have much weaker driving forces than their active counter parts. Therefore, it is important to consider fluid mechanics issues, as well as disturbances or changes in operating parameters. In summary, the uncertainties of passive safety systems are usually higher than those in active systems. Two different sources of uncertainties usually exist in safety analysis of passive safety systems: randomness due to intrinsic variability in the actual geometrical properties, material properties and the initial/boundary conditions, known as aleatory uncertainty and incomplete knowledge due to lack of data on some underlying physical phenomena and translate in uncertainties in the models and parameters used to represent them, known as epistemic uncertainty (Apostolakis, 1990; Zio and Pedroni, 2009b, 2011). Because of these uncertainties, there is always a nonzero likelihood that a physical phenomena utilized by the passive systems fails to perform intended functions even though there is no hardware failure. Hence, it is necessary to quantify the reliability of such systems first. The unreliability of passive safety systems can have two aspects: malfunctions of systems/components, i.e. hardware failure and absence of intended physical phenomena, referred to as functional failure (Burgazzi, 2003, 2004; Mathews et al., 2008; Fong et al., 2009; Zio and Pedroni, 2009a,b). The present paper mainly focuses on the reliability analysis of the functional failure in passive safety systems.

Several methodologies have been developed for the evaluation of functional failure probabilities of passive safety systems, known as Reliability Evaluation of Passive Safety (REPAS) (D'Auria et al., 2002;

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Jafari et al., 2003; Zio et al., 2003), and Reliability Methods for Passive Safety (RMPS) (Marquès et al., 2005; Bassi and Marquès, 2008), respectively. These methods have been applied to residual heat removal systems in light water reactors (Wang et al., 2013). Similar approach is used for decay heat removal systems in gas-cooled fast reactors (Pagani et al., 2005; Mackay et al., 2008; Zio and Pedroni, 2009a,b) and sodium-cooled fast breeder reactors (Mathews et al., 2008, 2011; Arul et al., 2009, 2010). Among all these methods, a primary cause for the functional failure is assumed to be arising mainly from the existence of the uncertainties in the system model and input parameters and consequently, the system cannot accomplish its required mission even if no hardware failure occurs. In this work, the passive safety system is modeled by a deterministic thermal hydraulic code and the functional failure probability is estimated based on a Monte Carlo (MC) sample simulation which propagates the epistemic uncertainties in the model and the numerical values of its input parameters.

MC simulation is well known to be robust to the realistic estimation of a passive safety system functional failure probability (Zio and Pedroni, 2009b). In practice, the probability of functional failure for a passive safety system can be relatively low. Hence, a large number of samples are required to gain a sufficient confidence level. Unfortunately, the computational cost is normally prohibitively high, if a direct MC simulation (DMCS) is used with a deterministic thermal hydraulic model code (Schueller and Pradlwarter, 2007; Zio and Pedroni, 2009b; Wang et al., 2013). To reduce the computational cost, efficient sampling techniques can be adopted to perform functional reliability estimations of passive systems.

To improve efficiency, the Subset Simulation (SS) approach, originally developed to estimate the reliability of multidimensional structures (Au and Beck, 2001, 2003), is introduced. Structural reliability problems are naturally formulated within a functional failure framework of analysis, because structural systems fail when the load exceeds their capacity (Schueller and Pradlwarter, 2007). This makes SS suitable for the application to the functional failure reliability analysis of a passive thermal hydraulic safety system, because a passive system fails to perform its function when deviations from its expected behavior lead the load imposed on the system to exceed its capacity (Bassi and Marquès, 2008; Patalano et al., 2008; Zio and Pedroni, 2009b). The SS method is efficient to perform the reliability analysis in a progressive manner. A set of intermediate failure events are introduced first, SS separates the original probability space into a sequence of subsets, the small failure probabilities can be expressed as a product of large conditional failure probabilities. For given conditional probability density function (PDF), Markov Chain Monte Carlo (MCMC) can be used to generate conditional samples and to estimate the conditional probability (Au and Beck, 2001, 2003; Zio and Pedroni, 2009b). However, MCMC simulation relies on certain PDF. Therefore, additional simulations based on a thermal hydraulic code have to be used, which further increases the computational cost. Moreover, the conditional samples generated by MCMC simulation are typically dependent. These samples are used for statistical averaging as if they are independent and identically distributed (i.i.d.) with some reduction in efficiency (Song et al., 2009). Considering this limitation, an improved Subset Simulation method, known as Subset Simulation based on Importance Sampling (SS-IS) is developed. The concept of IS procedure is employed to generate the i.i.d. conditional samples in the failure region to effectively calculate the conditional failure probability under specified levels of failure probabilities. The advantage of this methodology is demonstrated by comparing it to DMCS, IS and SS-MCMC in a functional reliability analysis of a passive residual heat removal system.

A sensitivity analysis, which concerns with ranking of the individual uncertainty parameters according to their relative contribution on the functional failure probability, has been carried out. A usual approach is to base the sensitivity analysis on a linear regression method, which is based on the hypothesis of a linear relation between the response variables and input parameters. This, in case of passive safety systems is often restrictive (IAEA, 2005; Mathews et al., 2008). In this case, an alternative approach is applied to identify and rank influential individual uncertainty parameters based on the sensitivity of the cumulative distribution function (CDF) of the functional failure probability. The approach doesn't assume a linear or other explicit functional relationship between the response and the input parameters, and provide more information than the traditional regression-based methods. The sensitivity coefficient is expressed as an expectation of the partial derivative of the failure probability with respect to the distribution parameter.

The remainder of paper is organized as follows. A reliability analysis methodology for passive safety systems in terms of the concept of functional failure is summarized in Section 2. In Section 3, the functional reliability assessment analysis procedure for the passive residual heat removal system of a 1000 MWe Pressurized Water Reactor (PWR) is carried out. The functional failure probability estimation by SS-IS and comparison of results DMCS, IS and SS-MCMC is discussed in Section 4. The sensitivity analysis is performed to determine the contributions of the individual uncertain parameters in Section 5 and some conclusions are given in Section 6.

2. A methodology for functional reliability analysis of passive safety systems

In reliability analysis of a passive thermal hydraulic safety system, the probability that the corresponding response variable (e.g. coolant outlet temperature at critical location) exceeds the limiting threshold value is termed as the functional failure probability. A procedure for the evaluation functional failure probability has been proposed known as RMPS methodology. The organization of the methodology for the evaluation the functional reliability is depicted in Fig. 1. The basic steps of the functional reliability analysis of passive safety systems are as follows (Marquès et al., 2005; Zio and Pedroni, 2009a,b; Arul et al., 2010; Wang et al., 2013):

1. Detailed modeling for the passive safety system using deterministic thermal–hydraulics code.
2. Identification of the uncertainty relevant parameters/variables in the passive safety system.
3. Quantification of appropriate probability density functions to these parameters/variables.
4. Evaluation of the failure criteria for the passive system on basis of its function and failure modes.
5. Propagation of uncertainties through the deterministic thermal hydraulic code by using MC simulation.
6. Quantification of functional failure probability, Let $\boldsymbol{X} = \{x_1, x_2, \ldots, x_n\}$ be the vector of the uncertainty parameters, $Y(\boldsymbol{X})$ be the indicator of the performance of passive system, A_Y be the threshold value defining the failure criterion. By introducing a variable called Limit State Function (LSF) as $g(\boldsymbol{X}) = A_Y - Y(\boldsymbol{X})$, failure occurs if $g(\boldsymbol{X}) < 0$. The system failure probability $P(F)$ can be evaluated by the following integral: $P(F) = \int \cdots \int_{g(\boldsymbol{X})<0} f_{\boldsymbol{X}}(\boldsymbol{X}) \mathrm{d}x_1 \cdots \mathrm{d}x_n$, where $f_{\boldsymbol{X}}(\boldsymbol{X})$ is the joint probability density function, and
7. Determination of the contributions from each uncertainty parameter via parametric sensitivity analysis.

Though this has been the general framework structure proposed for the passive systems reliability estimation, there have been several studies especially in the field of the probabilistic safety