Reliability Engineering and System Safety 151 (2016) 12–19

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Invariant methods for an ensemble-based sensitivity analysis of a passive containment cooling system of an AP1000 nuclear power plant

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ARTICLE INFO

Available online 22 October 2015

Keywords:
Invariant sensitivity analysis methods
Pearson correlation ratio
Delta method
Beta Method
AP1000 Nuclear Power Plant
Ensemble of methods

ABSTRACT

Sensitivity Analysis (SA) is performed to gain fundamental insights on a system behavior that is usually reproduced by a model and to identify the most relevant input variables whose variations affect the system model functional response. For the reliability analysis of passive safety systems of Nuclear Power Plants (NPPs), models are Best Estimate (BE) Thermal Hydraulic (TH) codes, that predict the system functional response in normal and accidental conditions and, in this paper, an ensemble of three alternative invariant SA methods is innovatively set up for a SA on the TH code input variables. The ensemble aggregates the input variables raking orders provided by Pearson correlation ratio, Delta method and Beta method. The capability of the ensemble is shown on a BE–TH code of the Passive Containment Cooling System (PCCS) of an Advanced Pressurized water reactor AP1000, during a Loss Of Coolant Accident (LOCA), whose output probability density function (pdf) is approximated by a Finite Mixture Model (FMM), on the basis of a limited number of simulations.

1. Introduction

The reliability analysis of passive safety systems of advanced Nuclear Power Plants (NPPs) must consider that when uncertainties of counter-forces (e.g., friction) have magnitude comparable to the driving ones (e.g., gravity, natural circulation), physical phenomena may fail performing the intended function even if (i) safety margins are met, (ii) no hardware failures occur (Burgazzi, 2007) [24,39].

Many approaches have been proposed for identifying and quantifying the uncertainties affecting the code outputs and generated by simplifications, approximations, round-off errors, numerical techniques, user errors and variability in the input parameters values [27] e.g., Code Scaling, Applicability, and Uncertainty (CSAU) [36], Automated Statistical Treatment of Uncertainty Method (ASTRUM) and Integrated Methodology for Thermal-Hydraulics Uncertainty Analysis (IMTHUA) [17]. All these methods deal with the need of addressing the problem of uncertainty quantification of the Thermal Hydraulics (TH) codes that are used to predict the response of the systems in nominal and accidental conditions. Traditionally, these calculations were performed on very conservative TH codes, that were supposed to "cover" the system from undesired and/or unknown system (uncertain) behaviors (Zio et al., 2008). More recently, Best Estimate (BE) codes have been adopted to provide more realistic results, thus avoiding over-conservatism, [1,40] although, requiring a detailed, precise and rigorous treatment of the related uncertainties.

This has brought into the reliability analysis of NPPs passive systems an increasing computational complexity that has been recently addressed in literature: for example, a combination of Order Statistics (OS) [18,37] and Artificial Neural Networks (ANN) has been proposed to speed up the computations [33]. However, these approaches allow determining only some percentiles and not the whole distribution, and do not provide insights on the sensitivity to input variability [21,23].

In this respect, several SA methods have been proposed [31]: some are quantitative and model-free, whereas some others are specifically tailored to the model. Among those belonging to the former group, global SA methods offer great capabilities but, again, high computational costs, especially if compared to local and regional SA methods. The most used global SA methods are: non-parametric methods, variance-based methods, moment independent, value of information-based methods and Monte Carlo filtering (the interested reader may refer to Ref. [8] for a detailed review of the methods). Examples of global non-parametric SA methods are the Standardized Regression Coefficient [19] and the Pearson

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http://dx.doi.org/10.1016/j.ress.2015.10.006
0951-8320/

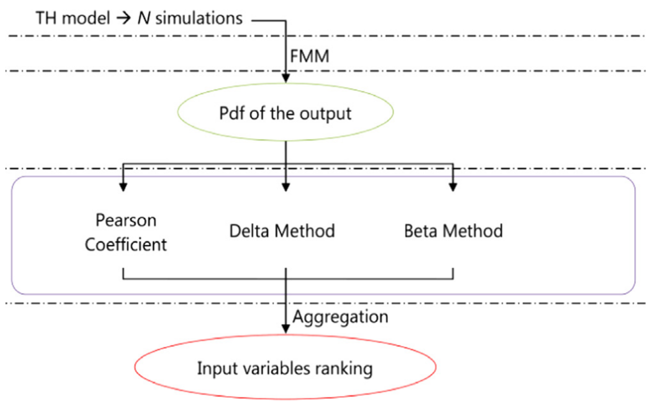

Fig. 1. Flowchart of the proposed framework for ensemble sensitivity analysis.

coefficient [29]. The functional ANOVA expansion of the input-output mapping [19,30,9] is at the basis of variance-based methods, which are widely used in global SA. However, ANOVA expansion requires independence among the model inputs and, if the number of parameters is high, a high computational cost is required for computing interaction terms [34]. Variance-based sensitivity measures have been originally defined by Pearson in 1905 and are known under the name of correlation ratio and have been further improved by Sobol in 1993. In general terms, when used as measures of statistical dependence, first order variance-based sensitivity measures as well as non-parametric methods may lead to misleading conclusions, especially when model inputs are correlated. These limitations are overcome by moment independent sensitivity measures. Among these, the invariant method Delta [4] and Kolmogorov-Smirnov distance between cumulative distribution functions [2] have to be cited as viable solutions[5] .

In this work, to avoid a large number of TH code runs for the numerical estimation of the selected sensitivity measures, we propose an innovative framework of analysis whose flowchart is shown in Fig. 1. The idea is to directly rely on the information available in the multimodal pdf of the output variable for performing global SA of a TH code. First, a limited number N of simulations of the TH code are performed and a Finite Mixture Model (FMM) is used to reconstruct the pdf of the model output [10]. The natural clustering made by the FMM on the TH code output [12,25] is exploited to estimate global sensitivity measures using a given data approach [26]. As shown in Ref. [3], in fact, variance-based and distribution-based sensitivity measures rest on a common rationale that allows them to be estimated from the same design of experiments. We can, then, employ an ensemble of three SA indicators: first-order variance-based sensitivity measure (i.e., the Pearson's correlation ratio), the Delta method [4] and a new sensitivity measure based on the Kolmogorov–Smirnov distance between cumulative distribution functions [2].We use these sensitivity measures for ranking the input variables most affecting the output uncertainty. The rationale behind the selection of these sensitivity measures is that we want to show that, even with a limited quantity of data, the aggregated ranking is robust and reliable even though a commonly used sensitivity measure (i.e., the Pearson's correlation ratio), that is reckoned to have limitations when model inputs are correlated, is used in an ensemble with other moment independent sensitivity measures better performing when model inputs are correlated (i.e., the Delta and the Beta measures).In other words, we show that the ensemble strategy allows combining the output of the three individual methods (that perform more or less well depending on the data) to generate reliable rankings [13]. The idea of using an ensemble of methods for sensitivity analysis will be shown particularly useful when the number of TH code simulations is small, for a low computational cost: due to the limited quantity of data in this situation, in fact, possible misleading rankings can arise from the individual SA methods, whereas the diversity of the methods integrated in the ensemble allows overcoming the problem. As a last remark, it is worth pointing out that if different sensitivity measures are chosen, where none of them can properly deal with correlated inputs, the results would be different and either the given data approach, nor the ensemble would be capable of overcoming the misleading rankings of the single sensitivity measures. In fact, the aggregation of the multiple rankings cannot add any knowledge regarding the modeled phenomena and/or the input variables correlation/dependence, but can only increase the robustness and the reliability of the result (if there is agreement among the different ranking), or suggest the analyst that the result is not reliable and, thus, other sensitivity measures should be adopted (if the different rankings lack of agreement).

Our application concerns the sensitivity analysis of a TH code that simulates the behavior of the Passive Containment Cooling System (PCCS) of an Advanced Pressurized water reactor AP1000 during a Loss Of Coolant Accident (LOCA). The combination of the three sensitivity methods is shown to make the results robust, with no additional computational costs (no more TH code runs are required for SA).

The paper is organized as follows. In Section 2, the case study and the relative TH code are illustrated. In Section 3, the basis of FMM are presented along with the ensemble of sensitivity methods, i.e., Pearson correlation, Delta method and Beta method. In Section 4, the experimental results are reported. Section 5 draws some conclusions.

2. Case study

The AP1000 NPP is a 1117 MWe (3415 MWth) pressurized water reactor (PWR),with a passive Residual Heat Removal System (RHRS) and a Passive Containment Cooling System (PCCS). The PCCS cools the containment following an accident, so that pressure is effectively controlled within the safety limit of 0.4 MPa. During an accident (for example, during a Loss Of Coolant Accident (LOCA) or a Main Steam Line Break (MSLB) accident), the produced steam is injected into the containment and (i) an air baffle incorporated into the concrete structure outside the steel vessel creates the tunnel for continuous, natural circulation of air, and (ii) water that drains by gravity from a tank located on top of the containment shield building (by means of three redundant and diverse water drain valves) supplements, by evaporation, the heat removal. The steel containment vessel provides the heat transfer surface through which heat is removed from inside the containment and transferred to the cold sink, i.e., the atmosphere. In addition, even in case of failure of water drain, air-only cooling is supposed to be capable of maintaining the containment below the failure pressure [32]. Fig. 2 shows the PCCS of the AP1000 (Westinghouse Electric Company).

For the quantification of the functional failure of the PCCS of the AP1000 following a LOCA, a TH model for stratified heat transfer with non-condensed gas has been developed, that consists in four phases [28]: (1) blowdown, from the accident initiation (by a double-ended guillotine pipe break in a primary coolant line affecting the normal operation of the reactor at steady-state full power) to the time at which the primary circuit pressure reaches the containment pressure; (2) refill, from the end of the blowdown to the time when the Emergency Core Cooling System (ECCS) refills the vessel lower plenum; (3) reflood, which begins when water starts flooding the core and ends when this is completely quenched; (4) post-reflood,