# Response Surface Methodologies for Passive Safety System Reliability Analysis

**Tom Elicson[a], Chloe Howard[b], Stephen Hess[a], Leo Shanley[a], and Eric Thornsbury[c]**
[a] Jensen Hughes, West Chester, PA, USA, telicson@jensenhughes.com, shess@jensenhughes.com, lshanley@jensenhughes.com
[b] Jensen Hughes, Edinburgh, Scotland, chloe.howard@jensenhughes.com
[c] EPRI, Cincinnati, OH, USA, ethornsbury@epri.com

---

**Abstract:** Passive safety systems (PSS) play a central role in advanced nuclear reactor designs, yet their reliability assessment is challenged by strong dependence on complex thermal–hydraulic phenomena and associated uncertainties. This paper presents a response surface based methodology developed under an Electric Power Research Institute (EPRI) – supported study for integrating phenomenological uncertainty into probabilistic reliability analysis of PSS. The approach combines traditional fault tree analysis with uncertainty propagation derived from detailed thermal–hydraulic best estimate simulations. To address the computational impracticality of large scale Monte Carlo sampling with high fidelity codes, response surfaces are constructed from a limited set of best estimate analyses and subsequently used as surrogate models for efficient uncertainty propagation. The methodology is demonstrated through a pilot application to a hypothetical, simplified passive containment cooling system, providing credible insights into system performance and reliability. A third order multivariate polynomial regression is employed to develop the baseline response surface, and alternative parametric and non-parametric formulations, including transformed linear regression, Gaussian process regression, and spline based models, are considered to assess their suitability for PSS applications. The paper discusses methodological tradeoffs, data selection strategies, and goodness of fit evaluation metrics, and highlights the implications of response surface choice on reliability estimates. The results support the use of response surface surrogates as a practical and flexible framework for risk informed assessment of passive safety system reliability in advanced nuclear reactors.

---

## 1. INTRODUCTION

The performance of passive safety systems (PSS) found in advanced reactor designs is strongly dependent on complex natural physical processes, therefore they are susceptible to uncertainties in the physical processes themselves. As advanced reactors may be licensed within a risk-informed framework, reliable estimates of passive safety system reliability are essential. Determining the PSS reliability includes assessing the phenomenological reliability.

Characterization of the PSS phenomenological reliability is commonly performed by implementing random sampling techniques to propagate uncertainties through a best estimate (BE) thermal hydraulic model. To obtain meaningful results using random sampling techniques several hundreds of thousands or several million BE case runs would be required, which would be computationally limiting. An alternate method is to build a response surface to approximate the BE code. The phenomenological uncertainties are then propagated through the response surface which can be exercised several hundreds of thousands of times in a matter of a few minutes.

The focus of this paper is to present a response surface methodology developed under an Electric Power Research Institute (EPRI)–supported study for integrating phenomenological uncertainty into probabilistic reliability analysis of PSS [1]. The paper discusses methodological tradeoffs, data selection strategies, goodness of fit evaluation metrics, and highlights the implications of response surface choice on reliability estimates. The methodology is then demonstrated through a pilot application to a hypothetical, simplified passive containment cooling system (PCCS), providing credible insights into system performance and reliability.

## 2. RESPONSE SURFACE METHODOLOGY FOR PSS RELIABILITY ANALYSIS

### 2.1 Key Components of the Response Surface Methodology

A response surface is a statistical technique used to develop a mathematical model that approximates the relationship between input variables and output responses. In the context of PSS reliability analysis, a response surface serves as a computationally efficient alternative to direct thermal-hydraulic code calculations. Key components of a response surface methodology for PSS analysis identified in the EPRI-sponsored study [1] include,

1. **Identification of Critical Parameters**: Through structured approaches like Phenomenon Identification and Ranking Table (PIRT), critical parameters affecting PSS performance are identified and ranked based on importance and knowledge level.
2. **Parameter Range Definition**: Operating ranges are defined for each critical parameter, considering both normal and off-normal conditions. The parameter ranges should extend beyond typical design limits while avoiding excessive conservatism.
3. **Sensitivity Analysis**: Each parameter is varied independently across its defined range to evaluate its impact on system performance against defined success criteria.
4. **Probability Distribution Assignment**: Probability density functions (pdfs) are assigned to critical parameters to quantify their epistemic uncertainty, ideally informed by experimental and operational data.
5. **Response Surface Development**: A limited number of thermal-hydraulic code calculations are performed to develop a mathematical model (response surface) that relates critical parameters to system performance.
6. **Uncertainty Propagation**: Random sampling of the critical parameters is used to propagate parameter uncertainties through the response surface to determine PSS phenomenological reliability.

The assignment of probability distributions listed in item 4, above, is often complicated by a lack of data. However, the following general guidelines can be applied to commonly used probability distribution functions.

**Normal distributions** are often used to represent uncertainty in physical properties and can be used when parameter values are most likely to be close to their mean values with extreme values possible to either side of the mean. In some instances, data modeled by a normal distribution has physical limits at the extremes (e.g., the uncertainty in an initial water temperature at atmospheric pressure may be represented by a normal distribution but has physical limits at the freezing and boiling points), in which case a truncated normal distribution should be applied.

In the absence of data, the nominal value of a critical parameter can be assigned to the distribution mean and a standard deviation can be assigned such that the extreme limits (selected based on engineering judgment, physical limitations, a review of the literature, or other analyses) would have a probability of occurrence of approximately 0.001 to 0.0001 which corresponds to events that are subjectively determined to be extremely unlikely or almost impossible to occur. For the normal distribution, this corresponds to data values that fall approximately +/- 3 to 4 standard deviations from the mean.

**Lognormal distributions** are often applied to quantities formed by multiplying many random factors. As an example, if a single BE code input is used to represent multiple phenomenological parameters, then the lognormal distribution may be representative of the critical parameter uncertainty. Failure data for certain components, such as electrical components, is also often lognormally distributed.

**Exponential distributions** are often used to represent degradation as a function of time or for parameters representing systems that are most likely in an intact state with zero degradation. As with the normal distribution, in the absence of data, a standard deviation can be assigned such that the pre-determined extreme limit has a probability of occurrence in the range of 0.001 to 0.0001 which corresponds to events that are subjectively determined to be extremely unlikely or almost impossible to occur.

**Uniform distributions** can be applied when no information is available regarding a parameter uncertainty and the parameter varies between two known limits. The uniform distribution assigns equal probabilities to any value of the parameter within the pre-defined range. As more information becomes available, a more realistic uncertainty distribution can be applied.

### 2.2 Types of Response Surface Models

Response surface models are divided into parametric response surfaces and non-parametric response surfaces. The parametric response surface models are, perhaps, easier to understand, as they apply multivariate regression techniques using a predefined functional form to correlate a dependent variable, Y, to a set of independent predictor variables, $x_i$ [2]. Commonly used parametric response surface models are polynomial models with interactions which have the general form of [3],

$$\boldsymbol{Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon} \quad (1)$$

The independent variables, $x_i$, are called predictor variables to distinguish them from the critical parameters because the predictor variables can be a function of one or more critical parameters. For example, in a second order polynomial model with two critical parameters, $z_1$ and $z_2$, the equation would be,

$$\boldsymbol{Y = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 {z_1}^2 + \beta_4 {z_2}^2 + \beta_5 z_1 z_2 + \epsilon} \quad (2)$$

This can be expressed in terms of predictor variables, where the predictor variables are $x_1 = z_1$, $x_2 = z_2$, $x_3 = z_1^2$, $x_4 = z_2^2$, and $x_5 = z_1z_2$. The multivariate regression then becomes,

$$\boldsymbol{Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \epsilon} \quad (3)$$

Prior to developing the response surface, each of the critical parameters should be examined separately to determine if the model adequately represents the data. Common regression models include linear, exponential, power, logarithmic, and second or third order polynomials. If the system response to variations in a critical parameter is best represented by an exponential, power, or logarithmic model, the data can be linearized to facilitate the multivariate regression using the transformations provided in Table 1.

As is shown below for the pilot application of PCCS phenomenological reliability, a third order polynomial with interactions and six critical parameters was selected with a success criterion based on peak containment pressure. The third order polynomial is referred to as the response surface and has a dependent variable, Y, equal to the peak containment pressure with a general form based on 83 predictor variables,

$$\boldsymbol{Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{83} x_{83}} \quad (4)$$

**Table 1: Linear Transformations for Selected Functions**

| Function | Variable Transformations | Linear Form |
|---|---|---|
| Exponential: $y = \alpha e^{\beta x}$ | $y' = \ln(y)$ | $y' = \ln(\alpha) + \beta x$ |
| Power: $y = \alpha x^{\beta}$ | $y' = \log(y)$ , $x' = \log(x)$ | $y' = \log(\alpha) + \beta x'$ |
| Logarithmic: $y = \alpha + \beta \cdot \log(x)$ | $x' = \log(x)$ | $y = \alpha + \beta x'$ |

Non-parametric response surface models are highly flexible and can capture complex, non-linear patterns that do not easily fit into the predefined functional forms often used for parametric response surfaces. Common non-parametric response surface methods include,

- Artificial Neural Networks (ANNs): ANN models can be used as a fast running, empirical regression model to reduce computational burden. Created from a limited-size set of data representing examples of the input/output nonlinear relationships underlying the original T–H code. Various studies have used ANNs to reduce computational times in TH code runs [4,5].
- Gaussian Process Regressors (GPR): GPR models can be used to predict a distribution for regression problems and provide a variance to indicate uncertainty with the output. When used to construct a response surface, GPR models learn from a limited set of high-fidelity simulation or experimental data points and interpolate the response across the input space [6,7].
- Splines: Splines are typically used to represent non-linear data by generating a smooth surface. This is especially useful when the relationship is smooth but not easily captured by polynomials. Software tools are available to utilize methods such as multivariate adaptive regression splines, such as the Design Analysis Kit for Optimization and Terascale Applications (DAKOTA) [8].

The response surface models investigated as part of the EPRI-supported study include the polynomial regression model, logarithmic transformation model, and the multivariate adaptive regression spline (MARS) model.

### 2.3 Selection of Response Surface Truth Data

For any polynomial regression, the minimum number of data points required to perform the regression is $n = k + 1$ where k is the number of predictor variables. Thus, for the cubic fit with interactions shown in Equation 4, $k = 83$ predictor variables and the minimum number of data points required to define the response surface is $n = 83 + 1 = 84$. The data points needed to define, or train, the response surface is sometimes referred to as the "truth" data and is obtained by running the BE code with various values of the critical parameters. Additionally, the minimum number of truth data points is recommended to be 1.5 to 3 times the number of predictor variables [8]. Thus, for the example here with 84 predictor variables, an adequately sized truth data set would contain between 126 and 252 data points.

When developing the response surface data, the critical parameters values should be strategically selected, rather than randomly generated, to ensure that a sufficient number of data points are generated near the response surface boundary. With this approach, it is likely that the critical parameter values will be weighted toward their lower probability extremes rather than their higher probability values.

One strategy for developing response surface data is to select values of the critical parameters to obtain a good fit of the data independently for each critical parameter and then add additional cases to examine interactions between the critical parameters. Thus, for the case of a cubic fit examined here, a minimum of four data points would be required to fit each of the critical parameters independently. Ultimately, the response surface is used with randomly selected values of the critical parameters to obtain results from interpolation. Exercising the response surface with critical parameter values outside of their limiting minimum and maximum values range (i.e., extrapolation) can lead to significant errors. Therefore, when selecting the critical parameter data points to develop the response surface data set, it is important to include the limiting minimum and maximum values for each critical parameter.

Prior to performing the multivariate regression, it is beneficial to normalize the values of the critical parameters to provide increased numerical accuracy by reducing round off errors. This is especially important in multivariate regressions where the variation in data values between critical parameters is large in magnitude. Various normalization techniques can be used, such as comparing the data value to the standard deviation or comparing data values to the central value. The following equation shows one method for scaling based on the standard deviation [3]:

$$X_i = \frac{x_i - \overline{x_i}}{\sigma_i} \tag{5}$$

where,

| | | |
|---|---|---|
| $X_i$ | = | Normalized value of predictor variable i |
| $x_i$ | = | True value of predictor variable i |
| $\overline{x_i}$ | = | Mean value of predictor variable i |
| $\sigma_i$ | = | Standard deviation of predictor variable i |

Another method for scaling against a central value can be performed as follows [2]:

$$X_i = \frac{x_i - x_i^{central}}{x_i^{upper} - x_i^{central}} \tag{6}$$

where,

| | | |
|---|---|---|
| $X_i$ | = | Normalized value of predictor variable i |
| $x_i$ | = | True value of predictor variable i |
| $x_i^{central}$ | = | Central value of predictor variable i |
| $x_i^{upper}$ | = | Upper limit of predictor variable i |

### 2.4 Goodness of Fit

Similar to the case of fitting a parameter distribution, once the response surface is generated, the "goodness of fit" of the response surface should be examined and additional response surface data points added, as needed, to improve the fit. Typical methods for examining the goodness of fit are to calculate statistics based on the residuals and to interpret diagnostic plots. Two methods used for the current effort are the use of a calibration plot and an analysis of residual errors.

A calibration plot is simply an x-y plot comparing the predicted response (x) to the observed data values (y). Predicted responses that exactly match the observed data fall along a diagonal line in the calibration plot, while data points to the right of the diagonal indicate overprediction of the observed data and data points to the left of the diagonal indicate an underprediction of the observed data.

The residuals are the difference between the observed and predicted data values. If the observed data value is $y_i$ and the predicted data value is $Y_i$, then the residual is $y_i - Y_i$. The residuals are often expressed in terms of the sum of the squares of the errors:

$$SSE = \sum (y_i - Y_i)^2 \tag{7}$$

The SSE can be compared to the total sum of the squares of the data about their mean:

$$SST = \sum (y_i - \overline{y})^2 \tag{8}$$

The SSE and SST can be used to calculate the multivariate coefficient of determination, $R^2$:

$$R^2 = \frac{SST - SSE}{SST} \tag{9}$$

For a multi-variate regression, the variance, $\sigma^2$, and standard deviation, $\sigma$, for the response surface can then be computed from the coefficient of determination as:

$$\sigma^2 = \frac{SST \cdot (1 - R^2)}{n - (k+1)} = \frac{SSE}{n - (k+1)} \tag{10}$$

where n is the number of data points used to develop the response surface and k is the number of predictor variables. As an example, for the cubic regression discussed above with six critical parameters, there are k = 83 predictor variables, therefore, $\sigma^2$ = SSE / (n – (84 + 1)) = SSE / (n-85).

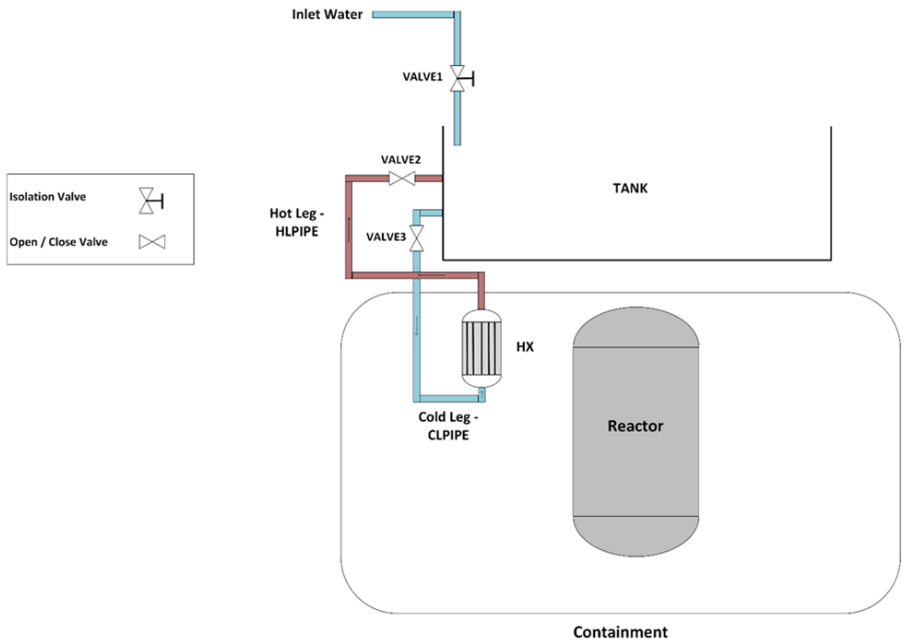
## 3. PILOT STUDY: PHENOMENOLOGICAL RELIABILITY OF A PASSIVE CONTAINMENT COOLING SYSTEM

A pilot case study was conducted on a simplified hypothetical Passive Containment Cooling System (PCCS) to demonstrate the use of a response surface to determine the PCCS phenomenological reliability. The PCCS was analyzed with a hypothetical plant model that has some similarities to potential current SMR designs, though it is not based on any known design. A schematic of the PCCS used in the current study is provided in Figure 1. The PCCS provides passive heat removal from the containment structure following reactor shutdown or accident conditions through natural circulation.

The BE code used for this analysis was the Modular Accident Analysis Program, Version 5.06 (MAAP5) [9]. MAAP5 is a computer code that simulates the response of LWR power plants during severe accidents. MAAP5 treats the full spectrum of important phenomena that could occur during an accident, simultaneously modeling those that relate to the thermal-hydraulics of the system and the fission products.

The key safety function for the PCCS is to remove heat from the containment structure, which prevents pressurization of the containment and reduces the risk of containment failure. Thus, the figure of merit used to assess the PCCS phenomenological reliability is the peak containment pressure and a limiting case with regard to peak containment pressure, a Loss of Coolant Accident (LOCA) represented by a main steam line break into the containment space, was selected for analysis. The containment is assumed to fail at 120 psig (134.7 psia, 0.93 MPa). Therefore, the success criteria for this study is containment pressure maintained at less than 120 psig (134.7 psia, 0.93 MPa).

**Figure 1: Hypothetical Passive Containment Cooling System (PCCS) Layout**



The pilot study began by performing a PIRT to identify and rank key phenomenological uncertainties affecting the PCCS performance. The PIRT identified 30 key phenomenological uncertainties which were correlated to MAAP5 modeling parameters. Sensitivity studies were performed using MAAP5 and several modeling parameters were determined to have minimal impact on PCCS effectiveness. For example, the containment pressure response for the steam line break for various passive containment cooling water storage tank (PCCT) initial water temperatures is shown in Figure 2. The water temperatures for the sensitivity study reflect the nominal initial water temperature and bounding water temperatures based on technical specification limits. As shown, the PCCT initial water temperature has a minimal effect on the long-term containment pressure. Thus, this parameter was removed from further consideration. In contrast, as shown in Figure 3, the peak containment pressure is sensitive to PCCS heat exchanger tube outside surface condensation heat transfer effectiveness. Therefore, the condensation heat transfer effectiveness is retained as a critical parameter.

**Figure 2: Passive Containment Cooling Water Tank Initial Water Temperature Sensitivity Analysis**

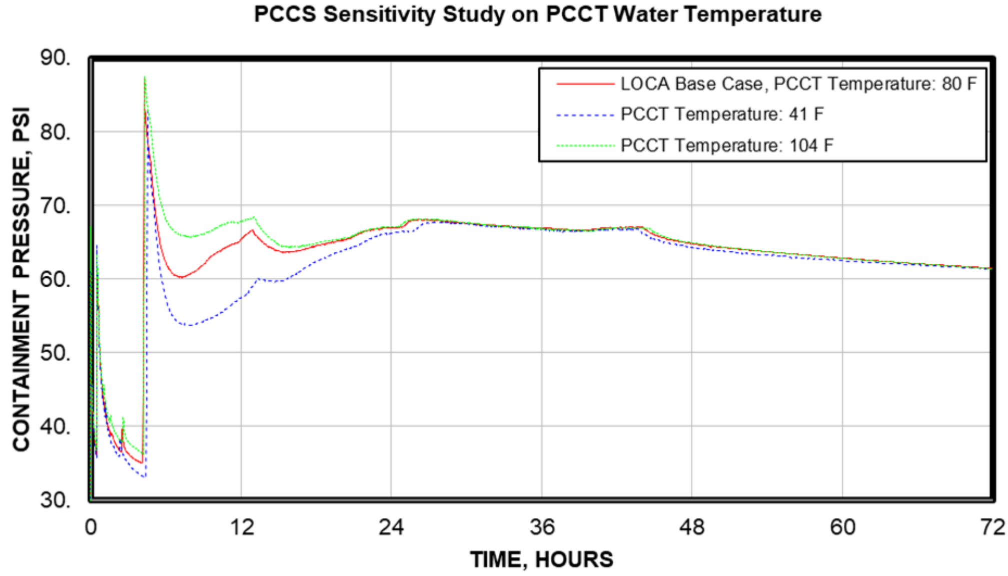



**Figure 3: PCCS Heat Exchanger Tube Outside Surface Condensation Heat Transfer Effectiveness Sensitivity Analysis**

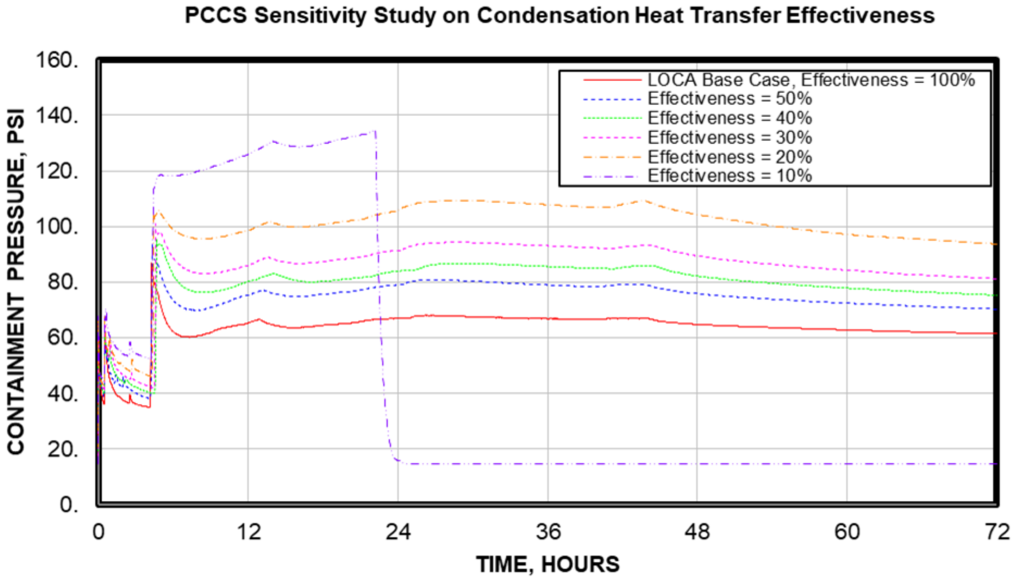


**Table 2: Probability Distributions for Critical Parameters**

| Parameter | Distribution | Min, Mean, and Max Values and Standard Dev. (σ) | Basis |
|---|---|---|---|
| PCCS HEX tube blockage (%) (Number of. tubes blocked) | Exponential | Min: 0%<br>Mean: 9.346% (208 tubes blocked)<br>Max: 100%<br>σ = 9.346 % | An exponential distribution is characterized by a decay constant, λ, where the distribution mean and standard deviation are identical and are both equal to 1/λ.<br><br>Literature was used in the absence of experimental data to select the decay constant value [2]. |
| Tube material thermal conductivity (W/mC) | Truncated Normal | Min: 0.3<br>Mean: 17.35<br>Max: 24.7<br>σ = 2.45 W/mC | Standard deviation was chosen based on the stainless steel conductivity change over temperature range 300-600K. |
| Tube outside surface condensation heat transfer effectiveness | Exponential | Min: 0.005,<br>Mean: 0.1087,<br>Max: 1.0<br>σ = 0.1087 | An exponential distribution is characterized by a decay constant, λ, where the distribution mean and standard deviation are identical and are both equal to 1/λ.<br><br>A standard deviation was assigned such that the minimum value has a probability of occurrence in the range of 0.0001 which corresponds to events that are subjectively determined to be almost impossible to occur. |
| Water droplet entrainment in the break flow (% of total liquid flow appearing as suspended water droplets) | Uniform | Min: 0%<br>Mean: 5%<br>Max: 10%<br>σ = N/A | The maximum droplet entrainment fraction suggested in MAAP is 10% for a LOCA accident sequence<br><br>Uniform distribution is chosen as this parameter is unknown and potentially scenario dependent. |
| Gas flow at the PCCS Hx inlet ($m^2$) | Truncated Normal | Min: 1 $m^2$<br>Mean 55 $m^2$<br>Max 100 $m^2$<br>σ = 15 $m^2$ | Gas flow area at the PCCS Hx tube surface represents geometry effects on gas flow in the vicinity of the PCCS Hx<br><br>A standard deviation was assigned such that the minimum value has a probability of occurrence in the range of 0.0001 which corresponds to events that are subjectively determined to be almost impossible to occur. |
| Core decay heat as a function of time (MW) | Truncated Normal | Min: 1660 MW<br>Mean: 1850 MW<br>Max: 2040 MW<br>σ = 63.5 MW | A standard deviation was assigned such that the minimum value has a probability of occurrence in the range of 0.001 which corresponds to events that are subjectively determined to be almost impossible to occur. |

Overall, sensitivity studies were used to reduce the 30 key phenomenological uncertainties identified in the PIRT to 10 critical parameters. After further evaluation, some parameters with low likelihood of occurrence were removed, leaving 6 critical parameters for the uncertainty analysis:

- PCCS Hx tube blockage caused by foreign material or accumulation of oxidation products
- Tube material thermal conductivity
- Hx tube outside surface condensation heat transfer effectiveness
- Steam concentration in containment caused by break flow and water droplet entrainment
- Gas flow at the PCCS tube surface affected by containment geometry

- Core decay heat

For each critical parameter, appropriate probability distributions were assigned based on available data or expert judgment, as summarized in Table 2.

A truth data set was then created by sampling each critical parameter at its extreme and intermediate values while keeping all other critical parameters at their nominal values. Additional cases were then created to examine parameter interactions. Each critical parameter was also examined separately to determine the best data set and model to represent the data. Ultimately, a 3rd order polynomial regression model was used. However, not all critical parameters were well-represented by a 3rd order polynomial regression, therefore the truth data set used to develop the response surface was adjusted to obtain reasonable results. As an example, Figure 4 and Figure 5 show various models for peak containment pressure as a function of tube thermal conductivity. Figure 4a shows the best fit of the data using a 3rd order polynomial. This model captures the lowest thermal conductivity value leading to containment failure but does not accurately capture the rapid increase containment pressure with decreasing thermal conductivity. For rapidly, but smoothly changing data, a data transformation of the types listed in Table 1 may be beneficial. An example of a log-log transformation of the thermal conductivity data is provided in Figure 4b. Figure 5 shows another option which is to use a cubic spline to represent the data.

**Figure 4: 3rd Order Polynomial Regressions for Thermal Conductivity Response**

(a) Reduced data set (b) Full data set with log-log transformation

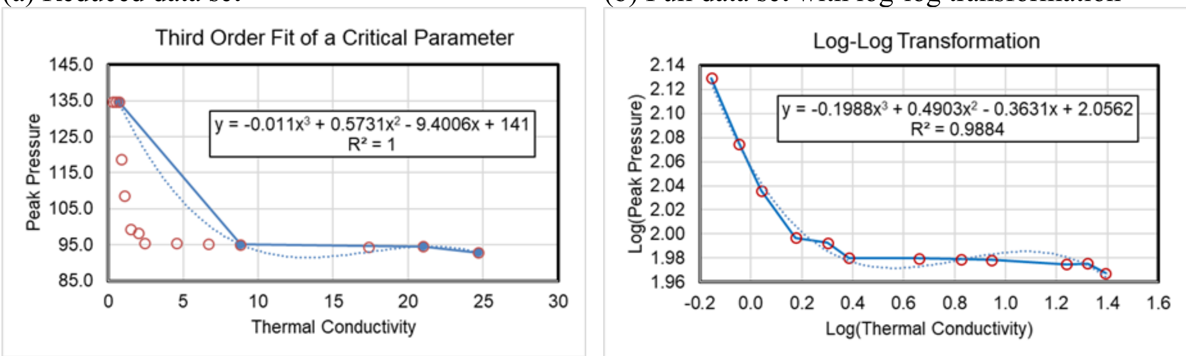
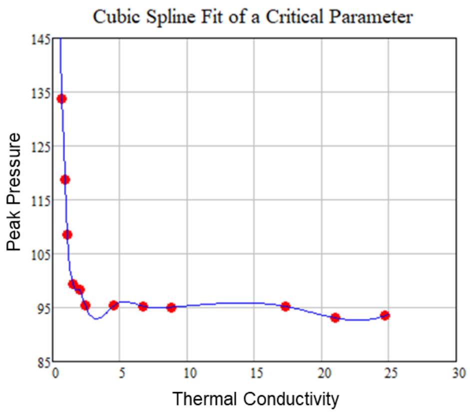



**Figure 5: Cubic Spline Fit Over the Full Range of Thermal Conductivity Value**




Once the responses of the individual critical parameters were investigated, parameter interactions were examined. Figure 6 shows one example of the interactions between tube thermal conductivity and tube bundle condensation heat transfer effectiveness. Visualizing interactions between pairs of critical parameters is instructive to determining system response to phenomenological uncertainties and can be used as a guide when developing the truth data set.

Ultimately, two response surfaces were developed. The first was a parametric response surface model using a 3rd order polynomial multi-variate regression in 6 variables. The parametric response surface was developed with MathCad ® using the *polyfitc* and *regress* functions. The response surface was exercised using the *interp* function. The truth data set consisted of 108 data points. Although this is less than the recommended data set size of 126 to 252 data points, the response surface produced reasonable results. To judge the goodness of the fit of the response surface, the response surface was exercised using the data set from the 108 MAAP runs and the residual errors were analyzed indicating a standard deviation of 7.707 psi (see Table 3).

**Figure 6: Examination of Parameter Interactions**

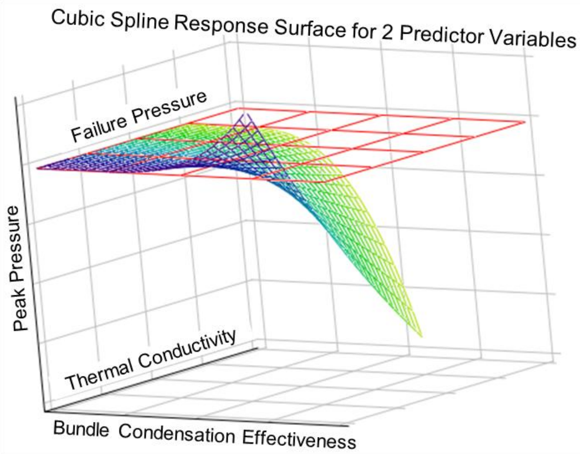



**Table 3: Response Surface Residuals and Phenomenological Reliability Estimate**

| Parameter | 3rd Order Polynomial Response Surface | MARS* Response Surface |
|---|---|---|
| Mean of Truth Data | 112.2 psia | 109.7 psia |
| Sum of squares of the residual error, SSE | 1426 | 4572 |
| Total sum of the squares of the data about their mean, SST | 3934 | 44443 |
| Variance $\sigma^2$ | 59.42 | 33.62 |
| Standard deviation, $\sigma$ | 7.707 psi | 5.798 |
| Phenomenological failure rate | 1.9E-4 | 3.1E-4 |

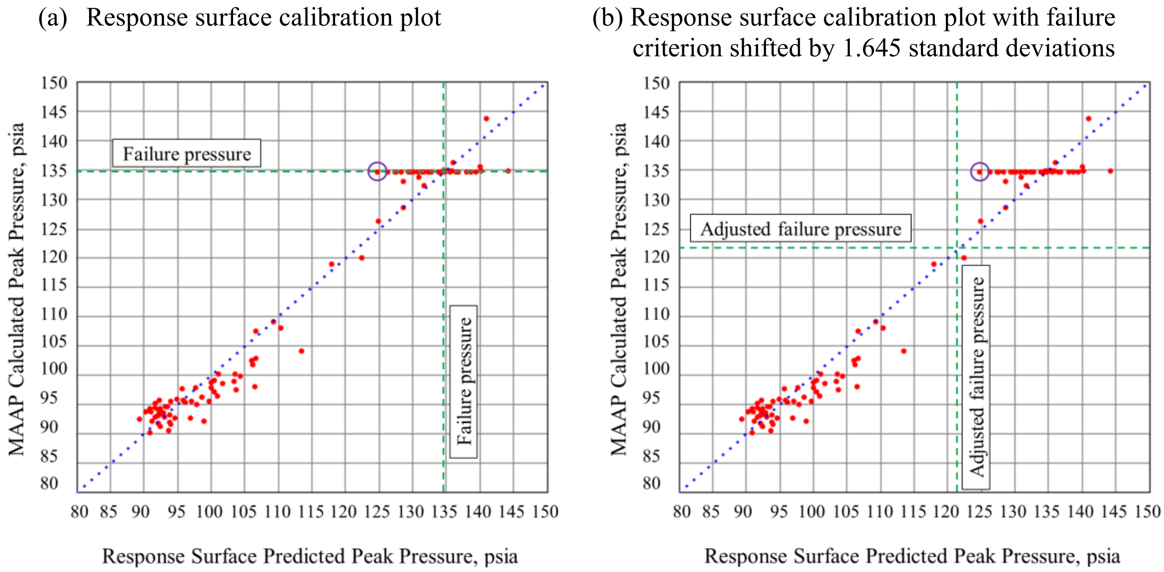
Figure 7a presents a calibration plot for the 3rd order polynomial response surface comparing the response surface predictions to the MAAP calculated peak pressures. The horizontal and vertical green dashed lines are at 134.7 psia (120 psig, 0.93 MPa) which represents the containment failure pressure. Data points to the left of the dotted diagonal line indicate the response surface predicted a pressure is less than the observed pressure (i.e., MAAP-calculated peak pressure). As an example, there is a data point on the green dashed line that is circled in purple. For this case, MAAP predicted a containment failure with a peak pressure of 134.7 psia (0.93 MPa). But the response surface predicted a peak pressure of only 124.6 psia (0.86 MPa).

Since the response surface is only an approximation of the observed data, there can always be observed failures that are not predicted by the response surface. Due to the nature of the regression analysis, the errors are expected to be approximately normally distributed around observed values. Therefore, the predicted values, or the failure criterion, can be adjusted based on the calculated standard deviation to capture more of the observed failures. As an example, for normally distributed data, 95% of the data lies within ±1.645 standard deviations of the mean. Thus, to capture 95% of the failures, the failure criterion or the response surface predictions can be shifted by 1.645 x 7.707 = 12.678 psi (0.087 MPa). With this shift, all failures in the limited data set of 108 MAAP calculations are predicted by the response surface, as shown in Figure 7b. This approach also predicts a handful of additional failures

* Multivariate Adaptive Regression Spline (MARS)

where no failure is observed from the MAAP calculation which ensures that the reliability is not overpredicted.

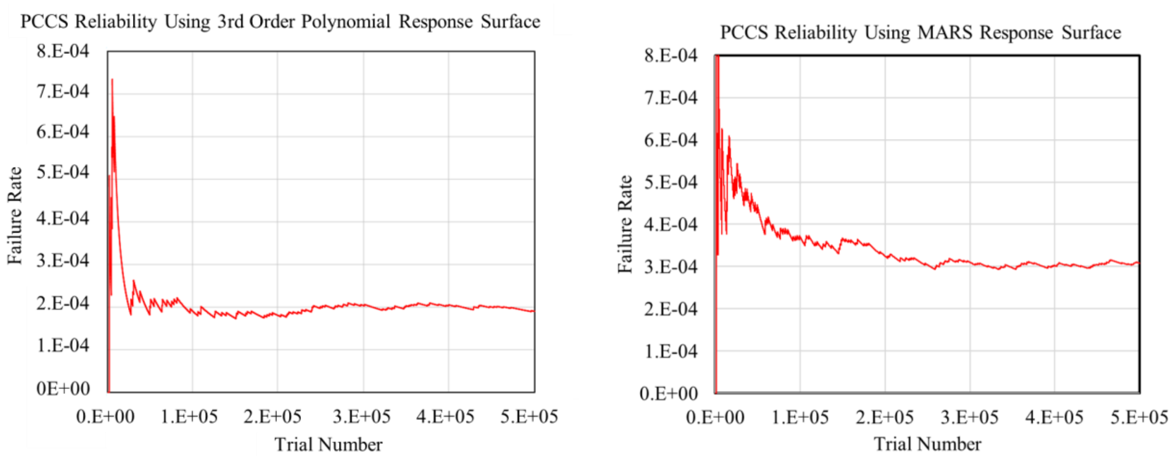
**Figure 7: Calibration Plots for 3rd Order Polynomial Response Surface**




Next, a non-parametric response surface was developed using a multivariate adaptive regression spline (MARS) model with a truth data set consisting of 137 data points. DAKOTA software from Sandia National Labs [8] with its MARS options was used to develop the response surface. The response surface was exercised using the truth data set from the 137 MAAP runs and the residual errors were analyzed indicating a standard deviation of 5.798 psi (see Table 3).

To determine the PCCS phenomenological reliability, Latin Hypercube Sampling (LHS) techniques were used to generate 500,000 critical parameter data sets for interrogation of the response surfaces. The predicted peak pressures were then compared to the failure pressure to determine the failure rate. To account for response surface errors, the failure pressure was reduced by 1.645 standard deviations. The calculated failure rate was then plotted as a function of trial number to ensure that enough trials were performed to obtain meaningful results. For the 3rd order polynomial response surface, Figure 8 indicates convergence to a failure rate of 1.9E-4 within a few hundred thousand trials. For the MARS response surface, Figure 8 indicates convergence to a failure rate of 3.1E-4.

**Figure 8: PCCS Phenomenological Failure Rates from Response Surfaces**




Although the calculated phenomenological failure rate using either response surface is shown to be on the order of 1E-4, the failure rate is largely controlled by the distribution parameters selected for the critical parameters. The sample calculations indicate that the number of trials needed to obtain meaningful results may be an order of magnitude larger than the failure rate (e.g., 100,000 trials for a failure rate of 1 in 10,000). Thus, if the failure rate is much lower than indicated here (e.g., 1E-6 instead of 1E-4), then the number of trials could extend into the millions or 10's of millions to determine the phenomenological reliability. For comparison, the 500,000 trials performed with DAKOTA for the MARS response surface required 153 CPU seconds on a modern laptop computer. This suggests that CPU requirements would still be reasonable if several 10's of millions of trials were executed.

## 4. CONCLUSION

The response surface methodology demonstrated here provides a structured and computationally efficient approach for passive safety system reliability analysis. By developing mathematical models that approximate complex thermal-hydraulic behavior, the response surface methodology allows for comprehensive uncertainty propagation and reliability assessment that would be impractical with direct BE code calculations.

It should be noted that an overall PCCS reliability was not calculated since each accident scenario may present different conditions that would result in a different phenomenological reliability calculation. Thus, each scenario may require its own set of calculations. Also, the quantitative results presented in the demonstration may not directly reflect actual plant results. The goal of the demonstration was to provide an example that reflects reasonably low failure rates expected from modern passive systems while avoiding very low results that would not be useful to demonstrate the process.

**Acknowledgements**

This paper summarizes ongoing research sponsored by EPRI, Palo Alto, CA.

**References**

[1] *Advanced Nuclear Technology: Guidance for Passive Safey System Analysis.* EPRI, Palo Alto, CA: 2025. 3002032223.

[2] C. Fong, G. Apostolakis, D. Langewisch, P. Hejzlar, N. Todreas, and M. Driscoll,, *"Reliability Analysis of a Passive Cooling System Using a Response Surface with an Application to the Flexible Conversion Ratio Reactor,"* Nuclear Engineering and Design. Volume 239, p. 2660-2671 (2009).

[3] J. Devore, *"Probability and Statistics for Engineering and the Sciences*", Wadsworth, Inc, Belmont, CA (1982).

[4] E. Zio, G. Apostolakis, and N. Pedroni, *"Quantitative Functional Failure Analysis of a Thermal–Hydraulic Passive System by Means of Bootstrapped Artificial Neural Networks,"* Annals of Nuclear Energy. Volume 37, Issue 5, p. 639-649 (2010).

[5] N. Pedroni, and E. Zio, *"An Adaptive Metamodel-Based Subset Importance Sampling approach for the assessment of the functional failure probability of a thermal-hydraulic passive system,"* Applied Mathematical Modelling. Volume 48, p. 269-288 (2017).

[6] H. Iwamoto, *"Generation of Nuclear Data Using Gaussian Process Regression,"* Journal of Nuclear Science and Technology, Volume 57, Issue 8, p. 932-938 (2020). DOI: 10.1080/00223131.2020.1736202.

[7] L. Puppo, N. Pedroni, A. Bersano, F. Di Maio, C. Bertani, E. Zio*, "Failure Identification in a Nuclear Passive Safety System by Monte Carlo Simulation with Adaptive Kriging,"* Nuclear Engineering and Design. Volume 380, p. 111308 (2021).

[8] B. M. Adams, W. J. Bohnhoff, K. R. Dalbey, M. S. Ebeida, J. P. Eddy, M. S. Eldred, R. W. Hooper, P. D. Hough, K. T. Hu, J. D. Jakeman, M. Khalil, K. A. Maupin, J. A. Monschke, E. E. Prudencio, E. M. Ridgway, P. Robbe, A. A. Rushdi, D. T. Seidl, J. A. Stephens, L. P. Swiler, and J. G. Winokur. "*Dakota 6.21.0 Documentation. Technical Report,"* SAND2024-15492O, Sandia National Laboratories, Albuquerque, NM, (2024). Available online from http://snl-dakota.github.io

[9] *"Transmittal Document for MAAP5 Code Revision MAAP 5.06*," EPRI, Palo Alto, CA (2021).