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Probabilistic risk assessment based model validation method using Bayesian network

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ABSTRACT

Past few decades have seen a rapid growth in the availability of computational power and that induces continually reducing cost of simulation. This rapidly changing scenario together with availability of high precision and large-scale experimental data has enabled development of high fidelity simulation tools capable of simulating multi-physics multi-scale phenomena. At the same time, there has been an increased emphasis on developing strategies for verification and validation of such high fidelity simulation tools. The problem is more pronounced in cases where it is not possible to collect experimental data or field measurements on a large-scale or full scale system performance. This is particularly true in case of systems such as nuclear power plants subjected to external hazards such as earthquakes or flooding. In such cases, engineers rely solely on simulation tools but struggle to establish the credibility of the system level simulations. In practice, validation approaches rely heavily on expert elicitation. There is an increasing need of a quantitative approach for validation of high fidelity simulations that is comprehensive, consistent, and effective. A validation approach should be able to consider uncertainties due to incomplete knowledge and randomness in the system's performance as well as in the characterization of external hazard. A new approach to validation is presented in this paper that uses a probabilistic index as a degree of validation and propagates it through the system using the performance-based probabilistic risk assessment (PRA) framework. Unlike traditional PRA approaches, it utilizes the power of Bayesian statistic to account for non-Boolean relationships and correlations among events at various levels of a network representation of the system. Bayesian updating facilitates evaluation of updated validation information as additional data from experimental observations or improved simulations is incorporated. PRA based framework assists in identifying risk-consistent events and critical path for appropriate allocation of resources to improve the validation.

1. Introduction

Given the events at Fukushima–Daiichi nuclear power plant, there is an increased emphasis on using high fidelity simulation tools to evaluate the vulnerability of nuclear facilities subjected to external hazards. Availability of sophisticated computer models capable of simulating multi-physics multi-scale phenomena has increased the need for verification and validation of such high fidelity simulations. Among the many challenges in this process, the two primary ones are: (1) lack of relevant plant-level data needed for validation of high-fidelity simulations, and (2) non-availability of a practical platform for implementing rational, consistent, and quantitative approaches for validation. While first item above is essential in any validation effort, it is usually restricted by high cost of collecting such data and in some cases inability to conduct large-scale experiments. The confidence in high-fidelity simulations decreases due to excessive reliance on expert opinion for establishing the acceptability of high simulation models.

The uncertainties due to inherent randomness and incomplete knowledge needed to predict behaviors of real physical complex systems in different operating conditions as well as natural hazards pose significant challenges to the model validation assessment. Fidelity of a system-level computer simulation model is difficult to assess even though a model for each component of the system can be individually validated with available component-level data. The quantitative system-level validation process involves a validation at component level, establish the degree of validation in each case, determine a relationship between component-level and system-level performance, and finally establish an inference of the degree of validation at system-level. The validation goal is difficult to achieve particularly in a quantitative sense because of the uncertainties in the relationship between different levels as well as in the parameters used for characterizing the performance at both the component and system levels. Consequently, four key aspects in this process are: (1) validation metric: characterization of an appropriate validation metric for quantitative comparison of simulation and test data, (2) predictive capability and confidence: inference on the degree of validation at system-level, (3) scaling: quantitative characterization of the relationship between component-level and higher-level performance, and (4) decision: an acceptance criterion to determine effective strategies for improving the validation.

Validation metric: Many different approaches have been examined in existing literature for characterizing an appropriate metric for the model validation under uncertainties. In most cases, a graphical comparison is employed to determine the degree of agreement between the simulation predictions and the actual observations. Classical statistical

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hypothesis testing has often been employed for comparison of two sets of random variables [1–4]. The outcome of such a comparison is expressed in terms of the probability which can then be combined with error statistics to determine the degree of validation. The Bayesian hypothesis testing approach has been also applied to validation problem [5–11]. More specifically, Kennedy and O'Hagan [5] define model bias as the difference between the means of experimental and simulation data. Zhang and Mahadevan [6] use the probability of Bayes factor exceeding a specified value as the decision criterion for the model acceptance/rejection. A direct comparison of mean values from simulation and experiment has also been used for the validation of simulation models [12–15]. Alternatively, probabilistic measures have also been used [16–19].

Scaling: Some studies have also addressed the inference of the system-level validation starting with the component-level validation metric. A building block or hierarchical approach has been proposed for propagation of component level information to the system level through intermediate sub-system levels [20–23]. In general, the amount of available experimental data decreases as one proceeds from lower to higher levels. Therefore, a Bayesian network (BN) can be employed very effectively to update the statistical information for all nodes when additional information becomes available within the Bayesian hypothesis testing framework [24,25].

Effective use of Bayesian network requires availability of an explicit quantitative relationship between the component levels and the higher levels of the network. To do so, Mahadevan and Rebba [24] utilize mechanistic equations to relate the higher-level output with lower-level input/output.

Uncertainty modeling: For problems that could not be characterized by an analytical relationship, Rebba and Mahadevan [25] construct a stochastic response surface between lower-level and higher-level data. Jiang and Mahadevan [26] use a structural equation modeling approach to utilize the lower-level data for the higher-level model validation under uncertainty through a collective use of lower-level data, higher-level data, computational model, and latent variables. In order to address the acceptability of a model validation, Jiang and Mahadevan [27] propose a decision-making methodology by considering a risk-benefit approach in which the risk/benefits of using the current model and the data support for the current model are evaluated with respect to the cost of acquiring new information for improving the model under the Bayesian hypothesis testing.

In the context of the various existing studies summarized above, the validation problem continues to be challenging one due to a few different reasons. First, the existing definitions of a quantitative validation metric need significant improvement especially for addressing validation problems that have large degree of uncertainties associated with them. Second, the existing studies are restricted to problems in which the system level simulation model is characterized mathematically. Such a mathematical description is neither available nor possible especially for evaluating the performance of nuclear systems subjected to external hazards. In addition to these restrictions, it is important to note that existing approaches do not identify whether or not an improvement in the validation of a given component or subsystem is important/critical with respect to system level performance.

This paper focuses on exploring a novel performance-based risk-informed validation approach that aspires to be rational, efficient, and quantitative in nature. The intent of the proposed approach is to provide a quantitative assessment of validation for a system-level simulation model based on component-level validation information. It uses performance-based criteria to judge the efficacy of a particular validation and a risk-informed framework to determine whether additional validation of a certain component or subsystem is needed or not. The applicability and effectiveness of the proposed approach is explored in the context of a structural system subjected to a natural hazard due to an earthquake. Yet, the approach is quite generic in nature and is applicable to a variety of validation problems.

2. Performance-based probabilistic risk assessment (PRA)

In the current methodology, the overall risk (i.e. annual probability of occurrence or failure) for an individual hazard is evaluated by a convolution of hazard curve and the corresponding fragility as follows:

$$P_f = \int P_{f|\lambda} \cdot \left| \frac{dH(\lambda)}{d\lambda} \right| d\lambda \tag{1}$$

in which λ is a hazard intensity parameter, $P_{f|\lambda}$ is the fragility curve, and $H(\lambda)$ represents hazard curve. The hazard curve expresses the probability of annual exceedance in a domain of the intensity measure used for characterizing the external hazard. The fragility curve for basic events is obtained by using empirical, experimental, and/or numerical simulation data and represents the conditional probability of failure under each hazard's intensity. The system-level risk is calculated by employing either a series-parallel system as a simplistic representation of the system or by conducting a fault tree analysis in which the events are assumed to be statistically independent, mutually exclusive, and collectively exhaustive. In realistic applications, fault trees are used in conjunction with event trees to conduct an in-depth risk analysis. In recent years, researchers have recommended improving such a logic tree approach by utilizing Bayesian networks [28–30]. A Bayesian network based approach can be quite powerful in probabilistic risk assessment particularly in the context of multi-hazard risks [31–33]. Unlike a logic tree based approach in which the basic events are considered to be statistically independent, a Bayesian network can consider statistical correlations between basic events which is particularly true for multi-attribute multi-hazard risk assessments [33]. A Bayesian approach can directly incorporate probabilistic gates, correlated events, and multi-state variables. It can also accommodate additional evidence through a unified single formulation.

Probabilistic hazard analysis: In order to develop a hazard curve, the hazard is characterized in terms of an engineering design parameter. For example, probabilistic seismic hazard analysis (PSHA) focuses on quantifying uncertainties in the sources, size, distance, and ground motion characteristics of future earthquakes and incorporating this information to produce a distribution of possible ground motions that can occur at a site of interest. The end result of PSHA is represented by seismic hazard curves where the annual rates of exceedance are plotted against a ground motion intensity parameter such as peak ground acceleration (PGA) or spectral acceleration (SA). A detailed description of PSHA is given in McGuire [34]. The US Geological Survey (USGS, http://earthquake.usgs.gov/hazards/products/) provides hazard information and hazard curves at any site of interest within the US.

Performance-based fragility assessment: The fragility of a structure, system, or component (SSC) is defined as the conditional failure probability, $P_{f|\lambda}$, to attain or exceed a specified performance function, G, under a given measure of specific intensity parameter λ. Mathematically,

$$P_{f|\lambda} = P(G < 0|\lambda) \tag{2}$$

G is a function of the random variables representing uncertainties in material properties, physical behavior, mechanistic models, and loading conditions. It can be described in a simplistic form as:

$$G(S, R) = S - R \tag{3}$$

where S represents the "Strength" or "Capacity" corresponding to the specified loading condition and R represents the "Response" or "Demand" corresponding to the given hazard intensity parameter. Eq. (3) can be written by various forms such as physics or mechanics based models, experimentally obtained data, empirical relations, simulations, or a combination of these. It can then be solved in many different ways such as Monte Carlo simulation, first/second order reliability methods, random vibration based approach, statistical inference approach, etc. In most implementations, the fragility curves are represented as the cumulative distribution function for a lognormal model.