EPRI Guidance for Passive System Reliability Analysis

March 2026

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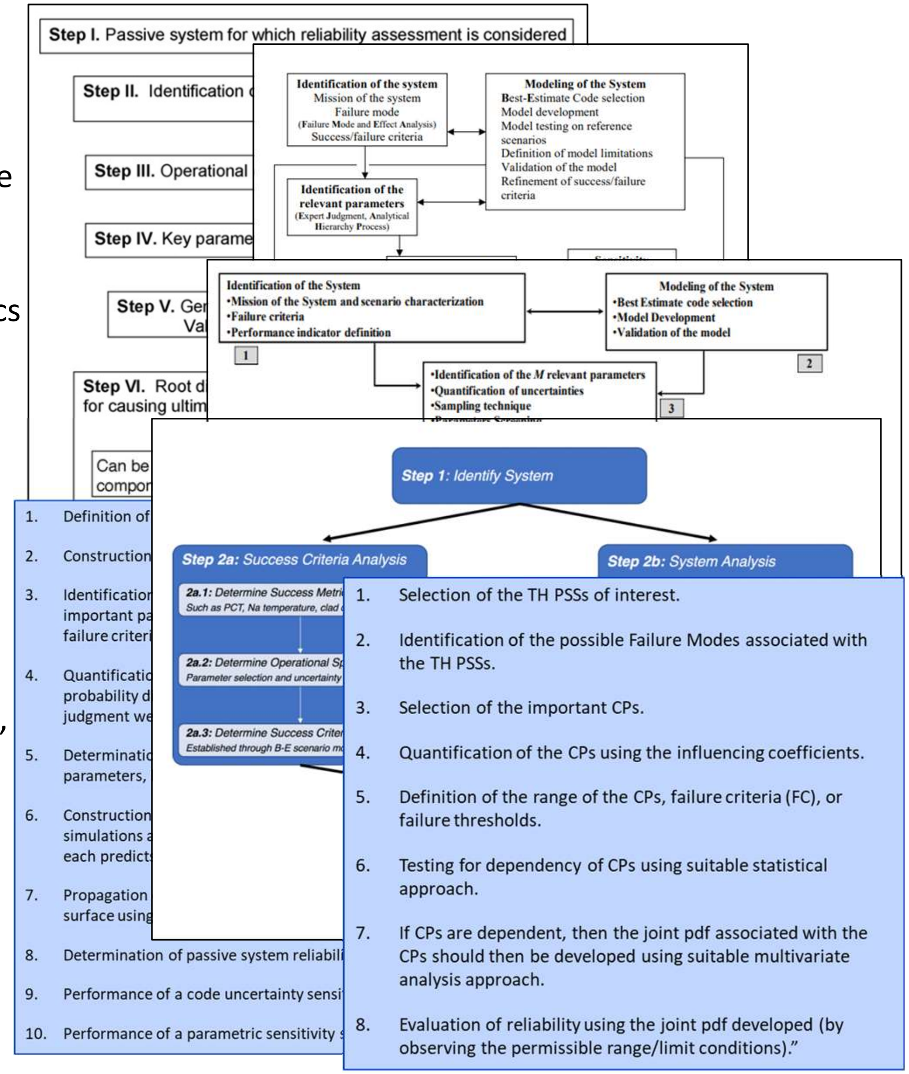
EPRI Passive System Reliability Project

- Phase 1 - Evaluation of Passive System Reliability Approaches
  - Review literature for state-of-the-art reliability methods
  - Summarize efforts developed within the modeling and experimental community to address normal and abnormal operating conditions that can occur in passive systems
  - Investigate and consolidate regulatory and licensing landscape for recent passive safety system reliability analysis

Reliability Frameworks

- APSRA (Assessment of Passive System ReliAbility)
  - Critical Parameters (CPs) with failure surface via thermal-hydraulic code calculations
- APSRA+
  - Integrated dynamic reliability method for dynamic failure characteristics
- RMPS (Reliability Methods for Passive Systems) & REPAS (Reliability Evaluation of Passive Systems)
  - Identifies CPs and their probability distributions, Monte Carlo simulations with thermal-hydraulic codes
- RMPS+
  - Performance indicator (PI) directly linked to the design failure criteria, response surface sensitivity analysis
- MIT (2009)
  - Response surface relies on fewer thermal-hydraulic model calculations, uncertainty analysis of the code
- GE-Hitachi/Argonne (2015)
  - Iteratively develops plant level and system level success criteria, describes how to integrate the framework into an overall PRA
- Harbin Engineering University (2018-19)
  - CP dependency in more detail, more statistical analysis



Codes, Test Facilities, & Research Projects

- Thermal-Hydraulic Codes
  - Most codes are used for transient and safety analyses for licensing and operation
  - Codes are also used in finalizing the design of advanced reactors
  - Codes have been predominantly developed and validated for LWR applications
  - Computational fluid dynamics (CFD) and multiphysics simulation tools may be used to model complex flow and heat transfer phenomena but in a much smaller geometry
  - Monte-Carlo (MC) sampling has been used extensively to estimate system reliability coupled with code simulations

- Test Facilities
  - Several test facilities have been or are being used to conduct testing for validation of passive system code predictions
  - Examples
    - APEX-1000
    - MASLWR
    - NIST-1/NIST-2
    - PUMA/PUMA-E
    - VISTA-ITL (SMART)
    - INKA (KERENA)
    - PANDA
    - PERSEO

- Other Research
  - ETHARINUS (OECD/NEA)
  - SYSTHER (Framatome/LUT/CEA)
  - ANItA (Swedish industry/academia)
  - SMR program (US DOE/GEH/GNF/Holtec)
  - PASTELS (European)
  - EASI-SMR (EDF)

Licensing Considerations

- NEA/CSNI survey report provides insights from several national regulators
- WENRA highlights passive system characteristics to align with European regulatory practices
- US has several designs certified that include passive systems
  - AP600/1000, ABWR, ESBWR, NuScale, APR1400
  - USNRC perspectives documented in SECY papers from 1993-1997 and NUREG-0800 Standard Review Plan
  - Currently approved designs often have active non-safety systems that reduce reliance on the passive safety systems

Insights from Phase 1

- Critical parameter (CP) identification and quantification is a key aspect of all existing frameworks
- Expert judgement is still incorporated in the absence of experimental or operational data/experience
- Uncertainty analysis and model simplification are key items to address
  - Definition of the CP statistical distributions are needed
  - Realistic thermal-hydraulic uncertainty computations can be resource intensive
- Recent literature is generally academic as opposed to actual implementation that is ready for industrial applications
  - Realism in the analysis is a key to turn it into a practical approach

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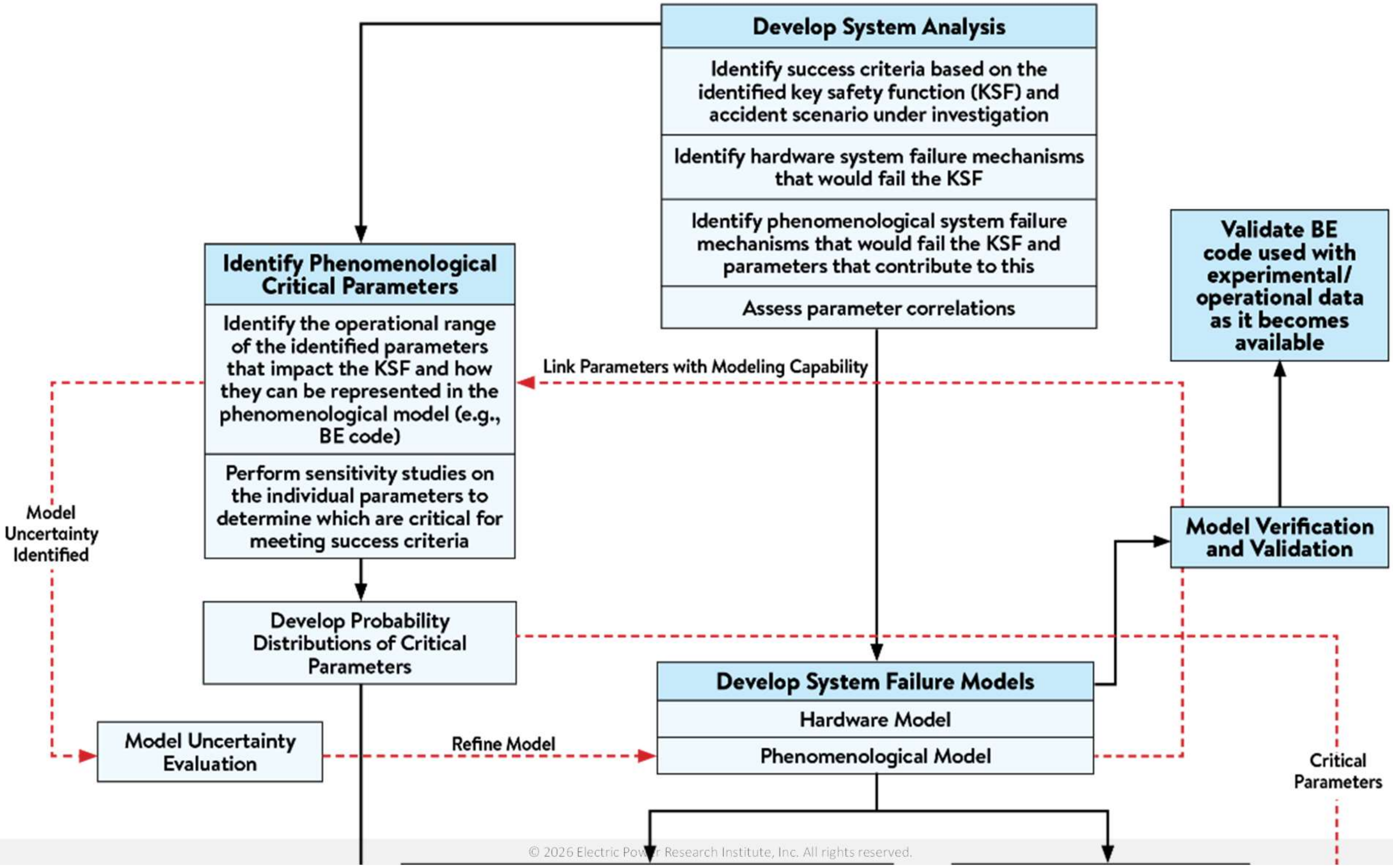
  - Investigate and consolidate regulatory and licensing landscape for recent passive safety system reliability analysis
  - Phase 1 Report published July 2025

- Phase 2 - Guidance for Passive System Reliability Analysis
  - Developed guidance for a common, consolidated, realistic approach to passive system reliability assessment for use in advanced reactor risk analysis applications
  - Performed a realistic demonstration assessment of the common consolidated approach on a simplified passive system
  - Engaged stakeholders to identify potential pilot plant applications of the recommended approach on a passive system for an advanced reactor design
  - Phase 2 Report published November 2025

Guidance for PSS Reliability



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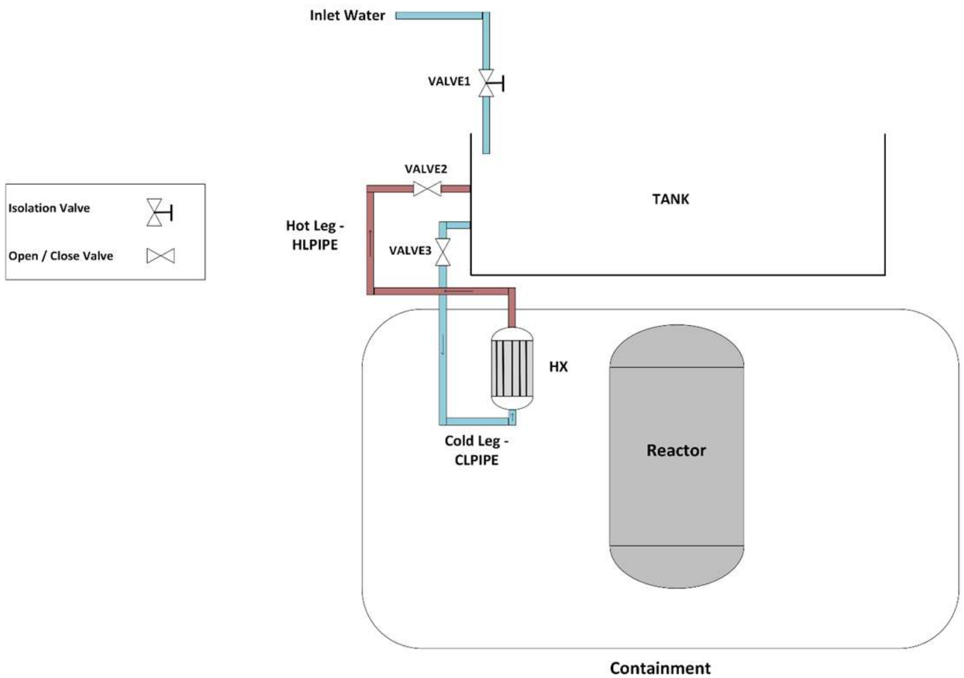
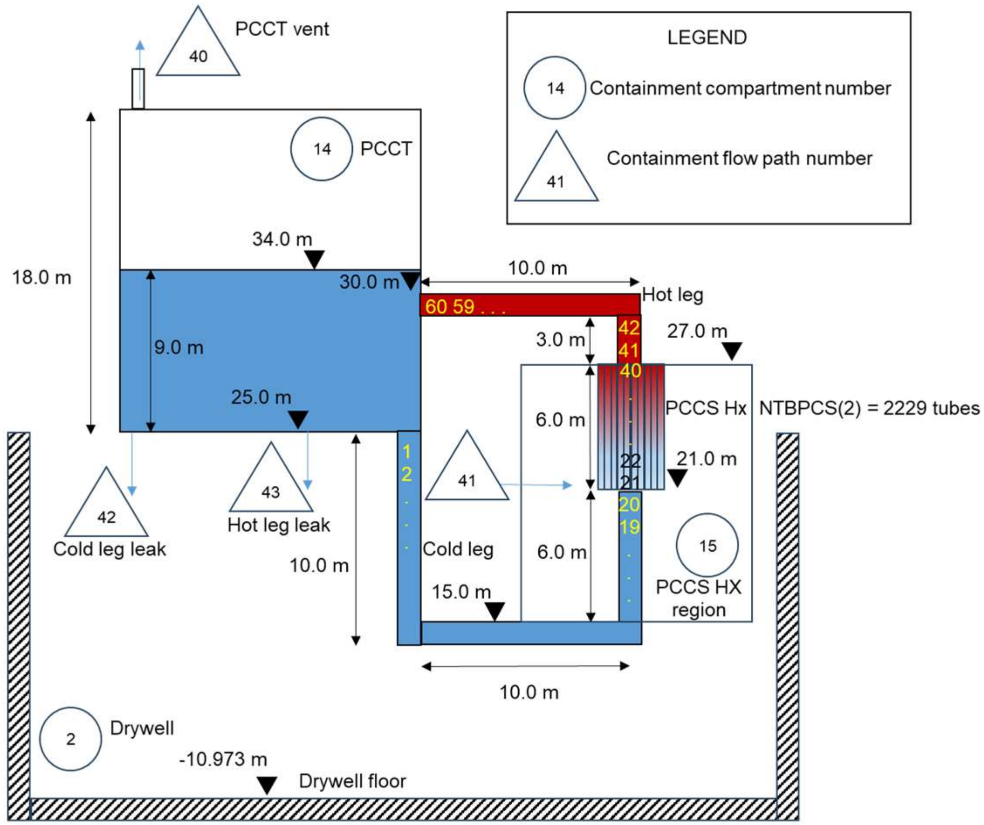
Hypothetical PCCS for Example



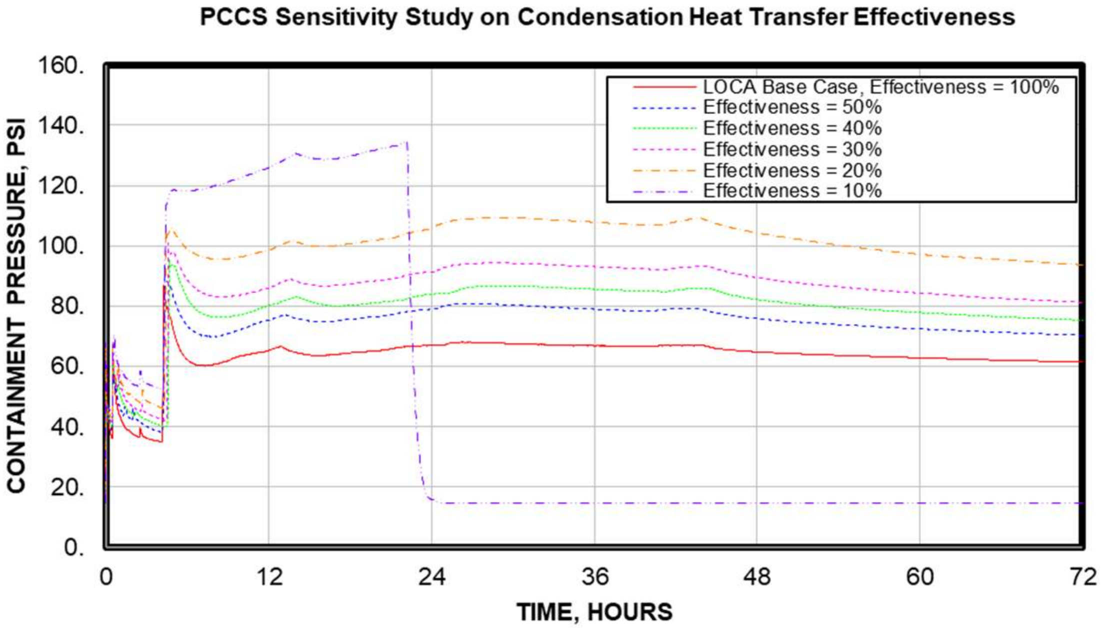


System Analysis

- Identify success criteria
- Identify hardware failure mechanisms
- Identify phenomenological failure mechanisms
  - Typically, FMEA and HAZOP processes have been used for PSS reliability studies with modifications to consider phenomenological failures
  - In addition to the FMEA-type approach, we recommended to also apply a structured methodology solely focused on phenomena
  - A Phenomenon Identification and Ranking Table (PIRT) study can be used to identify, assess, and prioritize parameters that can affect system reliability
- Identify parameter correlations

Identify Phenomenological Critical Parameters

- Parameter operational range assessment
- Sensitivity analysis on parameters



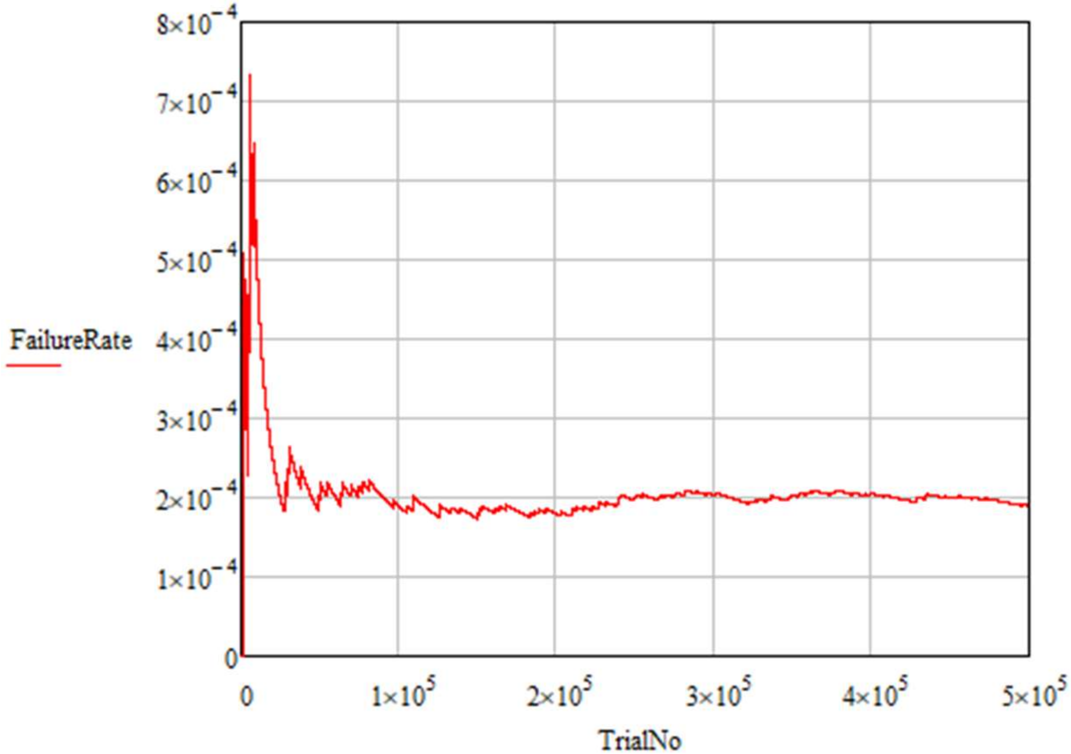
Outside surface tube condensation heat transfer coefficient sensitivity analysis – MAAP Input Variable FHTBNDPCS

Characterize PSS Phenomenological Reliability

- Uncertainty analysis
  - First, develop probability distributions on critical parameters
  - Option 1: Direct parametric uncertainty propagation through best-estimate TH codes
    - Number of runs is inversely proportional to expected reliability
    - For a failure probability of 10^{-4}, need 10,000-100,000 trials
  - Option 2: Phenomenological uncertainty propagation through a response surface
    - The response surface is used as a surrogate for the BE code
    - The response surface is typically a single equation developed by performing a multivariate regression using the CPs as predictor variables
    - The resulting equation provides faster solutions than the BE code run
      - $\boldsymbol{Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon}$

Phenomenological Reliability Convergence

- PCCS Phenomenological Failure Rate Predicted from the Response Surface Using 500,000 Trials



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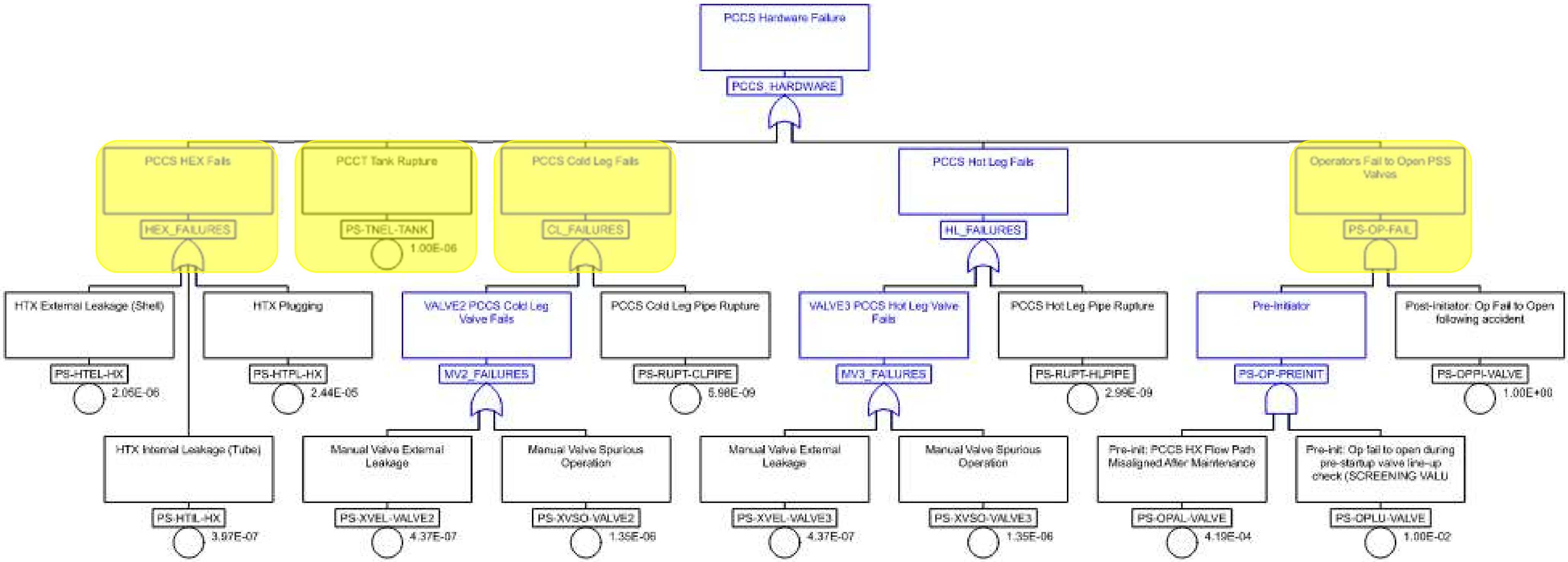
PCCS Hardware Fault Tree



PSS Reliability Example

- For this pilot case study, the reliability of the PCCS is:
  - $P_{fail}(PCCS|scenario) =$
    - $P_{fail}(Hardware|scenario) + P_{fail}(Phenomenology|scenario)$
  - $P_{fail}(PCCS|scenario) = 3.6\text{E-}5 + 1.9\text{E-}4$
  - $P_{fail}(PCCS|scenario) = 2.3\text{E-}4$

Insights from Phase 2

- Overall PSS reliability is not calculated since each scenario may present different conditions that would result in a different phenomenological reliability calculation
  - Each scenario may require its own set of calculations
- The demonstration provides 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
- If a PSS supports more than one function, thermal-hydraulic calculations may be able to simultaneously produce results for all figures of merit that support the functions
- Design is iterative, and improved reliability results may be obtainable through modifications that impact the accident behavior, success criteria, or other inputs

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Response Surface Methodologies for Passive Safety System Reliability Analysis

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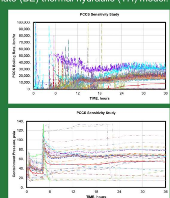
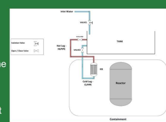
Why do we need a response surface?

Passive safety systems (PSS) found in advanced reactor designs rely on natural physical processes; therefore they are susceptible to uncertainties in the physical processes themselves.

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 (TH) model.



PCCS Sensitivity Analysis

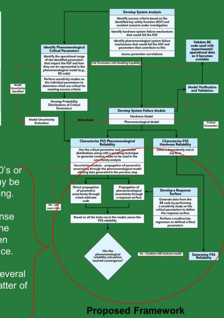


Hypothetical Passive Containment Cooling System (PCCS)

To obtain meaningful results, several 10's or 100's of thousands of BE case runs may be required, which is 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.

A response surface can be exercised several hundreds of thousands of times in a matter of a few 10's of minutes to a few hours.



Proposed Framework

How to build a response surface

A response surface for PCCS performance is created by performing a multivariate regression using 6 critical parameters (CPs) to estimate containment peak pressures.

The multivariate regression, or response surface, correlates a dependent variable, Y, to a set of independent predictor variables, x_i. The general form of the equation for a multivariate polynomial regression then becomes:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon$$

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

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

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 $x_5 = z_1 z_2$. The second order polynomial regression equation is then,

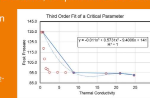
$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \epsilon$$

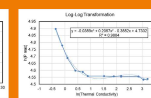
For the PCCS, a third order polynomial multivariate regression with 6 CPs was selected to predict peak containment pressures. This third order polynomial is referred to as the response surface and has the general form,

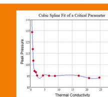
$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{83} x_{83}$$

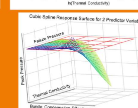
One strategy for developing response surface data is to select values of the CPs to obtain a good fit of the data independently for each CP and then add additional cases to examine interactions between the CPs. The data points are obtained by running a best-estimate (BE) code with various values of the critical parameters.

Second and third order polynomials are often used to develop response surfaces. However, other options exist, such as using exponential, power law, or logarithmic transformations prior to performing the regression. Additionally, non-parametric methods can be used, such as artificial neural network (ANN) models, Gaussian process regressor (GPR) models, or spline fits of the data.







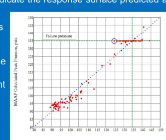


Response surface goodness of fit and calculation of PSS reliability

Data input for the PCCS response surface development was generated by performing 108 BE calculations using the MAAP 5.06 computer program. 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.

A calibration plot was used to compare the predicted to observed data values. Data points to the right of the dotted line indicate the response surface predicted a pressure higher than MAAP and data points to the left of the dotted line indicate the response surface predicted a peak pressure less than MAAP.

The response surface goodness of fit to the data was quantified by analyzing the residual errors. The residuals are often expressed in terms of the sum of the squares of the errors (SSE) or the total sum of the squares of the data about their mean (SST). The residuals can then be used to calculate the coefficient of determination and the variance. For the cubic regression with six critical parameters, there are k = 83 predictor variables, therefore, σ^2 = SSE / (n – (84 + 1).



Calibration Plot

$$y_i = observed\ data$$
$$Y_i = predicted\ data\ value$$
$$y_i - Y_i = residual$$

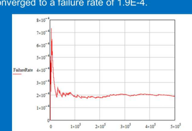
$$SSE = \sum (y_i - Y_i)^2 \qquad SST = \sum (y_i - \bar{y})^2$$

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

Measure	Value
Mean value of MAAP-calculated peak pressure	112.2 psia
Sum of squares of the residual error, SSE	1426
Total sum of the squares of the data about their mean, SST	3934
Coefficient of determination, R^2	0.964
Variance σ^2	59.4
Standard deviation, σ	7.707 psi

For the analysis of PCCS reliability, critical parameters (CPs) were assigned probability distributions and Latin Hypercube Sampling (LHS) techniques were used to generate 500,000 CP data sets for interrogation of the response surface. 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 to capture 95% of the failures.

The calculated failure rate was then plotted as a function of trial number to ensure that enough trials were performed to obtain meaningful results. As the number of trials increased, the failure rate converged to a failure rate of 1.9E-4.



Response Surface Reliability Calculation Convergence Plot

Alternate methods for building a response surface

The PCCS response surface was based on a 3rd order polynomial regression with 6 critical parameters (CPs). The multivariate regression was performed in Mathcad ® using the *polyfitc* and *regress* functions and the response surface was exercised using the *interp* function.

Other methods, referred to a non-parametric methods, are also available for building response surfaces. Examples include:

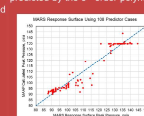
- Artificial Neural Networks (ANNs): ANN models can be used as a fast running, empirical regression model to reduce computational burden. Created from a limited-size set of data representing examples of the input/output nonlinear relationships underlying the original TH code. Various studies have used ANNs to reduce computational times in TH code runs.
- 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.
- 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.

DAKOTA (Design Analysis Kit for Optimization and Terascale Applications) software from Sandia National Lab was used with its multivariate adaptive regression splines (MARS) options to develop an alternate response surface for the PCCS. [Ref. 1]

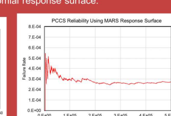
The data set used to develop the MARS response surface was the same as that used to develop the 3rd order polynomial response surface. Ideally, the data set would be optimized for the spline fit.

LHS methods were used to generate 500,000 data sets for the 6 CPs to interrogate the MARS response surface.

DAKOTA calculated the MARS response surface goodness of fit statistics and reported a standard deviation of 5.218 psia. The MARS response surface produced a phenomenological failure rate for the PCCS of 2.7E-4. This is somewhat higher than the failure rate of 1.9E-4 predicted by the 3rd order polynomial response surface.



MARS Response Surface Calibration Plot



MARS Response Surface Reliability Calculation Convergence Plot

Ref. 1: 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, November 2024.