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Stochastic uncertainty quantification for safety verification applications in nuclear power plants

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ABSTRACT

There is an increasing interest in computational reactor safety analysis to systematically replace the conservative calculations by best estimate calculations augmented by quantitative uncertainty analysis methods. This has been necessitated by recent regulatory requirements that have permitted the use of such methods in reactor safety analysis. Stochastic uncertainty quantification methods have shown great promise as they are better suited to capture the complexities in real engineering problems. With advances in computational capabilities in recent times, these methods when utilized would provide distributions of safety important parameters computed by thermal hydraulic codes. In this study, a transient is simulated with a best estimate thermal hydraulic code, CATHENA. Stochastic uncertainty quantification and sensitivity analysis were performed using the OPENCOSSAN software which is based on the Monte Carlo method. The uncertainty and sensitivity analyses results were then utilized to update the dynamic Fault Semantic Network for safety verification. The effect of uncertainty in two input parameters (initial temperature and pressure) was investigated by analyzing the probability distribution of two output parameters. The first four moments of the output pressure and fuel pin temperature were computed and analyzed. The uncertainty in output pressure was 0.087% and 0.048% was found for the fuel pin temperature. These results are expected to provide insight for safety analyses by their utilization in updating the dynamic FSN.

1. Introduction

In Nuclear Power Plants (NPPs), various computational tools are used to perform safety analysis and verification. These tools are designed to simulate transients and in some cases, accident scenarios for various systems in a NPP. For example, for thermal hydraulics; RELAP, STAR CCM+ and CATHENA are used. For neutronics; MCNP, DRAGON and WIMS are used. The codes mentioned above are used by regulators, operating organizations and researchers to perform safety assessment and verification of NPPs. Most of the analyses performed using the above tools have been based on conservative assumptions. These assumptions are selected such that sufficient margins to safety are attained with compromises on efficiency in certain instances. Recent regulatory requirements have permitted the use of these best estimate codes supported by uncertainty quantification (BEPU) (10 CFR 50.46; Glaeser, 2008).

1.1. Uncertainty quantification in NPP simulations

Uncertainty quantification (UQ) is an important exercise that needs to be conducted as part of NPP simulations. This is due to the fact that uncertainties arise from various sources during the modeling and simulation process, these sources include: uncertainties in the input parameters used, model uncertainties arising from assumptions made in modeling a physical system as well as the type of numerical methods used in solving the problem. UQ basically asks the question, what range of outputs will be observed given the range of uncertain input parameter values? The UQ process therefore involves the determination of the range and probability of the outputs or the output probability density function (PDF). UQ methods can be broadly classified into the following: a) sampling based methods, b) Code Surrogates and c) Ad joint methods. Both sampling based methods and code surrogates can be described as computer codes in black box mode. Examples of these category include regression analysis and Monte Carlo methods. Code surrogates are simplified mathematical models of inputs and outputs, examples include; Unscented Transform (UT), Alternating Conditional Expectation (ACE) and Gaussian Process Model

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(GPM). In regression analysis, input/output relationships are estimated from datasets (Fynan, 2014).

Although there are several sources of uncertainty as noted above, the focus of this study is input parameter uncertainty propagation through the code. The models implemented in the code are assumed to be good enough and the effect of uncertainty in selected input parameters is quantified by observing their effect on output parameters.

1.2. Stochastic methods for uncertainty quantification

The use of stochastic methods to perform UQ has gained significant interest in recent times. These methods include Bayes and Laplace's subjective interpretation of probability as a state of information and their wide acceptance relative to other methods is due to the well-developed concept of probability. In the stochastic methods, uncertainties are represented mathematically by random variables and by suitable probability distributions. The stochastic analysis allows for UQ and its propagation to the outputs, which may be mathematically perceived as random variables adequately described by their probability distribution. UQ yields certain benefits including assessing the reliability and variability of outputs as well as providing useful information that would enhance the design process and increase the fidelity of the prediction. Closely related to UQ is sensitivity analysis which involves mainly uncovering the quantities responsible for the variability of the outputs. The uncertainties that may be due to the lack of knowledge would be reducible by obtaining more information on the quantities causing the variability in the output. Irreducible uncertainties must be factored in the design such that the safety of the system is not compromised (Patelli et al., 2012). Sensitivity measures such as the Spearman rank correlation is used and it provides the variation of the output in terms of standard deviations when the input uncertainties varies by one standard deviation (Glaeser, 2008).

1.3. Modeling uncertainties

Probability can be used to effectively model uncertainties. In this way, scalar values of inputs and outputs can be represented by random variables. The uncertainty modeling approach used in the software OpenCOSSAN is described in this section. Details of the software implementation are given in the methodology section.

Various distributions are used to specify a random variable, they include normal, log-normal and uniform. If experimental data is available, these maybe used to construct the set of random variables. A maximum likelihood method is then used to determine parameters that result in an optimal fit of the experimental data by a particular distribution. The maximum likelihood method is an efficient tool that obtains estimators of the distribution parameter having optimal statistical properties (Myung, 2003).

An uncorrelated multivariate distribution is obtained by transformation of the multiple correlated distribution. This is achieved in the standard normal space which is a multi-dimensional random variable space with zero mean, a unit standard deviation and Gaussian marginal probability density functions. This step is necessitated by the fact that pseudo-random number generators usually generate independent samples.

Stochastic processes such as Monte Carlo (MC) and random fields can be applied to model parameters which vary randomly and are functionally dependent in a multi-dimensional continuous space (Schenk and Schuëller, 2005; Vanmarcke, 1998). If the stochastic process is Gaussian, then it is adequately defined by the mean function and the covariance function. The covariance function may be considered the mutual influence of the process at two different spatial-coordinates or time-instants (Patelli et al., 2012). The MC method is applied in the OpenCOSSAN software and used in this study to model uncertainties of input parameters used to simulate a transient by CATHENA.

1.4. Sensitivity analysis

Sensitivity analysis is performed in order to estimate the effect of uncertain input parameters on an output parameter. The results from such analyses are useful in providing information on areas where designs can be changed in order to improve performance. It identifies variables that affect model results the most (Saltelli et al., 2000; Patelli et al., 2010) and can be used for model calibration and validation.

Local sensitivity analysis, screening methods and global sensitivity analysis are the major types of sensitivity analysis used. The computationally intensive nature of global sensitivity analysis makes the local sensitivity analysis the most utilized method in practical applications (Saltelli, 2002). In local sensitivity analysis, the response of a model is obtained by varying the inputs one-at-a time while holding the other inputs fixed. Global sensitivity analysis considers the entire range of variation of input parameters with the aim of accounting for the entire output uncertainty according to the different sources of uncertainties in the model inputs (Saltelli et al., 2000).

In this study, a methodology is proposed for performing uncertainty and sensitivity analyses and subsequently utilizing these results for safety verification. The application of uncertainty quantification results for safety verification is demonstrated in this study using the Fault Semantic Network (FSN).

1.5. Fault semantic network

FSN is an application of Semantic Networks to represent various faults, their causes as well as consequences in a system. The nodes in FSN represent various faults/causes/process variables and the link between the nodes represent the dependencies between them. Directed arcs are used to indicate the connections between the nodes. For instance, two nodes randomly selected are linked by a directed arc which shows how a plant state may lead to another state during the occurrence of a particular fault. The strength of connections between nodes depend on the type of interaction that exist between them. FSN can be used for performing fault propagation analysis as well as safety verification. In applying FSN for safety verification, a database comprising various faults, process variables, components and fault consequences is created. This database is also referred to as the static FSN. The dynamic FSN is then developed by updating the data in the static FSN with the real time state of the plant. These plant states can be obtained from simulation as well as experimental results. The static FSN also comprises a rule base which describes in detail various plant states and their implication on plant safety. At any given time and under any operational condition, safety verification can be undertaken by providing as input to the FSN results from experiments or simulations. Based on the rule base usually developed by soliciting expert opinion, the FSN can provide feedback regarding the safety or otherwise of the plant. This procedure constitutes the dynamic updating of FSN.

1.6. Risk management review

(Bjerga and Aven, 2015) in their study defined adaptive risk management as adapting actions by responsible individuals and systems in a changing environment. The study considered a case in the oil and gas industry and concluded essentially that adaptive risk management produces valuable insights during a transient or an accident scenario even in cases of deep uncertainty. They also