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Deterministic sampling for propagating epistemic and aleatory uncertainty in dynamic event tree analysis

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ABSTRACT

Dynamic Event Tree (DET) analysis allows for integrated deterministic and probabilistic safety assessment by coupling thermal-hydraulic system models with safety system and operator response models. It is a realistic but computationally challenging approach for risk quantification in a nuclear power plant. DET can also provide a two-loop nested framework to quantify uncertainty arising from aleatory and epistemic parameters of the risk assessment model. However, the propagation of uncertainties in a DET is a challenge, since the set of uncertain parameters is often very large and the computational cost of each run can be significant (e.g. prolonged station-blackout scenarios). In this case, the intensive calculation required to propagate epistemic and aleatory uncertainty in two-loop approaches with usual Monte Carlo sampling makes the DET computationally impractical for uncertainty quantification in many complex nuclear power plant transient applications. To overcome this computational burden, a sampling approach called Deterministic Sampling (DS) is adapted and evaluated in this work as a potentially more efficient alternative to Monte Carlo sampling. The application and performance of DS are first tested by quantifying the system failure probability for an illustrative problem, including the propagation of uncertainties. Subsequently, DS is applied to a DET analysis of a realistic nuclear power plant transient, namely, a Station Blackout with feed and bleed sequence. The impact of epistemic and aleatory uncertainty on the core damage frequency contribution from the accident sequence of Zion power plant is evaluated using discrete DET and deterministic sampling based DET approaches. The comparison and analysis of the results reveal that the DS-based approach is computationally efficient and practical.

1. Introduction

The risk of a Nuclear Power Plant (NPP) is typically evaluated through Probabilistic Safety Assessment (PSA). The Core Damage Frequency (CDF) is one of the risk measures estimated in classical PSA (e.g. level 1); it is determined using event tree / fault tree analysis for numerous accident sequences. In risk quantification, both epistemic and aleatory uncertainties are present due to inherent physical and safety system variability and their model parameters. Aleatory uncertainties are inherent and irreducible in nature, like the response of a safety system on demand, the initial core power or the break size when a Loss of Coolant Accident (LOCA) is assumed, whereas epistemic uncertainties arise from lack of knowledge. Uncertainties in failure probability distribution parameters of safety equipment or in Thermal Hydraulic (TH) closure models parameters are epistemic. Both types of uncertainties can significantly impact the accident dynamics and consequently the risk estimate. Therefore, both should be considered in the uncertainty quantification. Ignoring any one could lead to inappropriate estimation of risk and its uncertainties. PSA of a NPP as currently implemented propagates the epistemic uncertainties in failure probabilities, rates, and frequencies, but the uncertainties in physical model (parameters) are not propagated.

DETs [1, 2], which integrate plant physics models with stochastic equipment and crew response models, can provide a framework to treat uncertainties of both physical model and safety system models, besides capturing the impact of their dynamic interactions. Several DET implementation tools such as ADS-RELAP [3], MCDET-MELCOR [4], ADAPT-MELCOR [5,6], SCAIS [7,8] and RAVEN-RELAP [9] are available in the literature. However the propagation of uncertainties in a DET is a challenge, since the set of uncertain parameters is often very large and the computational cost of each run can be significant (e.g. prolonged station-blackout scenarios). In this case propagating epistemic and aleatory un-

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Nomenclature

AFW	Auxiliary Feed W
AFWS	Auxiliary Feed Water System
CDF	Core Damage Frequency
DDET	Discrete Dynamic Event Tree
DET	Dynamic Event Tree
DSDET	Deterministic Sampling based Dynamic Event Tree
DS	Deterministic Sampling
FB	Feed and Bleed
FP	Failure Probability
IL	Inner Loop
LHS	Latin Hypercube Sampling
LOCA	Loss of Coolant Accident
LOSP	Loss of Offsite Power
MC	Monte Carlo
NPP	Nuclear Power Plant
OL	Outer loop
PCE	Polynomial Chaos Expansion
PCT	Peak Cladding Temperature
PDF	Probability Distribution Function
PORV	Power Operated Relief Valve
PRZ	Pressurizer
PSA	Probabilistic Safety Assessment
PWR	Pressurized Water Reactor
SG	Steam Generator
SI	Safety Injection
SP	Sigma Point
SBO	Station Blackout
TH	Thermal Hydraulic
UKF	Unscented Kalman Filter
UQ	Uncertainty Quantification
UT	Unscented Transformation

certainty in two loop approaches with usual Monte Carlo (MC) sampling requires enormous computational requirements which can easily challenge even today's computational infrastructure [10,11]. To the knowledge of the authors, the treatment of the epistemic uncertainties and variability in initial conditions in DET frameworks has not been demonstrated for realistic PSA of power plants. The main reason for this limitation is that the computational requirements to achieve reasonable accuracy in the risk estimate are very large. Usage of parallel or distributed computing is desirable; for example the DET tool ADAPT which focuses on level-2 PSA scenarios was equipped with such capability [6].

To reduce the computational effort different sampling techniques are introduced in the literature. For example adaptive sampling is reported in [12]. In this sampling method a few output responses are obtained from the simulation, a surrogate model is built to represent the response space, and new samples are selected based on the model constructed. The surrogate model is then updated based on the simulation results of the sampled points. Thus, effort has been given to gain the most information possible with a small number of selected samples and consequently reduce the number of computationally expensive trials needed to understand features of the response space [12]. An application of adaptive sampling to evaluate maximum core temperature depending on two uncertain parameters is presented in [13]. Other sampling technique available in the literature are stratified Latin Hypercube Sampling (LHS) [14,5], Taguchi orthogonal array based sampling [15], etc.

Other possible way to overcome the computational burden is to build a fast-running surrogate regression model (e.g. response surface) in order to approximate the input/output function of the real process simulation model [16,17]. An example on the development of a core relocation surrogate model for the prediction of debris properties in lower head in an ex-vessel severe accident sequence based on the MELCOR code (considered as the full model) is provided in [18].

Adaptive sampling requires building a response surface, which involves a substantial and complex model calibration effort. Further, the efficacy of adaptive sampling for problems with more than two uncertain parameters has not yet been demonstrated. The convergence of LHS compared to MC is better but the number of samples required for LHS is still not appealing. Hessling showed with an illustrative one-parameter problem that, even for 100 samples, the second moments of true results vary noticeably [19]. The convergence is generally poorer for higher order moments. Regarding the application of the orthogonal array-based sampling for uncertainty propagation, very limited information can be found in the literature. The construction of fast running surrogate (regression) models requires significant model training efforts and building of a code surrogate in place of the original simulation model is application specific.

To overcome the above mentioned shortcomings, recently Polynomial Chaos Expansion (PCE) was explored by Eldred et al. [20]. A PCE is a general framework of representing an arbitrary random variable of interest as a function of another random variable with a given distribution, and of representing that function as a polynomial expansion. Orthogonal polynomials (e.g. Hermite, Legendre, Laguerre, Jacobi) are used for approximating the effect of uncertain variables described by a probability distributions (e.g. normal, uniform, exponential, beta, gamma). The objective of a PCE is to determine the unknown coefficients of the polynomials in the series expansion. Usually, these coefficients can be calculated from a limited number of model simulations. There are different techniques to calculate these co efficient as described details in [20]. Application of PCE for propagating epistemic and aleatory uncertainty in a two loop approach is presented in [20]. The efficiency of PCE over LHS is demonstrated by evaluating a limit function of a short column test problem (see more details in [20]).

In this study we focus on Deterministic Sampling (DS) [19], an alternative method. The method appears to be efficient since relatively few simulations are required, and many parameters can be handled with few deterministic samples. The sample size is a key aspect which provides motivation for evaluating deterministic sampling as an efficient uncertainty quantification method in reactor safety analysis.

1.1. Scope and objectives of the work

The purpose of this work is to adapt and evaluate DS [19] as a computationally efficient Uncertainty Quantification (UQ) method for reactor safety analysis. Especially with this sampling strategy we want to alleviate the computational requirements that limit the application of DET to realistic NPP transients and simulation with system TH codes.

DS has its origin in the field of Unscented Kalman Filter (UKF) developed by Julier and Uhlmann [21] and used in several domains of electrical engineering [19,21,22]. The basic idea behind DS is that a continuous Probability Distribution Function (PDF) can be substituted by a set of discrete weighted samples, called Sigma Points (SP), if the two representations have the same statistical moments [23]. These SP are few in number. As a result the number of required simulations reduces substantially. This is the key point enabling for practical uncertainty quantification. However, application of DS beyond its original implementation in the UKF is quite limited. Hedberg et al. in [23] applied DS to propagate uncertain input parameters in a classical computation fluid dynamic simulation of turbulent flow over a backward facing step. In our recent contribution [24], DS was applied to a probabilistic analysis of realistic NPP transient. However, in that study, epistemic and aleatory uncertainty were mixed and treated together, limiting the ability to determine the respective contributions of epistemic and aleatory parameters to the total uncertainty, information that is essential for the effective management of uncertainty as well as decision-making. Further, uncertainty in PSA parameters was not included in that study.