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Original Article

Implicit Treatment of Technical Specification and Thermal Hydraulic Parameter Uncertainties in Gaussian Process Model to Estimate Safety Margin

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ABSTRACT

The Gaussian process model (GPM) is a flexible surrogate model that can be used for nonparametric regression for multivariate problems. A unique feature of the GPM is that a prediction variance is automatically provided with the regression function. In this paper, we estimate the safety margin of a nuclear power plant by performing regression on the output of best-estimate simulations of a large-break loss-of-coolant accident with sampling of safety system configuration, sequence timing, technical specifications, and thermal hydraulic parameter uncertainties. The key aspect of our approach is that the GPM regression is only performed on the dominant input variables, the safety injection flow rate and the delay time for AC powered pumps to start representing sequence timing uncertainty, providing a predictive model for the peak clad temperature during a reflood phase. Other uncertainties are interpreted as contributors to the measurement noise of the code output and are implicitly treated in the GPM in the noise variance term, providing local uncertainty bounds for the peak clad temperature. We discuss the applicability of the foregoing method to reduce the use of conservative assumptions in best estimate plus uncertainty (BEPU) and Level 1 probabilistic safety assessment (PSA) success criteria definitions while dealing with a large number of uncertainties.

1. Introduction

Safety margin is an important concept for nuclear power plant (NPP) design and safe operation. Adequate safety margin ensures that the plant design can withstand transients and accidents without fuel damage and the release of radionuclides into the environment. Operationally, safety margin provides flexibility allowing for optimization of plant operations and maintenance, improving the safety, performance, and economics of the plant. Accurate characterization of safety margin has become increasingly important as many older NPPs seek power uprates changing the design basis.

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A detailed safety analysis must be performed to determine the safety margin of the NPP. The safety analysis can include operational and experimental data from scaled separate effects tests and integral experimental facilities, design basis accident (DBA) analysis, and probabilistic safety assessment (PSA). Deterministic simulation of transients using best-estimate thermal hydraulic computer codes is commonly used. However, accurate characterization of the safety margin for all plant states and configurations over the plant lifetime and all possible accident scenarios is extremely challenging, so practical approaches such as incorporating conservative and bounding assumptions must be implemented. Furthermore, if large changes to the plant design basis such as a power uprate or many small additive changes occur, a potentially large number of safety analyses including computer simulations must be redone. Accounting for the uncertainties of the computer models adds an additional layer of complexity. Best estimate plus uncertainty (BEPU) methodologies have been developed to address uncertainties in DBA analysis.

In this paper, we propose a methodology to make realistic estimates of the safety margin, reducing the need for excessive conservative and bounding assumptions in a safety analysis. The methodology uses best-estimate computer models to simulate a large (but manageable) number of transients that span a range of possible NPP safety system configurations and timing of safety system actuation to resolve a spectrum of plant responses during an accident. Simultaneously, many code input parameter uncertainties are sampled representing technical specifications, limiting conditions for operation, and thermal hydraulic model parameter uncertainties. The methodology adopts the Gaussian process model (GPM) to serve as a surrogate model used to characterize the safety margin. The GPM performs multivariate regression on the dominant input parameters, safety system configuration and sequence timing, for a predictive model of the safety parameter of interest, while modeling the other uncertainty contributors implicitly as measurement noise terms. The safety parameter probability distribution that can be used to quantify the safety margin is expressed as the GPM mean function and local uncertainty bounds defined by the GPM prediction variance. The unique features of the GPM as a nonparametric regression method with an automatic quantification of prediction model uncertainty are key aspects of the methodology.

This paper is organized as follows. Section 2 provides an overview of GPMs for nonparametric regression analysis. Specifically, the unique features of the GPM including the prediction variance, covariance function selection, and implementation issues are discussed. Section 3 presents the MARS code [8] model of the reference plant (Hanul Units 3&4, formerly known as Ulchin Units 3&4; one of the optimized power reactor, OPR1000, series) used to simulate the injection phase of a large-break loss-of-coolant accident (LBLOCA) serving as the demonstration application for the methodology. Section 4 presents the best-estimate simulation data of the LBLOCA and the training process of the GPM. Section 5 presents an analysis and discussion of the safety margin results derived from the GPM. Finally, limitations of the proposed methodology, future work and applications, and some concluding remarks are provided in Section 6.

2. Gaussian process model

In the context of thermal hydraulic simulations of NPP accidents, the best-estimate code or model can be interpreted as a general nonlinear function of the form

$$y = h(\mathbf{x}) \tag{1}$$

with a vector of inputs $\mathbf{x} = [x_1, x_2, \ldots x_p]^T$ and a limiting safety parameter of interest as the output variable y. The actual code output from a simulation contains time histories of many plant parameters from which any number of limiting safety parameters can be obtained. However, for clarity we will consider only a single output. A regression analysis can be performed on a dataset from simulations $\{X = [\mathbf{x}_1, \ldots \mathbf{x}_n], \mathbf{y}\}$ to estimate the functional relationship between the input variables and output variable. The dataset used in regression is called the training set. The regression function becomes a surrogate model to the best-estimate code and can be evaluated many times with minimal computational cost to obtain large samples used for uncertainty quantification, design optimization, safety margin characterization, etc.

GPMs are a popular class of surrogate models that can be used for multivariate regression. Rasmussen and Williams [1] and their associated GPML code package [2] are prominent resources on GPMs. Chapter 4 of Yurko [3] provides a nice summary of and practical implementation recommendations for GPMs. For consistency, we will generally follow the notation in Rasmussen and Williams [1] to present the mathematical formulation of the GPM and describe the unique features in the context of regression and characterizing large datasets from computer simulations.

2.1. *GPM mean function and prediction variance*

The GPM is unique among regression methods because it defines a *predictive distribution* of the dependent variable y at any input test location x_*. The GPM is fully defined by the mean function and prediction variance. The predictive distribution is assumed to be Gaussian parameterized by the mean function and prediction variance. The mean function and prediction variance are

$$\bar{y} = \bar{f}(\mathbf{x}_*) = \mathbf{k}_*^T (K + \sigma_n^2 I)^{-1} \mathbf{y} \tag{2}$$

$$V[f(\mathbf{x}_*)] = k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{k}_*^T (K + \sigma_n^2 I)^{-1} \mathbf{k}_* \tag{3}$$

The predictive distribution for y is

$$y \big| \mathbf{x}_* \sim N\left(\bar{f}(\mathbf{x}_*), V[f(\mathbf{x}_*)] + \sigma_n^2\right) \tag{4}$$

From the perspective of conventional regression analysis, the mean function of Eq. (2) can be interpreted as the regression function approximating Eq. (1). The prediction variance of Eq. (3) is an empirical estimate of the GPM prediction uncertainty derived from the data measurement noise variance σ_n^2, density of the training data set, and the complexity of the inputs/output relationship estimated by the GPM. Although it is not necessarily required, the GPM usually assumes a zero mean so the vector of data output $\mathbf{y}$ has been shifted by its