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Time dependent model bias correction for model based reliability analysis

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ABSTRACT

Model based reliability analysis could be misleading if the simulation model were not validated at the intended design configuration. To improve model accuracy without conceptually revising the model, various model bias correction approaches have been proposed to firstly characterize model bias at training design configurations and then approximate model bias at the intended design configuration. Good accuracy improvement of the model has been shown in literature for not only single model output but also model prediction with multiple or high-dimensional outputs. To date, however, the bias correction approaches are mainly proposed for model prediction with time independent (or static) responses and they cannot be directly applied to the model prediction with time dependent responses. This paper presents such a framework of time dependent model bias correction for model based reliability analysis. In particular, three technical components are proposed including: i) an accuracy metric for time dependent model responses under uncertainty, ii) effective approaches for time dependent model bias calibration and approximation, and iii) reliability analysis considering the time dependent model bias. Two case studies including a structural thermal problem and a corroded beam problem are employed to demonstrate the proposed approach for more effective model based reliability analysis.
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1. Introduction

To date, reliability analysis relies significantly on computer simulation models or analytical models to predict the performance of interest given a set of design configurations. Majority of current research focuses on the development of various reliability analysis methods so that reliability evaluation can be conducted more accurately and efficiently. However, it is well known that models are built to approximate real physical systems on the basis of a series of assumptions and simplifications. Hence, model bias, i.e., the inherent model inadequacy for representing the real system, always exists because there is no perfect model that can represent the real physical system without any error. Ignorance of the model bias in reliability analysis or reliability based design could result in significant design errors by overestimating the system or structure reliability.

The key objective in model validation is to determine the degree to which the model is an accurate representation of the real world from the perspective of the intended uses of the model [1–3]. Traditionally, the research on validation of a simulation/analytical model was proposed to revise the model conceptually for credibility improvement of the model. From the model development perspective, the key advantage of revising the model conceptually is that accuracy of the model could be significantly improved. However, this approach is practically difficult and yet may not be feasible in reality due to three reasons: i) identification of the root cause for model inaccuracy is complicate particularly for large scale engineering systems; ii) fundamental modification of the model is time consuming, costly, and yet may not be practical; and iii) there is no perfect model that can represent the real physical system without any model bias.

The bias correction approach to quantify the model bias in the design domain, therefore, has recently gained significant attention [4–7]. The essential idea is to add the characterized model bias to the baseline simulation/analytical model so that the corrected model prediction could be more accurate and robust compared to the baseline model. This so called bias correction approach is mainly composed of three steps: i) characterization of model bias at a few training design configurations, ii) construction of a response surface for the model bias, and iii) approximation of

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model bias at the intended uses of the model and add it back to the baseline model prediction. The key research challenge is how to approximate model bias effectively based on available training data sets. Otherwise, adding the model bias to the baseline model could worsen the model accuracy [8].

To date, majority of the research in this field focuses on three topics: i) development of model accuracy metric considering limited test data, ii) correct characterization of the model uncertainty (i.e., uncertainty of the model bias) considering test uncertainty and model parameter uncertainty at available design configurations, and iii) development of various models for model uncertainty approximation. Good accuracy improvement of the model has been shown in literature for not only single model output but also model prediction with multiple or high-dimensional outputs [4–9]. However, it is worth noting that the proposed approaches are only applicable for model prediction with time independent responses. In other words, model uncertainty is characterized either by a univariate distribution or by a constant value at a given design configuration. New research challenges have to be addressed when model responses are time dependent such as: i) how to characterize model uncertainty as a random process considering limited test data and model parameter uncertainty; ii) how to build response surface for model uncertainty with the form of a random process; iii) how to extend the model accuracy metric for time dependent responses; and iv) how to effectively consider time dependent model bias for reliability analysis and design. Resolving these challenges is imperative because accurate prediction of time dependent responses is critical in many applications especially for time dependent reliability analysis. The contribution of this paper is to generalize the bias correction approach from time independent to time dependent model responses by addressing aforementioned challenges and further enable its seamless integration with advanced probability analysis methods for reliability analysis.

The rest of the paper is organized as follows. Section 2 provides a brief literature review of the bias correction approach. Section 3 elaborates the proposed framework and detailed technical approaches for addressing aforementioned research challenges. Section 4 presents two engineering case studies to demonstrate the proposed approach. Finally, conclusion is made in ection 5.

2. Literature review of the bias correction approach

Majority of the bias correction approach is based on the Bayesian calibration model proposed by Kennedy and O'Hagan [10] as shown in Eq. (1).

$$\hat{Y}(\mathbf{x}) + \delta(\mathbf{x}) = Y - \varepsilon \tag{1}$$

where $\hat{Y}$ is the baseline model prediction; δ is the model bias; Y is available test data; ε is test and measurement error; and $\mathbf{x}$ is a vector of model parameters. The application of this equation is straightforward. For example, maximum deflection of a bridge structure (i.e., $\hat{Y}$) under a given loading condition can be estimated by a finite element analysis (FEA) model. Due to model assumptions and simplifications, however, the estimation would not be exactly the same as the real measurement Y, if available. With ignorable test and measurement error ε, the difference between the model prediction and real measurement is defined as the model bias δ. If the model significantly underestimates the maximum deflection (i.e., δ is a large positive value), design error would be created if no tests were run for design verification. Therefore, it is desirable to accurately characterize the model bias as a function of model parameters $\mathbf{x}$ (e.g., parameters that define the topology, shape, and size of the structure) so that the corrected model prediction could be more accurate than the baseline model. In particular, the model parameter $\mathbf{x}$ could take the form of deterministic values, irreducible random parameters (i.e., aleatory uncertainty), and reducible random parameters (i.e., epistemic uncertainty). The Bayesian calibration model addresses the challenge of calibrating the model parameter $\mathbf{x}$, model bias δ, and test and measurement error ε with limited test data Y at given design configurations. Technically, prior distributions of the distribution parameters (e.g., mean and standard deviation of $\mathbf{x}$, δ, and ε) are updated to posterior distributions given available test data Y using a Bayesian updating mechanism.

Model bias should be accurately approximated in the design space if the model would be used to explore new designs without any test data for design verification. Various approaches were proposed for this purpose with the main idea of constructing a *meta*-model for model bias on the basis of calibrated model bias at available design configurations [4,11–13]. Among these approaches, regression models are the most popular method because of the well-established research in this field such as the Gaussian process (GP) regression model [11] and the moving least square method [4]. The GP regression model assumes a multivariate normal distribution for the model bias in the design space such that uncertainty of the model bias at each specific design configuration follows a univariate normal distribution and their correlations at different design configurations are modeled by an assumed covariance function. The moving least square method directly builds four response surfaces for the first four central moments (i.e., mean, standard deviation, skewness, and kurtosis) of the model bias so that distribution of the model bias can be approximated at any new design configuration using the Pearson system [18]. Due to the curse of dimensionality for regression-based approaches, a Copula-based approach was recently proposed to approximate the model bias through a general statistical relationship between model bias, the baseline model prediction, and the model design variables (i.e., a subset of the model parameter $\mathbf{x}$ that changes when design changes) [12]. However, none of the above approaches considers time dependent model responses where model bias takes the form of a random process at each design configuration instead of a univariate distribution. Hence, it is not feasible to directly apply the bias correction approach for the model with time dependent responses.

3. Bias correction of time dependent model responses for reliability analysis

Three research challenges should be addressed in order to apply the bias correction approach for time dependent model responses and reliability analysis. First of all, an accuracy metric needs to be developed to quantify accuracy of the model prediction. Majority of available model accuracy metrics are designed for static (or time independent) model responses such as the U-pooling [14] and the Bayes factor [18]. Though metrics for time dependent responses are also available [19], they are specifically designed for vehicle impact application and uncertainties are not considered in the metric. Secondly, effective approaches need to be developed for time dependent model bias calibration with the aid of the accuracy metric. Finally, effective algorithms should be developed to take account into the time dependent model uncertainty in reliability analysis. Proposed approaches for addressing these challenges are elaborated in the following subsections.

3.1. Accuracy metric for time dependent responses under uncertainty

U-pooling metric was proposed by Ferson et al. [14] as an accuracy metric and has been adopted by many researchers in the study of model validation [13,15–17]. The basic idea is to compare the cumulative distribution function (CDF) difference (i.e., the

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