APPLICATION OF GAUSSIAN PROCESS MODEL TO GENERATE A SUCCESS CRITERIA MAP WITH ESTIMATE OF SAFETY MARGIN AND UNCERTAINTY ANALYSIS

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A multi-dimensional success criteria map for a Level 1 PSA model is generated for the injection phase of a LBLOCA in a typical PWR that integrates the safety function of three systems: safety injection tanks (SIT), high-pressure safety injection, and low-pressure safety injection, using response surfaces derived from a Gaussian process model regression methodology. The safety margin is quantified for multiple configurations of the safety systems and as a function of the emergency diesel generator start, warm-up, and loading sequence timing representing the dominate sequence timing parameter relevant to the event tree. The maximum allowable warm-up time is identified that represents a bifurcation point in the thermal hydraulic response of the plant to the LBLOCA following SIT injection and the start of active safety injection systems. The demonstrated methodology retains high fidelity treatment of many input uncertainties during best estimate simulation of the transient, but allows the analyst to focus on a regression analysis on the most important application specific parameters thereby overcoming the curse of dimensionality inherent to the analysis of complex systems.

I. INTRODUCTION

Best estimate simulations of nuclear power plant (NPP) transients can be performed in support of success criteria definitions in a 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 of 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 methodology to estimate the safety margin while addressing the 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 a multivariate regression with an internal estimate of the model uncertainty,[1] 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 Hanul Units 3&4 (HU3&4), formerly Ulchin Units 3&4, and the success criteria are quantified. The success criteria for multiple safety systems are represented in an integrated manner on a success criteria map, a multi-dimensional surface derived from the GPM regression explicitly incorporating sequence timing as a continuous parameter. The map shows the safety margin quantified by the peak clad temperature (PCT) expected to occur for each safety system configuration conditioned on sequence timing.

II. OPR1000 SUCCESS CRITERIA FOR LBLOCA

II.A. Success Criteria for Injection Phase LBLOCA

HU3&4 is a representative OPR1000 (Optimized Power Reactor 1000 MWe), a 2x4 pressurized water reactor design with two hot legs, two steam generators, four cold legs and four reactor coolant pumps. The rated power is 2815 MWt. Safety injection (SI) systems designed to mitigate the LBLOCA are one safety injection tank (SIT) per cold leg, high-pressure safety injection (HPSI) system with two pumps, and a low-pressure safety injection (LPSI) system with two pumps. The SITs are predominantly passive components and automatically inject when the reactor coolant system (RCS) pressure falls below set points. Assuming a loss of offsite power (LOOP), the HPSI and LPSI pumps actuate following the start and loading of the emergency diesel generators (EDG) after the safety injection actuation signal (SIAS) is received at low pressurizer pressure.

The flow from each HPSI pump is split to all four cold legs safety injection headers while a flow from each LPSI pump is split to only two cold legs. From their initial configurations, the SI systems are designed to operate in injection mode until the refueling water tank (RWT) is depleted and recirculation mode is initiated.

Fig. 1 shows the Level 1 PSA model for the LBLOCA top event. Condensed fault trees are shown for the SITs and LPSI system which are the safety systems relevant to the injection phase of the LBLOCA, the topic of the present work. The HU3&4 success criteria for the injection phase of the LBLOCA are to inject water through at least 2 of 3 intact cold legs from 2 of 3 SITs and inject RWT water through at least 1 of 3 intact cold legs using 1 of 2 LPSI pumps.[2] The success criteria represent the single failure criterion and do not credit any SI flow to the broken cold leg. HPSI is not included in the LBLOCA event tree although the HPSI system was designed to automatically actuate and the HPSI system must be available during the recirculation phase. HPSI availability can lead to injection phase success even if the LPSI system has completely failed for some LBLOCAs, and thus HPSI should be considered.[3]

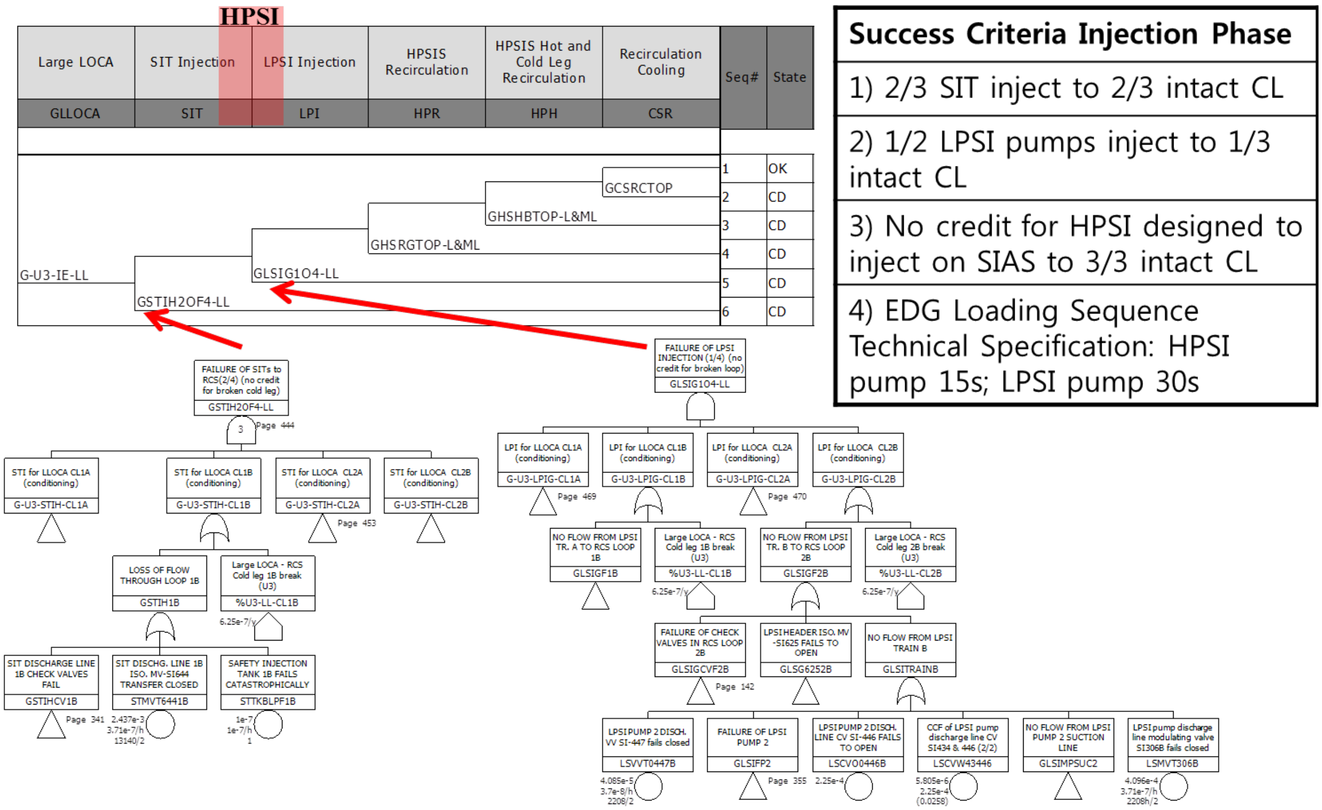

Fig. 1. OPR1000 Level 1 PSA model for LBLOCA with potential HPSI branch included in event tree.

II.B. MARS Model for Best-Estimate Simulation of LBLOCA and Reference Results

The MARS code version KS1.3 is used to simulate the injection phase of the LBLOCA with the HU3&4 model.[4] The double-ended guillotine break is assumed to occur in cold leg 1A between the SI header and reactor vessel inlet. The core is modeled with two coolant channels representing the hot pin channel and a core-averaged channel. The power distribution is a top-skewed cosine shape and the linear heat generation in the power peak of the hot pin was set to a limiting condition of operation of 13.9 kW/ft. The LPSI and HPSI systems are modeled as time dependent junctions injecting to the SI headers in each cold leg with user-supplied mass flow rates as a function of RCS pressure. The SITs are modeled individually as accumulator components injecting into the SI headers.

Fig. 2 shows the reference case results of the injection phase transient. The reference case represents the Level 1 PSA success criteria with 2 of 3 SITs modeled to inject from approximately 16 s to depletion at 85 s and 1 LPSI pump injecting to the broken loop with 1 of 2 intact cold legs at the minimum rated flow of approximately 138 kg/s. The LPSI pumps starts at 36.7 s, a 30 s delay after the SIAS. Both systems inject cold water into the cold leg piping during the same time period with SITs dominating the thermal hydraulic response of the plant during a refill and early reflood and the late reflood behavior more dependent on LPSI. During the late reflood at approximately 400 s, the top axial quartile of the hot pin experiences a temperature excursion (Fig. 2.A) that is *correlated* with the minimum collapsed water levels of the downcomer and core (Fig.2.B). The peak clad temperature (PCT) during the late reflood heat up is the figure of merit (FOM) that delineates the success or failure in the LPSI branch of the event tree. Compared to the PCT regulatory limit of 1477 K, the late reflood PCT quantifies the safety margin provided by the LPSI system configuration defined by the LPSI success criteria.

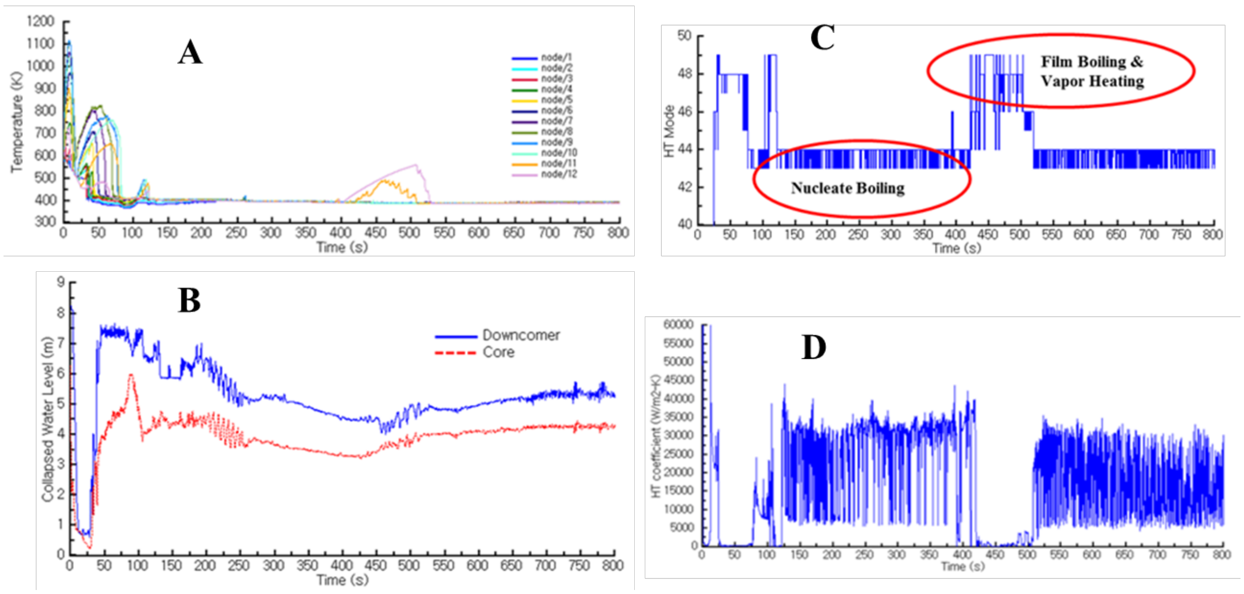

Fig. 2. Plant parameters during injection phase of LBLOCA. A) Axial clad temperature profile of hot pin. B) Collapsed water level in downcomer and core. C) MARS model active heat transfer mode and boiling regime. D) Heat transfer coefficient calculated by MARS code from the outer clad surface of a hot pin to the coolant.

The decreasing downcomer and core collapsed water levels from approximately 85 s to 450 s are FOMs of the evolving two-phase flow regime in the core, with a void fraction of the hydrodynamic volumes a key parameter, calculated by the MARS code. A MARS code calculated value of a PCT is an artifact of the heat conduction solution performed by the heat structure sub-model, and the collapsed water levels are artifacts of the hydrodynamic sub-model and solution of the field equations. The heat structure and hydrodynamic sub-models exchange energy through wall-to-fluid heat transfer using many empirical correlations, flow regime maps, and heat transfer modes. Figs. 2C and 2D show the active heat transfer modes and corresponding values of the wall-to-fluid heat transfer coefficient calculated by the MARS code during a late reflood. A clad heat up occurs when the simulation transitions to film boiling and single-phase vapor heating heat transfer modes when the void fraction is high, and inefficient heat transfer regimes, as evidenced by the small values of heat transfer coefficients. There are also high frequency oscillations between the heat transfer modes including intermediate states through transition boiling throughout the temperature excursion. During a reflood characterized by low pressure and low flow rates, the coupled flow and heat transfer regime is inherently unstable and the numerical solution tries to correctly resolve the phenomena. However, the results in Fig. 2 suggest that the coupled thermodynamic and thermal hydraulic state of the core, after the safety systems in the configuration defined by the success criteria respond to a LBLOCA, is treading about an unstable bifurcation point. If the code is incorrectly predicting a later transition time to film boiling or an earlier time to re-enter nucleate boiling, the calculated PCT will be underestimated. Thus, a single simulation is insufficient to assess the safety margin provided by the LPSI success criteria which are also coupled to the SIT success criteria. A small deviation in an input assumption such as the LPSI pump flow rate curve, pump actuation time, time step size, and containment pressure response could yield a significantly different late reflood PCT value, i.e., the FOM to measure the LPSI success criteria. The reference case provides no information about the modified ET, which includes HPSI.

II.C. Sequence Timing Parameter

The most important sequence timing parameter of the reference case simulation is the LPSI pump start time, which is a function of the EDG start and loading sequence, a technical specification of the HU3&4 plant. The LBLOCA is the most limiting transient that requires a rapid safety injection from active (AC powered) safety systems to replenish the RCS inventory. Thus, the EDG start and loading sequence is LBLOCA-centric, and anytime a complex system, in this case the EDG and loading of dozens of plant safety systems and components, is optimized for one function, i.e., an LBLOCA mitigation, other aspects of the complex system may suffer as the result of the design tradeoff. The HU3&4 EDG technical specification requires a cold start and warm-up of the EDG in 10 s. The loading sequence is as follows:[5] the HPSI pump, a large 1000 hp induction motor, loads at 15 s and accelerates to full speed in 5 s. At 20 s, an auxiliary feedwater pump (1052 hp) loads followed by a containment spray pump (800 hp), at 25 s. The LPSI pump (600 hp) loads at 30 s. A cold start, short warm-up time, and rapid loading of large electrical loads onto the EDG during regular testing and unplanned starts is known to cause irregular wear and premature aging on the engine components, reducing the reliability of the EDG and has been a long standing safety concern in the nuclear industry.[6] EDG unavailability due to maintenance is a common basic event in many of the minimal cut sets of the station blackout (SBO) initiating event fault tree in the HU3&4 PSA model. SBO is a major contributor to the overall risk. A technical specification that leads to more or unnecessary EDG maintenance is undesirable.

Nuclear power plants are not static facilities. Throughout the plant lifetime, the plant owner may request license amendments, perform power uprates, or replace or modify the safety system components. In the context of the living PSA of the plant, the PSA model and the supporting thermal hydraulic calculations that inform aspects of the model such as the success criteria should be flexible and detailed enough so that potential changes to the plant design, operation, or plant licensing basis can be quickly assessed in an economic manner without the need of reconstituting sometimes decades old thermal hydraulic models and simulation data often requiring a knowledge transfer between several generations of PSA practitioners. The objective of the present work is to demonstrate a methodology that can consolidate large amounts of data from thermal hydraulic simulations into the format of a success criteria map, which can be used for future living PSA applications. An example case study is a hypothetical license amendment requesting a change in the loading sequence technical specifications. The change in safety margin provided by the safety system configurations defined by the LBLOCA success criteria conditioned on the new loading sequence is quantified by the success criteria map.

III. GAUSSIAN PROCESS MODEL RESPONSE SURFACES FOR INJECTION PHASE FIGURES OF MERIT

III.A. GPM Methodology Overview

Fig. 3 outlines the GPM regression methodology used in the study. Reference 1 should be consulted for the details of the methodology including proper techniques for training and validating the GPM as a code surrogate or meta-model to the OPR1000 MARS model and the mathematical structure of the GPMs. Reference 7 is a general reference on GPMs for regression.

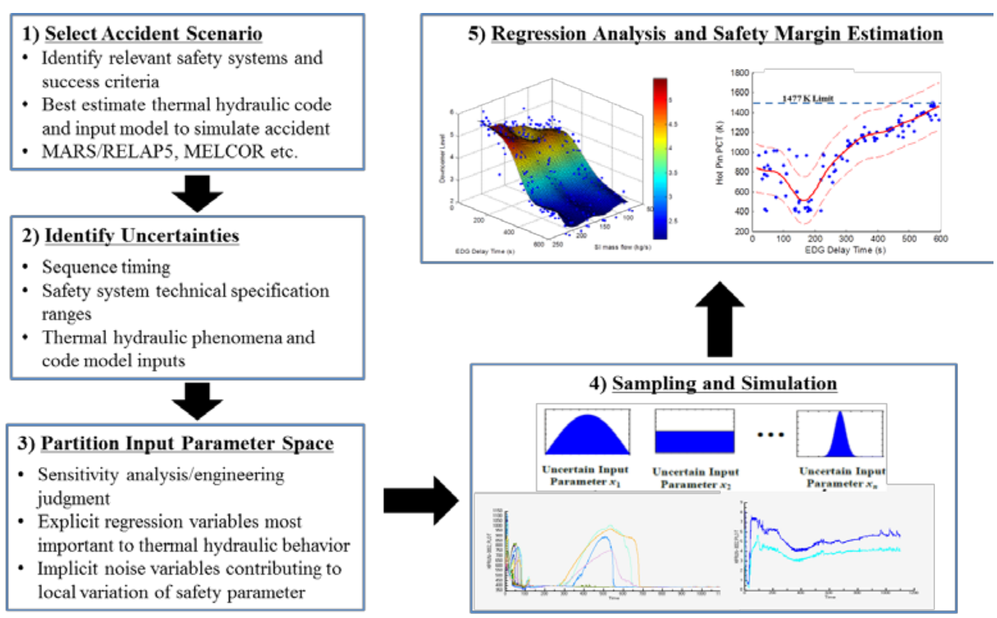

Fig.3. Flowchart of Gaussian process model regression methodology for safety margin estimation.

Herein we briefly introduce the GPM equations, the response surface functions from which the success criteria map is generated. The GPM is unique among regression methods because it defines a *predictive distribution* of the dependent variable *y*, the safety parameter or FOM, at any input "test" location $\boldsymbol{x}_*$, a safety injection flow rate and delay time representing the EDG loading sequence. The GPM is then 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

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

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

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

$$\Lambda = \mathrm{diag}(r_1^2, r_2^2) \,. \tag{5}$$

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

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

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

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

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

III.B. Response Surfaces for Injection Phase Success Criteria Safety Parameters and Figures of Merit

Over 300 MARS simulations of the LBLOCA injection phase were performed to generate a dataset of PCT values and the core and downcomer collapsed water levels FOMs as a function of the SI flow rate and EDG delay time representing the EDG warm-up and loading sequence of HPSI and LPSI pumps, the key sequence timing parameter. The EDG delay time was sampled between 15 s and 600 s with the lower bound representing the current the loading time of the HPSI pumps. The hypothetical change to the loading sequence technical specification considers loading of SI pumps up to 600 s after SIAS. SI flow rates were sampled between 80 kg/s representing the total flow rate delivered to 3 of 3 intact cold legs from 2 of 2 HPSI pumps running at the minimum rated flow to 215 kg/s representing one fully operational SI train the delivering maximum rated flows, one LPSI pump to 1 of 2 intact cold legs and one HPSI pump to 3 of 3 intact cold legs. By sampling a range of flow rates, all intermediate configurations of SI systems including failures of valves on the individual injection lines are well covered. The reference case simulation considering one LPSI pump delivering 138 kg/s is an intermediate configuration.

Fig. 4 shows the simulation data and the GPM response surface models fitted to the simulation data for the hot pin PCT during a late reflood, average core channel PCT, minimum downcomer collapsed water level, and minimum core collapsed water level. The nonlinear surfaces are smooth interpolants between the data points and overfitting does not to appear to be an issue although overfitting is often a major problem in meta-model development including GPMs. The PCT response surfaces show a general positive correlation trend between the EDG delay time and PCT. At low flow rates (< 100 kg/s) and short delay times representative of a 2 of 2 HPSI pump working with a completely failed LSPI safety system configuration, clad heat up during a late reflood is likely to occur, and thus the safety margin is less in that quadrant of the design space. The collapsed water level surfaces show a general negative correlation trend between the EDG delay time and minimum levels attained during a reflood indicating an increasing EDG warm-up time and lengthening the pump loading intervals can cause more voiding of the core during a reflood potentially leading to a clad heat up and reduced safety margins.

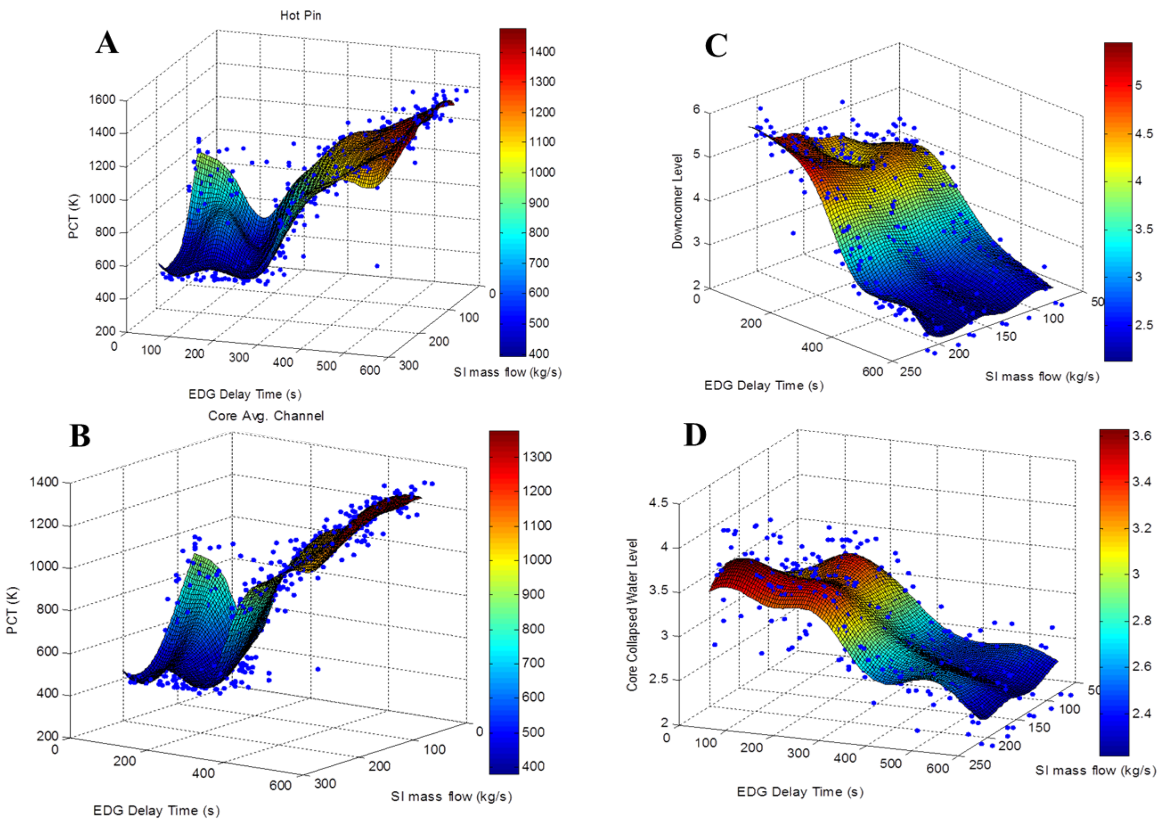

Fig. 4. Simulation data and GPM response surfaces for A) hot pin PCT, B) core average channel PCT, C) minimum downcomer collapsed water level, and D) minimum core collapsed water level.

The simulation data in Fig. 4 appear to be quite noisy. As discussed in section II.B, flow conditions during a reflood are naturally unstable and thus the data noise is partially an artifact of the prevailing thermal hydraulic conditions and the solution structure of the MARS code. The second contribution to the data noise was the random sampling of eight additional input variables during each MARS simulation. These variables include the technical specification range of the RWT water temperature, the water source of the LPSI and HPSI pumps affecting the subcooling margin of the SI flow, and technical specification ranges of the SIT parameters including the initial water volume, gas pressure, and water temperature. Normally distributed heat transfer coefficient multipliers were applied to transition boiling, film boiling and vapor heating heat transfer modes to model the heat transfer correlation uncertainty during time periods of a clad heat up. Decay power uncertainty was modeled using a normally distributed fission product yield factor. The latter group of variables represents code input parameter uncertainties that are often addressed in Best Estimate Plus Uncertainty (BEPU) methodologies applied in design basis accident analyses. The random sampling of the eight variables manifest as local variation analogous to random measurement noise in the MARS calculated FOMs. Here we interpret the calculated MARS simulation results not as exact numerical results up to the machine precision but rather more akin to experimental measurements where we control for EDG delay time and SI flow rate, where the other eight variables are the aleatory conditions of the laboratory environment. The effects of these eight variables are lumped together in the measurement noise term of the GPM, and thus the variables are implicitly treated in the GPM regression.[1]

Fig. 5 shows the 95% probability intervals for the FOMs predicted by the GPMs through Eqs. (2) and (3). To allow for a 2D visual inspection, the SI flow rate was held constant at 153 kg/s, which is equal to the mean rated flow of one LPSI pump delivering flow to 1 of 2 intact cold legs. The GPM means are the 2D slices from the 3D surfaces in Fig. 4. The key takeaway from Fig. 5 is that the PCT FOMs and water level FOMs are all approximately constant for EDG delay times of up to 200 s. At 200 s, a very clear trend develops in terms of increasing PCT negatively correlated to the decreasing water levels. At around 500 s to 600 s, the entire core is voided and core damage ensues. The uncertainty bounds are a first-order estimate invoking the Gaussian assumption of Eq. (3). Note the five outlier cases around 100 s where a considerable clad heat up occurred. These outliers exemplify the unstable nature of the low flow reflood regime being simulated as discussed in section II.B and how performing only a few reference calculations does not provide a complete understanding of the relevant phenomena.

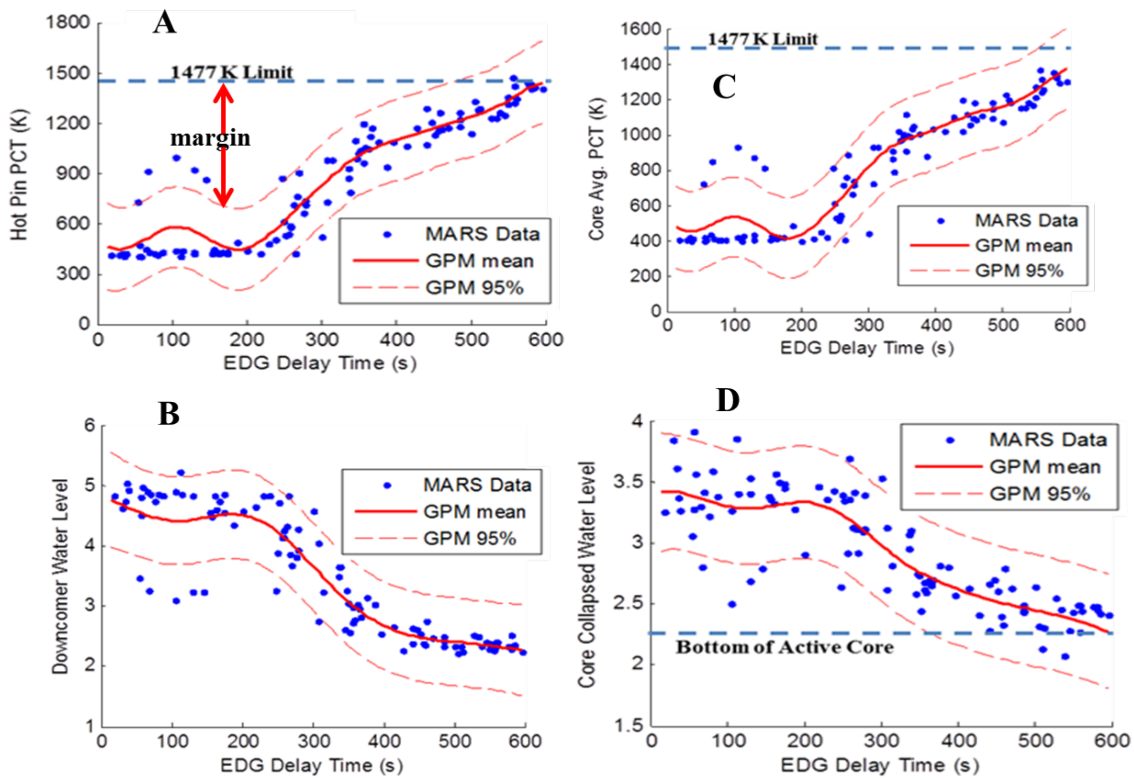

Fig. 5. Uncertainty bounds for A) Hot pin PCT. B) Core average channel PCT. C) Minimum downcomer collapsed water level. D) Minimum core collapsed water level.

IV. LBLOCA INJECTION PHASE SUCCESS CRITERIA MAP

IV.A. Injection Phase Success Criteria Map for LPSI and HPSI

Fig. 6 shows the success criteria map for the injection phase of the LBLOCA considering both LPSI and HPSI branches in the ET (Fig. 1). The color contours on the map represent the hot pin PCT predicted by the GPM response surface on a continuous grid of EDG delay time and SI flow rate. The PCT values on the map are of the 97.5 percentile, the GPM mean plus 1.96σ, and the upper bound of a 95% probability interval shown in Fig. 5A. Equivalent success criteria maps can be easily generated at any desired percentile from the GPM response surfaces. By using the hot pin PCT surrogate and 97.5 percentile, some conservatism has been incorporated into the success criteria map but the underlying data used to generate the map are from a best-estimate thermal hydraulic model.

The regions numbered 1-3 represent three configurations of LPSI and HPSI pumps with region boundaries delineated by the minimum to maximum rated flows of each pump type. Numerous intermediate safety system states and configurations exist within and in-between the three regions. Intermediate states include failures of valves on individual injection lines, manual throttling of pumps by operators, degradation of a net positive suction head available to the pumps, and additional flow from the charging pump injection to the RCS.

The dark blue area indicates the region of a very large safety margin of > 500 K to the clad temperature limit of 1477 K. This area delineates the success region with a high level of confidence. However, PCT and safety margin defined from a simple comparison to a regulatory edict is only a superficial measure of the safety margin. The dark blue area actually represents the SI flow rates and pump actuation times that are required to maintain a two-phase flow in the upper region of the core with a sufficiently small void fraction such that efficient heat transfer regimes such as nucleate boiling can be maintained over the fuel rods preventing any clad heat up. The upper edge of the dark blue contour starting at 200 s and 80 kg/s identifies the bifurcation boundary of the system with respect to the heat transfer regime. The failure space of the plant design is the green-yellow-red region representing undersized flow rate capacity and tardy actuation of active SI systems. The bifurcation boundary identified on the success criteria map is a limit surface delineating success and failure regions.

From a defense-in-depth perspective, there are two safety barriers of interest during a reflood protecting the fuel and cladding from heat up to the point of core damage. The first barrier is the coolant flow provided by the active SI systems and efficient heat transfer of decay energy to the fluid. The second barrier is the thermal mass of the fuel pellets and clad. During an LBLOCA blowdown and refill (Fig.2A: 0 s to 100 s), the thermal mass of the fuel is the primary barrier that allows the PWR system to ride out the rapidly evolving initial phases of the transient. During a reflood, it is the responsibility of the plant designer and operator to ensure that the capacity and reliability of the active safety systems is a formidable barrier to a clad heat up. Only as a second line of defense should the thermal mass of the fuel coupled with decreasing decay power be credited in a safety analysis or success criteria definition. Thus, the transition (green-yellow) region above the bifurcation boundary should be a hard ceiling imposed on success the criteria definitions. Even though the regulatory PCT limit has not been exceeded, the system is in a failure state because defense in depth principle has been violated.

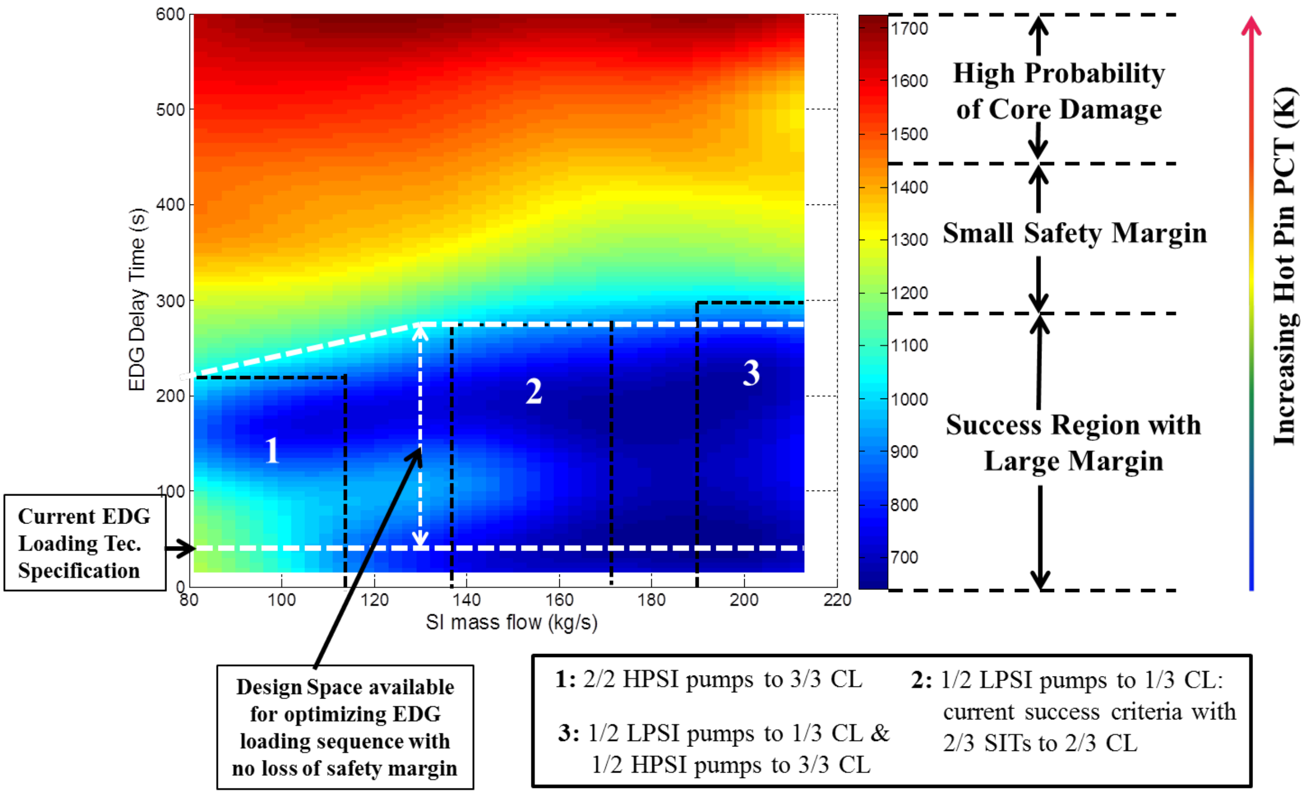

Fig. 6. Success criteria map for LPSI+HPSI pump configurations and EDG loading sequence timing with quantification of the safety margin.

IV.B. Application to EDG Loading Sequence Technical Specification

In the HU3&4 PSA model, LBLOCA initiating event frequency is $4.9e^{-6}$ y^{-1} compared to the LOOP initiating event frequency of $2.8e^{-3}$ y^{-1}. LBLOCA contributes less than 1% to the overall plant risk. The EDGs are the most important safety component to prevent LOOP from becoming an SBO, which is a risk significant event. Improvements to the EDG reliability and decreasing EDG unavailability due to maintenance will improve the safety of the plant and reduce risk. From the perspective of the LBLOCA, the large success region delineated in Fig. 6 provides a design space within which the EDG loading sequence can be optimized without a loss of safety margin. An upper bound on the total warm-up time and loading of the SI pumps is 3 to 3.5 minutes compared to 30 s required by the current technical specifications. Increasing the warm-up time will decrease wear on the EDG components requiring fewer maintenance overhauls and longer intervals between overhauls. Optimization of the loading sequence can also reduce the overspeed and load rejection trips of the EDG reducing the failure to run frequency. All other transients requiring timely actuation of the active safety systems will need to be reviewed and similar analyses performed to identify any loss of safety margin. If a conservative or bounding analysis is performed, the current success criteria configuration will likely be in the region with a small safety margin and a change to the EDG loading sequence will not be permissible. However, by accurately defining the safety margin, a proper cost benefit analysis of the design tradeoff can be performed possibly leading to a safer plant.

IV. SUMMARY AND CONCLUSIONS

Gaussian process model regression has been applied to best-estimate simulations of a LBLOCA to generate a success criteria map that quantifies the safety margin provided by safety system configurations defined in Level 1 PSA success criteria definitions. The success criteria map explicitly incorporates sequence timing information so that technical specification changes related to the EDG loading sequence can be quickly assessed without performing additional thermal hydraulic analyses. Key aspects of the demonstrated methodology are:

1) Random sampling of technical specification and code input parameter uncertainties similar to BEPU methodologies was performed during the simulation of the LBLOCA with the MARS code. The GPM was specifically chosen as the regression technique in the application because the local variation of FOMs as a function of the random sampling of these parameters could be implicitly treated in the regression as measurement noise uncertainty model avoiding the curse of dimensionality. As a data smoother, the GPM regression performed well by fitting smooth response surfaces to the noisy data sets.

2) After an initial figure of merit, the PCT during late reflood, was chosen as the target response of the surrogate model development, we went back to the original best-estimate model and reference simulations and reviewed in detail all of the sub-models, correlations, and solution structure of the code that were used to produce the numerical output value of the FOM. Through this process, additional correlated FOMs were identified that provided additional physical insight into the evolving thermal hydraulic conditions in the core. Furthermore, the process identified the subset of operational ranges of the safety systems and parameters to the code correlations most relevant to the application. Thus, phenomena identification and ranking table (PIRT) process, best-estimate simulation, and surrogate development should be a highly iterative process.

Code surrogates or meta-models are often developed using a “black-box” approach with respect to the best-estimate code; the analyst only considers the input and output data streams from the code. Secondly, there are dozens of very mathematically complex algorithms and regression methods in use as meta-models, e.g. GPMs, artificial neural networks, alternating conditional expectation, multivariate adaptive regression splines, multivariate additive regression trees, first/second order reliability methods, non-linear least squares, generalized polynomial chaos and many others. Thirdly, developing the meta-model involves several intermediate steps including sampling of inputs through an experimental design and training the surrogate through some additionally very mathematically complex optimization method often relying on several third-party software packages. For example, GPM studies often used Bayesian methods, Markov chain Monte Carlo (MCMC), or gradient based optimization for surrogate training. During our six years of experience with GPMs in realistic nuclear safety applications, all of our attempts to use MCMC have failed to obtain convergence and we have found gradient based method results are not always reliable.

Here we offer a few cautionary observations on the use of meta-models in support of nuclear safety applications and PSA. Meta-model studies are susceptible to become trivial numerical exercises where one black-box is used to analyze another black-box sometimes requiring additional intermediate black-box analyses. The analyst should remain vigilant and use the appropriate tools at the appropriate times in order to answer the important questions about a nuclear system, i.e. what is the safety margin of the NPP conditioned on the assumptions of the analysis? The nuclear safety study may become bogged down by the mathematical complexity of the meta-model diverting resources and time away from gaining a better understanding of the nuclear system and important thermal hydraulic phenomena that are being simulated by the best-estimate code. The meta-model does not provide any new information about the problem; the meta-model if used correctly is a tool for analyzing data and aids in organizing and visualization of information. Finally, selection of a meta-model algorithm is application specific and the particular meta-model should have advantageous features that justify the high cost of meta-model development.

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REFERENCES

1. D. A. FYNAN and K. I. AHN, “Implicit Treatment of Technical Specification and Thermal Hydraulic Parameter Uncertainties in Gaussian Process Model to Estimate Safety Margin,” *Nuclear Engineering and Technology*, **48**, 684 (2016).
2. KOPEC, “Probabilistic Safety Assessment of for Ulchin Units 3&4,” Korea Power Engineering Company (2004).
3. D. H. LEE, H. G. LIM, H. Y. YOON, and J. J. JEONG, “Improvement of the LOCA PSA Model Using a Best-Estimate Thermal-Hydraulic Analysis,” *Nuclear Engineering and Technology*, **46**, 541 (2014).
4. J. J. JEONG, K. D. KIM, S. W. LEE, Y. J. LEE, B. D. CHUNG and M. HWANG, “Development of the MARS Input Model for Ulchin 3/4 Transient Analyzer,” KAERI/TR-2620/2003, Korea Atomic Energy Research Institute (2003).
5. KEPCO, “Ulchin Units 3&4 Final Safety Analysis Report,” Final Safety Analysis Report, Korea Electric Power Corporation (1997).
6. K. R. HOOPINGARNER and F. R. ZALOUDEK, “Aging Mitigation and Improved Programs for Nuclear Service Diesel Generators,” NUREG/CR-5057, U.S. Nuclear Regulatory Commission (1989).
7. C.E. RASMUSSEN and K.I. WILLIAMS, *Gaussian Processes for Machine Learning*, MIT Press, Cambridge, Massachusetts (2006).