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Uncertainty and sensitivity analysis in the neutronic parameters generation for BWR and PWR coupled thermal-hydraulic–neutronic simulations

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ABSTRACT

The Best Estimate analysis consists of a coupled thermal-hydraulic and neutronic description of the nuclear system's behavior; uncertainties from both aspects should be included and jointly propagated. This paper presents a study of the influence of the uncertainty in the macroscopic neutronic information that describes a three-dimensional core model on the most relevant results of the simulation of a Reactivity Induced Accident (RIA).

The analyses of a BWR-RIA and a PWR-RIA have been carried out with a three-dimensional thermal-hydraulic and neutronic model for the coupled system TRACE-PARCS and RELAP-PARCS. The cross section information has been generated by the SIMTAB methodology based on the joint use of CASMO-SIMULATE.

The statistically based methodology performs a Monte-Carlo kind of sampling of the uncertainty in the macroscopic cross sections. The size of the sampling is determined by the characteristics of the tolerance intervals by applying the Noether–Wilks formulas.

A number of simulations equal to the sample size have been carried out in which the cross sections used by PARCS are directly modified with uncertainty, and non-parametric statistical methods are applied to the resulting sample of the values of the output variables to determine their intervals of tolerance.

1. Introduction

Best-estimate computer programs make use of the best physical models and numerical solution methods available to simulate the behavior of nuclear power plants. It is well known that their results are affected by the uncertainty in the methods and the models, and in order to draw proper conclusions from them, it is necessary to apply methodologies for the propagation of uncertainty so that it can be quantified. When the Best Estimate analysis consists of a coupled thermal-hydraulic and neutronic description of the nuclear system's behavior, uncertainties from both aspects should be included and jointly propagated. This paper presents a study of the influence of the uncertainty in the macroscopic neutronic information that describes a three-dimensional core model on the most relevant results of the simulation of a Reactivity Initiated Accident (RIA) which are part of the accident analysis for the licensing basis.

In this paper, the uncertainty and sensitivity analysis in a BWR NPP core configuration in a CRDA (Control Rod Drop Accident) and a PWR NPP core configuration in a REA (Rod Ejection Accident) are presented. These accidents are caused by the failure of the driving mechanism of a control rod. As a consequence, a continuous reactivity is inserted in the reactor which has to be compensated for by other reactor feedback mechanisms in order to maintain the values of its safety variables within the regulatory margins. The physical description of the reactor response is based on the coupled neutronic–thermal-hydraulic systems analysis program standard in the industry TRACE (NCR, 2007)/PARCS v2.7 (Downar et al., 2004) and RELAP5 (RELAP5/MOD3.3 Code Manual, 2001)/PARCS v2.7 respectively.

The data needed for the complete neutronic description of the core behavior, the cross-sections sets, are obtained by using the CASMO4 (Knott et al., 1995)-SIMULATE3 (Cronin et al., 1995) computer package and processed according to the SIMTAB methodology developed at the Polytechnic University of Valencia (UPV) together with Iberdrola (Rosello, 2004). In order to qualify the results obtained using these cross-sections sets, the model's results for steady-state conditions have been compared to the results of a stand-alone core simulation performed with SIMULATE3, a standard and extensively validated core analysis tool in the industry. Specifically, the core power axial profile and the nuclear integral parameter k_{eff}, that indicates its critical state, have been compared yielding very close results, thus validating the model employed in the paper.

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As in the case of PWRs, the transient is started by the ejection of rod with the maximum reactivity worth until it is completely extracted in 0.1 s. A continuous reactivity insertion drives the transient behavior of the reactor. The Doppler reactivity feedback mechanism resulting from the increase of the fuel temperature counterbalances the positive reactivity insertion due to the extraction of the control rod and finishes the transient by drastically stopping the power increase and then bringing it down to levels below nominal steady state conditions before the fuel enthalpy reaches values close or above the safety limits (170 cal/g or 711.756 kJ/kg) (OECD/NEA, 2001). As a result, the amount of energy deposited in the nuclear fuel stays below the maximum values accepted as safety limits, and assuring that the fuel will not be damaged.

2. Uncertainty and sensitivity analysis methodology

The methodology used in this work is based on the use of statistical techniques to calculate sensitivity and uncertainty information from the results of a computer simulation. The advantage of a methodology based on a statistical sample of input variables and code models is that there is no need to make an a priori selection of which of the input variables are more important for the simulation. Methods for sensitivity analysis can provide a posteriori assessment of the importance of the input parameters.

The first step in this methodology is to identify the relevant input variables and code models. After that, the next step consists of the quantification of their uncertainties.

In this work, only the neutronic parameters have been considered as relevant input variables. In another work (Barrachina et al., in press), it was observed that the core nodalization affects the power peak value reached during the transient. Future works will focus on the uncertainty and sensitivity analysis to core nodalization. For the present work, the core nodalization has been fixed as it is explained in the following sections.

The input variables are assumed to be random variables with respect to taking values within their ranges of variation. The range of statistical variation of all these variables needs to be determined with the help of experimentally observed ranges or from previous experience. According to this information, Probability Density Functions (PDFs) should be assigned to the input variables before the sampling process can take place. PDFs quantify the likelihood of these variables taking specific values within their range of variation. This initial phase of the analysis is the most subjective of the entire process. The determination of PDFs is not a simple task, and for many variables the actual functions are not known. When no data is available, the only recourse is to assign Subjective PDFs (SPDF) based on experience or subjective judgment. One of the most often used PDFs, the one that maximizes the lack of knowledge is the uniform distribution, since, based on the range of variation of a variable, it assigns equal probability to each value within its sample space. The Normal or Lognormal distributions are usually employed to describe experimental measurements and other natural variations. They can also be truncated to account for the fact that some parameters may have their range of variation limited by physical constraints, e.g., pressures too low or two high.

Clearly, the choice of PDFs for the input and code model parameters will influence the results of the analysis, since the stochastic characteristics of the input PDFs are propagated through the deterministic computer model to the output results. Therefore, special care should be taken when assigning uncertainty information to input and code model parameters.

Once the PDFs and ranges of variation have been assigned to the input variables and code models, the space of these random variables is sampled. It is important to note, that the precision of the results obtained is not dependent on the number of input parameters, but, among other factors, in the sample size and randomness of the sampling procedure. The latter condition ensures the randomness of the sample of output values.

The minimum number of the sample or the code calculations is given by the Wilks' formula (Wilks, 1962) according to the degree of precision desired for the uncertainty measures. An statistical analysis of output variables $(Y)_N$ with non-parametric methods can produce tolerance intervals, which are able to quantify the uncertainty of Y. A tolerance interval [*Lower Limit*, *Upper Limit*] is an estimate of an interval of variability of random variable that contains a specified fraction of the variable's probability, p, with a prescribed level of confidence, γ. Tolerance intervals are constructed from sampled data so as to enclose $p\%$ of the population of a random variable Y with a given confidence $\gamma\%$. They show where most of the population of Y can be expected to lie as the variable is affected by the uncertainty of the input variables and physical and mathematical models.

With the N sets of sampled values of input variables and code models, the computer code is executed N times, each one with a different randomly chosen set of sampled values, and the results recorded to form a sample of size N of the code results.

As a result of describing the uncertainties in the input variables with probability distribution functions, the code output results are also random variables. The PDFs of the code results contain all the information needed to compute their uncertainty. The problem is that such functions are usually unknown. Therefore, in order to quantify exactly the uncertainty one should generate the PDFs from the sampled output values. But this is not always feasible, thus, the only remaining alternative is to obtain as much information as possible about the PDFs properties and main parameters from empirical distribution functions and estimators. One of the most useful estimators is the quantile.

In uncertainty analysis the main goal is to quantify the variability of the code output due to the variability in the inputs. If a random sample of output values, $((Y)_1, \ldots, (Y)_n)$, has a normal PDF, it is possible to compute tolerance intervals from the sample mean, m_y, and sample standard deviation, s_y. It is not easy to guarantee, though, that the sample of the output values is normally distributed. Nevertheless, if the sample is a random one, statistical tests for normality can then be used to quantify how well the hypothesis of normality fits the sampled data. Three of these tests are the W-statistic, the Lilliefors test and the Kolmogorov's normality test (Conover, 1980).

The purpose of a sensitivity analysis is to quantify the influence of the input variables on the code results. Sensitivity measures can assign a numerical value to this influence, and thus, be useful for an a posteriori ranking of the importance of each of the input variables with respect to the output variable of interest.

Most of the global sensitivity measures are related to regression analysis. Some of them are useful to detect linear relationships, and some others, like the so-called Rank Correlations are useful to quantify relations between variables that behave monotonically with respect to each other (e.g., smooth variations of one variable correspond to smooth variations of the other one). Comparison between these two types of measures applied to the same set of data can detect non-linearity in the behavior of the computer code.

Examples of linear measures are the Simple Correlation Coefficient SCC or Pearson's moment product, and the Partial Correlation Coefficient (PCC). The most important advantage of the PCC is that it eliminates the linear influence of the remaining input variables on the output, leaving only that of the input variable whose sensitivity is being calculated.

In order to deal with models which are not clearly linear, Simple Rank Correlation (SRCC) or Partial Rank Correlation (PRCC) coefficients can be used. To calculate these two measures, the sample