Reliability Engineering and System Safety 79 (2003) 175–185

RELIABILITY ENGINEERING & SYSTEM SAFETY

www.elsevier.com/locate/ress

Comparison of global sensitivity analysis techniques and importance measures in PSA

E. Borgonovo[a], G.E. Apostolakis[a], S. Tarantola[b,*], A. Saltelli[b]

[a]Room 24-221, Department of Nuclear Engineering, Massachusetts Institute of Technology, 77 Massachusetts Av., Cambridge, MA 02139-4307, USA

[b]Institute for the Protection and Security of the Citizen, Joint Research Center of the European Commission, TP. 361-21020 Ispra, VA Italy

Abstract

This paper discusses application and results of global sensitivity analysis techniques to probabilistic safety assessment (PSA) models, and their comparison to importance measures. This comparison allows one to understand whether PSA elements that are important to the risk, as revealed by importance measures, are also important contributors to the model uncertainty, as revealed by global sensitivity analysis. We show that, due to epistemic dependence, uncertainty and global sensitivity analysis of PSA models must be performed at the parameter level. A difficulty arises, since standard codes produce the calculations at the basic event level. We discuss both the indirect comparison through importance measures computed for basic events, and the direct comparison performed using the differential importance measure and the Fussell–Vesely importance at the parameter level. Results are discussed for the large LLOCA sequence of the advanced test reactor PSA.

Keywords: Importance measures; Global sensitivity analysis; Probabilistic safety assessment; Sensitivity analysis; Epistemic uncertainty

1. Introduction

Probabilistic safety assessment (PSA) is a methodology that produces numerical estimates for a number of risk metrics for complex technological systems. The core damage frequency (CDF) and the large early release frequency (LERF) are the common risk metrics of interest in nuclear power plants (NPP).

The generic risk metric can be written as a function of the frequencies of the initiating events, i.e. events that disturb the normal operation of the facility such as a power excursion and the conditional probabilities of the failure modes of structures, systems and components (SSCs)

$$R = h(\underline{f}^{\mathrm{IE}}, \underline{q}) \tag{1}$$

where $\underline{f}^{\mathrm{IE}} = \{f_i^{\mathrm{IE}}\}$, $i = 1, \ldots, Z$, is the set of the frequencies of initiating events with Z the total number of initiating events included in the PSA model and $\underline{q} = \{q_j\}$, $j = 1, \ldots, N$, is the set of the basic event probabilities, with N, the total number of basic events in the PSA. More synthetically, $q_j = p(\mathrm{BE}_j)$, $j = 1, \ldots, N$.

Once the logical expression of the minimal cut sets is expanded and the rare event approximation is considered, R is linear in $\underline{f}^{\mathrm{IE}}$ and $\underline{q}$ [4].

Since Eq. (1) relates the risk metric to the basic events, we refer to Eq. (1) as the basic event representation or basic event level of the PSA model.

A 'point estimate' of the risk metric R can be produced by Eq. (1) using point ('best estimate') values of the inputs ($\underline{f}^{\mathrm{IE}}$ and $\underline{q}$ in this case). We write

$$R_0(\underline{\phi}_0) = h(\underline{q}_0, \underline{f}_0) \tag{2}$$

where we have introduced the symbol $\underline{\phi}$ to denote the generic q_j or f_i ($\underline{\phi} = \{q_j, f_i\}$, $j = 1, 2, \ldots, N$, $i = 1, 2, \ldots, Z$). One refers to R_0 as to the nominal value or the risk metric, or, shortly, the nominal risk.

The risk metric is often expressed as a function of more fundamental parameters. For example, the failure time of a component is usually assumed to follow an exponential distribution with a failure rate λ. In the case the component is renewed every τ units of time, then, its average (over time) unavailability is [2]:

$$q_j = p(\mathrm{BE}_j) = \frac{\lambda_j \tau}{2} \tag{3}$$

However, more rigorously, we acknowledge that these inputs are uncertain and express this uncertainty using

* Corresponding author. Tel.: +39-0332-78-9686; fax: +39-0332-78-5733.

E-mail address: stefano.tarantola@jrc.it (S. Tarantola).

0951-8320/03/$ - see front matter
PII: S0951-8320(02)00228-4

state-of-knowledge or epistemic probability distributions (Kaplan and Garrick, 1981) [1,12–15,17]. The propagation of these distributions produces the epistemic distribution of R. Epistemic or state of knowledge dependencies and conditional dependencies are not captured by the basic event expression of R. Eq. (1) needs to be replaced by its parametric representation, if we want to take them into account [4]. We denote the expression of the risk metric as a function of the PSA model parameters as:

$$R(\underline{x}) = g(x_1, x_2, \ldots, x_n) \tag{4}$$

The importance of a PSA element with respect to the risk is found applying PSA importance measures. Importance measures traditionally used are the Fussell–Vesely (FV), risk achievement worth (RAW) [8,26] These measures show shortcomings when applied to set of basic events (Eq. (1)). Furthermore, RAW cannot be used to compute the importance of parameters (Eq. (4)) [4]. The differential importance measure (DIM) proposed recently by Borgonovo and Apostolakis [4] remedies this situation. In addition, DIM is defined for both Eqs. (1) and (4), providing measures of the risk-significance of both basic events and parameters (Section 2).

PSA importance measures (FV, RAW and DIM) are local measures, i.e. they deal with a point value of R and of the parameters. However, to assess the relevance of a parameter with respect to the model uncertainty, the entire epistemic uncertainty in R and in the parameters should be taken into account. Global sensitivity analysis (GSA) techniques are the appropriate techniques for this task [21]. We have investigated several GSA techniques in this work. In this paper we focus on the results and performance of global sensitivity indices computed via extended fourier amplitude sensitivity test (FAST) [12,22,24].

We show that, due to epistemic dependencies, the appropriate level to perform GSA is the parameter level of the PSA model. Thus, the comparison of importance measures and GSA technique results is not direct, since importance measures are produced at the basic event level by most standard PSA software tools, while GSA techniques are computed at the parameter level. We propose both an indirect approach for the comparison of FV and RAW results at the basic event level to GSA results, and a direct comparison that makes use of DIM and FV at the parameter level as measures of risk. We provide quantitative results through the use of the large loss of coolant accident (LLOCA) PSA model of the advanced test reactor (ATR) [10].

In Section 2, we present DIM, FV, and RAW and discuss their properties. In Section 3, we introduce variance-based techniques and the definition of model coefficient of determination. In Section 4, we discuss dependencies caused by epistemic uncertainty. In Section 5, we present the application and results of GSA and importance measures, and their comparison for the large LLOCA sequence of the ATR PSA model. In Section 6 a number of conclusions is offered.

2. PSA importance measures

In this section, we discuss the definitions and properties at both the parameter and basic event level of DIM, FV and RAW.

DIM is defined for both PSA model parameters and basic events. The definition of DIM for parameters is as follows [4]:

$$\mathrm{DIM}_{x_i}(\underline{x}_0, \mathrm{d}\underline{x}) = \left.\frac{\mathrm{d}R_{x_i}}{\mathrm{d}R}\right|_{x_0} = \frac{\left.\dfrac{\partial R}{\partial x_i}\right|_{x_0} \mathrm{d}x_i}{\sum_j \left.\dfrac{\partial R}{\partial x_j}\right|_{x_0} \mathrm{d}x_j} \tag{5}$$

where $\underline{x}_0 = \{x_{1_0}, x_{2_0}, \ldots, x_{n_0}\}$ is the set of the parameters in Eq. (4) fixed at a reference point value, $\mathrm{d}\underline{x} = \{\mathrm{d}x_1, \mathrm{d}x_2, \ldots, \mathrm{d}x_n\}$ is the change vector,

$$\mathrm{d}R_{x_i} = \left.\frac{\partial R}{\partial x_i}\right|_{\underline{x}_0} \mathrm{d}x_i$$

is the differential of R with respect to x_i,

$$\mathrm{d}R = \left.\frac{\partial R}{\partial x_1}\right|_{\underline{x}_0} \mathrm{d}x_1 + \left.\frac{\partial R}{\partial x_2}\right|_{\underline{x}_0} \mathrm{d}x_2 + \cdots + \left.\frac{\partial R}{\partial x_n}\right|_{\underline{x}_0} \mathrm{d}x_n$$

is the total differential of R.

DIM (Eq. (5)) is the fraction of the local change in R that is due to a change in parameter x_i.

The definition of DIM at the basic event level is

$$\mathrm{DIM}_{E_j}(\underline{\phi}_0, \mathrm{d}\underline{\phi}) = \frac{\mathrm{d}R_{E_j}}{\mathrm{d}R} = \frac{\left.\dfrac{\partial R}{\partial \phi_j}\right|_{\underline{\phi}_0} \mathrm{d}\phi_j}{\sum_k \left.\dfrac{\partial R}{\partial \phi_k}\right|_{\underline{\phi}_0} \mathrm{d}\phi_k} \tag{6}$$

where E_j denotes the generic basic event or initiating event, ϕ_j denotes the corresponding probability (if E_j is a basic event) or frequency (if E_j is an initiating event), $\mathrm{d}R_{E_j}$ denotes the differential of R in ϕ_j, $\mathrm{d}R$ is the total differential of in R. Eq. (6) states that basic events that cause the greater change in the risk metric have the highest DIM. We note that Eq. (6) is based on the expression of R as function of the basic events (Eq. (1)), while the definition in Eq. (5) applies to the expression of the risk metric as a function of the parameters (Eq. (4)).

As it appears from Eqs. (5) and (6), DIM depends on both the parameter reference values and the vector of changes in the parameters. DIM can be computed under different assumptions regarding the way parameters or basic events are affected by the changes [4]. The following assumptions