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Modeling Sequence Timing, Technical Specification, and Code Parameter Uncertainties in Success Criteria Definition with Gaussian Process Model

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1. Introduction

Best estimate simulations of nuclear power plant (NPP) transients can be performed in support of success criteria definitions in Level 1 Probabilistic Safety Assessment (PSA). Reducing the use of conservatisms and bounding assumptions in the analysis can give a more realistic estimate of the safety margin provided by the safety systems configurations representing the success criteria. Furthermore, rigorous treatment sequence timing uncertainties in success criteria definitions is difficult within the conventional event tree/fault tree (ET/FT) methodologies used in Level 1 PSA. This paper presents a new methodology to estimate safety margin while addressing sequence timing, safety system configuration, technical specification, and thermal hydraulic code parameters uncertainties. The key aspect of the methodology is the Gaussian process model (GPM), a nonparametric regression method for multivariate regression with internal estimate of model uncertainty[1,2], is used to process data from many simulations and is a surrogate model for predicting safety parameter distributions as a function of input uncertainties. The methodology is demonstrated for the injection phase of a large-break loss-of-coolant accident (LBLOCA) and the safety margin of the Ulchin Units 3&4 (UCN3&4) success criteria are quantified.

2. GPM Methodology for Estimating Safety Margin

2.1 Methodology Overview

The following summarizes the methodology steps for estimating safety margin with a GPM:

1) Select accident scenario and identify relevant safety systems and success criteria. Select best estimate thermal hydraulic code and input model appropriate for simulating the accident.

2) Identify sequence timing uncertainties and the technical specification ranges for the safety systems. Identify relevant thermal hydraulic phenomena and code input parameter uncertainties similar to Best Estimate Plus Uncertainty (BEPU) methodologies.

3) Using sensitivity analysis or engineering judgment, partition input uncertainties into two groups: explicit regression variables representing most important inputs affecting thermal hydraulic phenomena and safety parameter, and implicit "noise" variables that only contribute to local variation of the safety parameter.

4) Sample explicit regression variables using a space-filling experimental design for coverage of the input space. Randomly sample all implicit variables using conventional Monte Carlo. Perform best estimate simulations for all samples and obtain safety parameter values from code outputs. Simulation data is the training set for regression.

5) Perform regression on the training data set using the GPM. The GPM is a response surface model predicting the safety parameter as a function of the explicit variables, namely sequence timing and safety system configuration. Uncertainty of safety parameter is estimated from the noise term of the GPM.

2.2 Gaussian Process Model for Regression

The GPM is unique among regression methods because it defines a *predictive distribution* of the dependent variable *y*, the safety parameter, at any input "test" location $\boldsymbol{x}_*$. 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

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

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

The predictive distribution for *y* is

$$y|\boldsymbol{x}_* \sim N\left(\bar{f}(\boldsymbol{x}_*), V[f(\boldsymbol{x}_*)] + \sigma_n^2\right) . \tag{3}$$

Equation (1) is a response surface model for predicting *y* and Eq. (2) is an estimate of the model uncertainty. The data noise variance is σ_n^2. The building block of Eqs. (1) and (2) is the squared exponential covariance function which defines covariance between data pairs using a distance based measure of the input locations

$$k(\boldsymbol{x}_q, \boldsymbol{x}_r) = \sigma_f^2 \exp\left(-\frac{1}{2}(\boldsymbol{x}_q - \boldsymbol{x}_r)^T \Lambda^{-1} (\boldsymbol{x}_q - \boldsymbol{x}_r)\right) \tag{4}$$

$$\Lambda = \mathrm{diag}(r_1^2, \ldots, r_p^2) \ . \tag{5}$$

The length scales r_i are sensitivities for each input dimension. The scaling factor σ_f^2 is the signal variance and is a measure of magnitude *y* can vary over r_i. The covariance matrix K of the training set defines the covariance between all n training data points with entries

$$K_{ij} = k(\boldsymbol{x}_i, \boldsymbol{x}_j); \{i, j = 1, \dots, n\} \ . \qquad (6)$$

The covariance between the training data and a test point is the vector

$$\boldsymbol{k}_* = [k(\boldsymbol{x}_*, \boldsymbol{x}_1);\ k(\boldsymbol{x}_*, \boldsymbol{x}_2); \dots;\ k(\boldsymbol{x}_*, \boldsymbol{x}_n)] \ . \qquad (7)$$

The GPM is a series of matrix and vector operations resulting in a weighted average or data smooth of the vector of code outputs $\boldsymbol{y}$.

The GPM parameters $\{\Lambda, \sigma_f^2, \sigma_n^2\}$ must be learned from the training data using Bayesian inference techniques. For the study, we use the leave-one-out method implemented in the GPML code [2]. References [1,2] provide additional algorithm details about the GPM.

2.3 LBLOCA Model and Reference Simulation

For our analysis, we use the MARS code [3] and the UCN3&4 input model [4] to simulate the LBLOCA. The reference case represents the current success criteria which are to inject to at least 2 of 3 intact CLs through 2 of 3 safety injection tanks (SITs) and inject refueling water tank (RWT) water to at least 1 or 3 CLs using 1 of 2 low pressure safety injection (LPSI) pumps [5]. The LPSI pump is assumed to inject with a 30 s delay after the safety injection actuation signal (SIAS) which is the time to start the emergency diesel generator (EDG) and load the pump according to the loading sequence technical specification [6]. The LPSI pump injects at the minimum rated flow. Figure 1 shows the reference result for the hot pin clad temperature during the injection phase of the cold leg (CL) LBLOCA.

The refill peak from 20 s to 100 s in Fig. 1 is a function of the large mass flow rates delivered by the SITs until they are depleted at 85 s. Continued injection from the LPSI pump beyond 100 s controls the reflood cooling. The increase in clad temperature for the top 1/3 of the core from 400 s to 500 s correlates to the decrease in downcomer and core collapsed water levels shown in Fig. 2 and the heat transfer regime transitioning from nucleate boiling to film boiling and single phase vapor heating, Fig. 3. Film boiling and vapor heating are much less efficient heat transfer regimes shown by small heat transfer coefficient values calculated by MARS code in Fig. 4 when these heat transfer modes are active. The peak clad temperature (PCT) during the reflood will be used as the safety parameter to estimate safety margin compared to the regulatory acceptance criteria limit of 1477 K. The minimum downcomer and core collapsed water levels can also be used as figures-of-merit because the clad temperature is correlated to the levels.

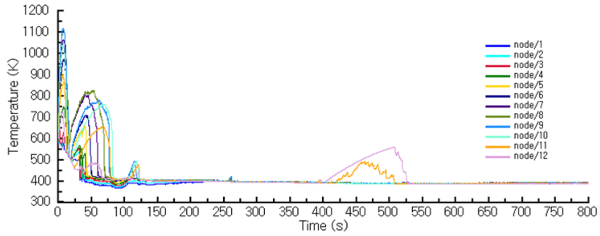

Fig. 1. Axial clad temperature profiles of hot pin during injection phase for 2/3 SITs injecting to 2/3 CLs and 1/2 LPSI pumps injecting to 1/3 CLs.

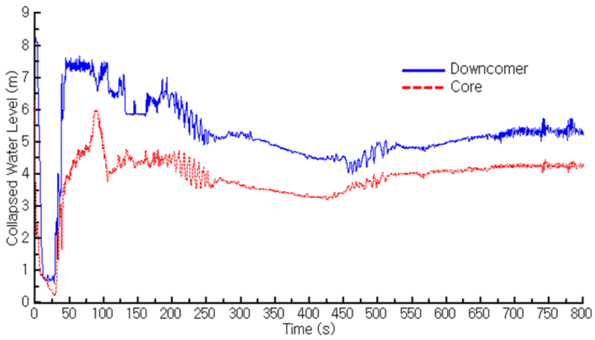

Fig. 2. Collapsed water level in downcomer and core for reference case.

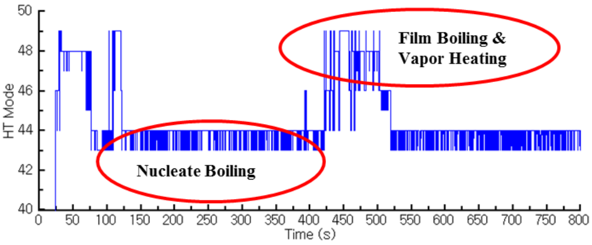

Fig. 3. Active heat transfer modes axial node 11 of hot pin for reference case.

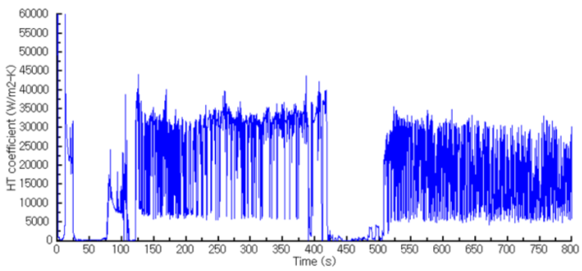

Fig. 4. Heat transfer coefficient calculated by MARS code for axial node 11 of hot pin for reference case.

2.4 Selection of Input Parameters and Sampling

Table I lists the selected input paramaters and uncertainty distributions selected for the LBLOCA application of the GPM methodology. The list is representative of sequence timing, safety system function and configuration, technical specification ranges for safety system components, and thermal hydraulic code parameters. The list of parameters is not comprehensive of all uncertainties and was not generated from a formal Phenomena Identification and Ranking Table (PIRT). The research scope of the paper is to demonstrate the GPM methodology so the parameters and distributions were selected using engineering judgment and are realistic for UCN3&4 and the MARS model in the context of our application.

Table I: Input Parameters and Uncertainties

Input Uncertainty	Distribution	Range or μ+/-σ
Sequence Timing		
EDG Delay Time	Uniform	15 s - 600 s
Safety Injection Flow Rate		
Configuration 1:		
2/2 HPSI to 3/3 CL	Uniform	80 kg/s - 115 kg/s
Configuration 2:		
1/2 LPSI to 1/3 CL	Uniform	135 kg/s - 170 kg/s
Configuration 3:		
1/2 HPSI to 3/3 CL & 1/2 LPSI to 1/3 CL	Uniform	190 kg/s - 215 kg/s
RWT Water Temperature	Uniform	276 K - 323 K
SIT Technical Specification Ranges		
Initial Water Volume	Uniform	51 m^3 - 54.2 m^3
Gas Pressure	Uniform	3.992 MPa - 4.42 MPa
Water Temperature	Uniform	280 K - 320 K
T/H Code Parameters		
Heat Transfer Coefficient Multipliers:		
Transition Boiling	Normal	1.0 +/- 5%
Film Boiling	Normal	1.0 +/- 5%
D-B Vapor HT	Normal	1.0 +/- 5%
Decay Heat:		
Fission Product Yield Factor	Normal	1.02 +/- 0.03

The delay time of EDG start, warmup, and loading of the SI pumps is the primary sequence timing parameter of the injection phase of the LBLOCA. For the study we extend the uncertainty range from the loading sequence technical specification of 15 s to 30 s out to 600 s in order to analyze the sensitivity of the safety margin to the demanding requirements on the EDG. The flow rate uncertainty range for each configuration of SI pumps represents the minimum to maximum rated flows of each pump type given in the FSAR [6]. The GPM regression will be explicitly performed on delay time and SI flow rate because these are the two dominant parameters affecting the clad temperature and the downcomer and core collapsed water levels during reflood.

The uncertainty ranges for RWT water temperature and SIT parameter uncertainties, initial water inventory, water temperature, and gas pressure, are the technical specification ranges for the components in the FSAR. During operation of the plant, these parameters may fluctuate with the ambient environment and the plant procedures require personal to periodically verify measured values do not exceed the specifications. These variables will be treated implicitly in the noise term of the GPM because they are related to the key safety systems, SITs and HPSI/LPSI, but only introduce minor variations in mass and energy balance during simulations with respect to nominal conditions.

The MARS code allows uncertainty multipliers to be applied to heat transfer coefficients calculated by the heat transfer modes. We assume a normal distribution with 5% standard deviation for the transition boiling, film boiling and vapor heating multipliers. Clad heatup occurs during reflood when these three heat transfer modes are active. A figure-of-merit, the reflood PCT, is sensitive to the heat transfer modeling. The decay heat is calculated using the ANS79-1 standard and the nominal rated power of 2815 MWt. The decay heat model uncertainty is modeled by assuming a normal distribution with mean of 1.02 and 3% standard deviation for the fission product yield factor. These input parameters will also be treated implicitly in the noise term of the GPM to demonstrate how to incorporate code parameter uncertainties into the analysis.

The training set for surrogate construction should be a space-filling design to provide adequate coverage of the input parameter space. We sample in a two-stage approach because the EDG delay time and SI flow rate are the explicit regression variables while the RWT water temperature, SIT parameters, and MARS code parameters are modeled implicitly as the noise term in the GPM. For the two-dimensional input space of EDG delay time and SI flow rate, the unscented transform with random orthogonal matrix (UTROM) sampling algorithm [7] is used to generate 100 data points for each configuration of SI pumps sampled between the minimum and maximum rated and the EDG delay time uncertainty range for a total training set size of 300 data points. The UTROM experiment design uses eigen decomposition of a randomly generated 50x50 matrix to obtain a random orthonormal basis whose projection onto the two-dimensional input space when properly scaled provides excellent space-filling properties and randomness similar to Latin hypercube designs. The second stage of sampling is Monte Carlo sampling of the remaining 8 input variables for every point in the two-dimensional input space. By Monte Carlo sampling, the "measurement" noise of each training point is a random contribution from the 8 probability density functions (pdfs).

Every MARS simulation gives a time history of the clad temperatures and the downcomer and core collapsed water levels. Figure 5 shows the time histories for the 100 simulations for configuration 2 with 1/2 LPSI pumps injecting. Also shown are the sampled SI flow rates and delay times. From the time histories, the PCT and the minimum downcomer and core collapsed water levels during reflood are extracted from the time histories becoming the output $\boldsymbol{y}$ values in the GPMs.

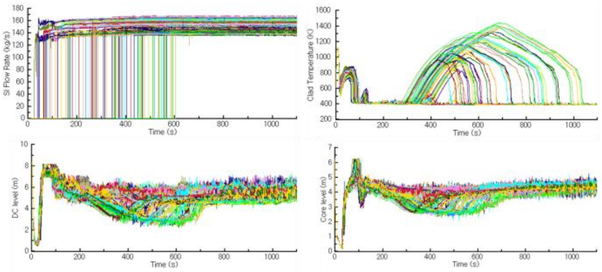

Fig. 5. MARS simulation data for 1/2 LPSI pumps injecting to cold leg 1B for LBLOCA. Clad temperatures are from axial node 9 of the hot pin.

2.5 GPM Results

Using the 300 data point training set, GPM parameters were learned using the leave-one-out method with Gaussian priors implemented in the GPML code [2]. Table II lists the learned parameter values for GPMs predicting PCT of the hot pin, minimum downcomer collapsed water level, and minimum core collapsed level during reflood. A surrogate for the PCT of the core averaged fuel channel is also provided. The maximum linear heat generation rate for the core averaged channel is 8.25 kW/ft compared to 13.9 kW/ft for the hot pin.

Table II: GPM Parameter Values

	PCT Core Avg.	PCT Hot Pin	Min DC Level	Min Core Level
Delay time scale (s): r_1	60.33	59.81	110.52	85.87
Flow rate scale (kg/s): r_2	80.38	30.21	26.01	30.93
Signal std: σ_f	156.41 (K)	162.62 (K)	0.793 (m)	0.245 (m)
Noise std: σ_n	110.65 (K)	114.82 (K)	0.074 (m)	0.223 (m)

Figures 6 - 9 are the surface plots for the GPM mean functions compared to the training data. The mean function surfaces can be interpreted as response surfaces in the context of conventional regression analysis. By visual inspection the nonlinear surfaces appear to be smooth interpolants between the training points and overfitting does not appear to be an issue. The spread or noise of the data is the contribution from the 8 inputs implicity modeled in the GPM as measurement noise.

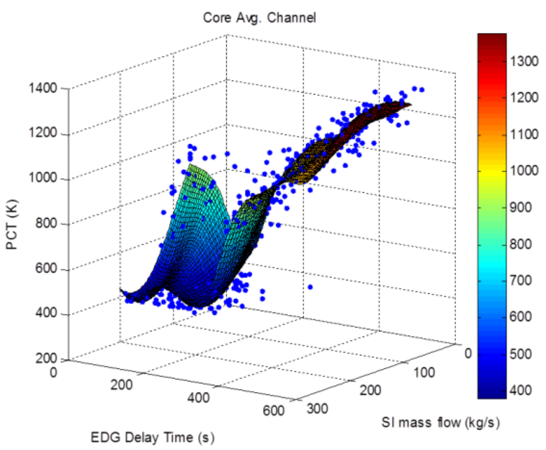

Fig. 6. GPM for core average channel reflood PCT.

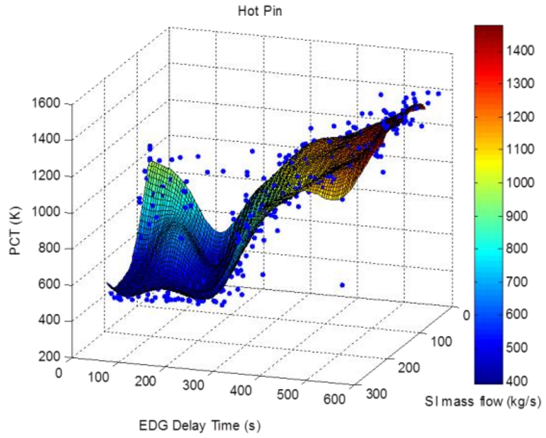

Fig. 7. GPM for hot pin reflood PCT.

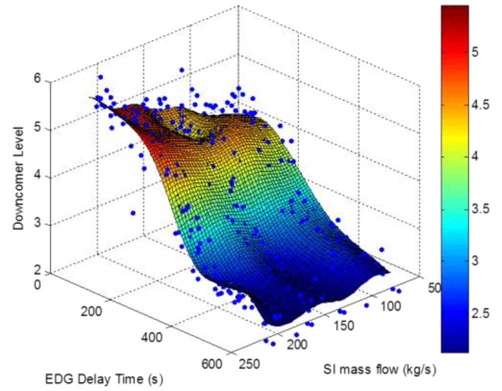

Fig. 8. GPM for minimum downcomer collapsed water level during reflood.

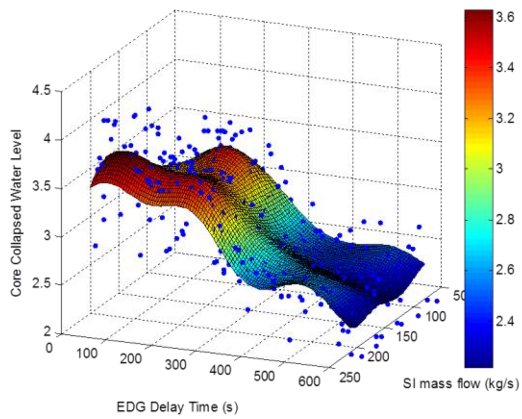

Fig. 9. GPM for minimum core collapsed water level during reflood.

2.6 Estimating Success Criteria Safety Margin

Figures 10 - 13 show the 95% probability intervals for PCT and water levels predicted by the GPMs for the 1/2 LSPI pump injecting to 1/3 CLs configuration, the LBLOCA success criteria definition, as a function of

EDG delay time. The LPSI flow rate is held at the mean value between the minimum and maximum rated flow to allow for easier visualization. The 95% probability intervals are obtained from Eqs. (2) and (3) and represent the uncertainty of the safety parameters due to the uncertainty of the implicit variables, the technical specifications and thermal hydraulic code parameters. The MARS training set data for the configuration 2 are overlain for reference.

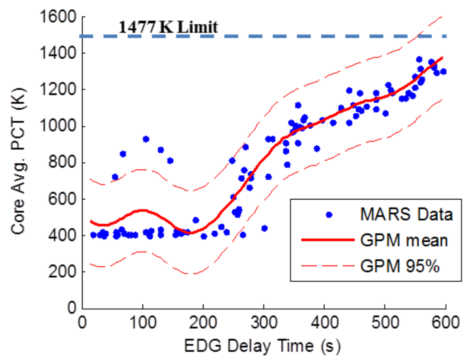

Fig. 10. PCT uncertainty bounds for core average channel.

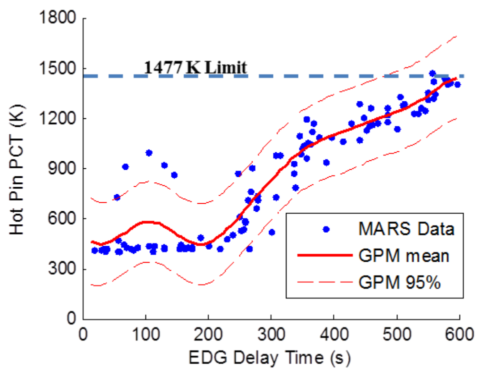

Fig. 11. PCT uncertainty bounds for hot pin.

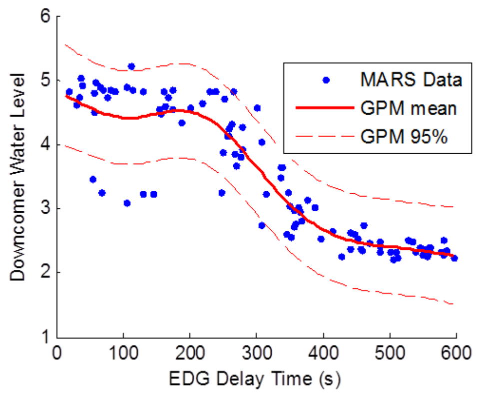

Fig. 12. Minimum downcomer collapsed water level uncertainty bounds.

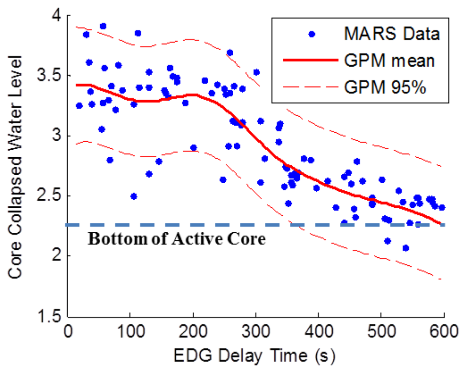

Fig. 13. Minimum core collapsed water level uncertainty bounds.

The GPM predicts the 50/97.5 percentiles of 448 K/692 K for the hot pin PCT for delay times of 30 s – 35 s, the current EDG loading sequence technical specification for the LPSI pump. The GPM only provides an estimate of the true PCT pdf subject to all uncertainties and is assumed to be the normal distribution provided by the GPM. The 1477 K limit is over 8 standard deviations from the mean and so probability of exceeding the acceptance criteria is infinitesimal. The success criteria of the UCN3&4 LBLOCA ET/FT model for the injection phase are conservative and significant safety margin exists for the specified safety system configuration and related technical specifications.

Closer examination of Figs. 10 and 11 reveals the PCT is relatively constant for delay times from 15 s to 200 s. The minimum downcomer and core levels are also approximately constant from 15 s to 200 s. For delay times greater than 300 s, the core level can reach the bottom of the fuel and the whole core will be under two-phase flow conditions during reflood leading to film boiling and vapor heating heat transfer regimes resulting in heatup of the fuel and clad. These results suggest the safety margin is insensitive to the loading sequence technical specification for LPSI loading between 30 s and 3 minutes. Cold start, short warmup time, and rapid loading of EDG during regular testing and unplanned starts is known to cause irregular wear and premature ageing on engine components reducing the reliability of the EDG and has been a long standing safety concern in the nuclear industry. The LBLOCA is the most demanding event that requires prompt SI so the stringent loading sequence technical specification and testing programs are directly related to the LBLOCA mitigation but comes at the cost of decreased EDG reliability increasing risk of other events such as loss-of-offsite power and station blackout. The plant operators could optimize the loading sequence to minimize engine wear using a mission time of three minutes for warmup and loading without comprising safety margin with respect to LBLOCA.

3. Conclusions

A new methodology to estimate safety margin of a NPP has been proposed and demonstrated for best estimate simulation of LBLOCA in support of Level 1 PSA success criteria definitions. The methodology simultaneously considers sequence timing, safety system configuration, technical specifications, and code model parameter uncertainties. A key aspect of the methodology is the input parameter space is partitioned into two subsets of inputs, explicit regression variables consisting of the dominant input uncertainties that are the fundamental drivers of thermal hydraulic behavior of the transient and implicit noise variables. A Gaussian process model performs regression on the explicit regression variables and output uncertainty is quantified by a measurement noise term representing the contribution of the implicit input noise variables to local variation or uncertainty of the safety parameter. This approach retains high fidelity treatment of all input uncertainties during best estimate simulation of the transient, but allows the analyst to focus regression analysis on the most important application specific parameters thereby overcoming the curse of dimensionality inherent to the analysis of complex systems.

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