BRANCH-AND-BOUND ALGORITHM APPLIED TO DYNAMIC EVENT TREES AND UNCERTAINTY QUANTIFICATION IN NUCLEAR REACTORS

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Abstract

Probabilistic Risk Assessment (PRA) is an important tool for evaluating risk in nuclear power plants. Dynamic PRA is an extension of traditional PRA methods that account for dynamic and phenomenological effects associated with the complex dynamic systems. This research focuses on dynamic event trees and addresses optimization in identifying the highest probability of system failure. The Branch-and-Bound algorithm is applied to dynamic event trees for nuclear power plants. The Branch-and-Bound algorithm relies and development of bounding functions to prune or delete branches that will not yield the optimal solution (i.e., clad failure). This research demonstrated the use of LENDIT metrics and S2R2 sets to support an expert-based approach to developing bounding constraints for the use of the Branch-and-Bound algorithm as applied to dynamic event trees. The use of the Branch-and-Bound algorithm has been shown to be effective in reducing simulation time. In addition, the optimized dynamic event trees are evaluated with respect to modeling uncertainty within the simulation code. This research demonstrates the ability to evaluate modeling uncertainty and develop a risk-informed Phenomena Identification and Ranking Table (PIRT). This PIRT can be used to improve thermal-hydraulic models and identify validation needs with respect to risk.

Two case studies, one for a Pressurized Water Reactor and a Boiling Water Reactor station blackout scenario are evaluated. The implementation of the Branch-and-Bound algorithm has been demonstrated to reduce simulation costs by more than 60% for these two case studies. The PIRT ranking for parameters important to cold safe shutdown of both reactor type transients was evaluated. The PWR station blackout scenario demonstrated that low fidelity models combined with system redundancy produces adequate results with respect to risk. Within in the BWR blackout condition, the modeling uncertainty does not present a challenge with respect to risk. Recovery of the station blackout transient requires either restoration of the AC power or activation of firewater injection combined with operator action to depressurize the system through the automatic depressurization system. Reactor power and firewater injection capacity provided the highest degree of correlation to model success.

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Dedication

I would like to thank my wife June for your support and helping me complete this work. I love you very much. I dedicate this work to my two wonderful children, Addison and Jayden. Daddy will always love you and I hope you always pursue your dreams and be the best you can be.

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Nomenclature

- ADAPT – Analysis of Dynamic Accident Progression Trees
- ADS – Automatic Depressurization System
- BWR - Boiling Water Reactor
- CCP – Centrifugal Charging Pumps
- CST – Condensate Storage Tank
- DOD – Department of Defense
- DET - Dynamic Event Tree
- DPRA – Dynamic Probabilistic Risk Assessment
- ET – Event Tree
- FT – Fault Tree
- HPCI – High Pressure Core Injection
- HPC – High Performance Computing
- HPI – High Pressure Injection
- INL – Idaho National Laboratory
- LOCA – Loss of Coolant Accident
- LOSP – Loss of Off-Site Power
- NASA –National Aeronautic and Space Administration
- PIRT – Phenomenological Identification and Ranking Table
- PORV – Power Operated Relief Valve
- PRA – Probabilistic Risk Assessment
- PSP – Pressure Suppression Pool
- RAVEN - Reactor Analysis and Virtual control Environment

- RCIC – Reactor Core Isolation Cooling
- RCP – Reactor Cooling Pump
- RPV – Reactor Pressure Vessel
- SA/UQ – Sensitivity Analysis/Uncertainty Quantification
- SI – Safety Injection
- SVR – Safety Relief Valve

Chapter 1: Introduction

This chapter provides an overview of the research performed to support this dissertation with regards to optimization and uncertainty quantification in a Dynamic Event Tree (DET) framework. Section 1.1 provides a problem description and the needs for this research. Section 1.2 provides a discussion of the purpose for the research and the scope of the research that is documented in this dissertation. Section 1.3 provides a summary of probabilistic methods currently in place and current research. The organization of this dissertation is provided in Section 1.4.

1.1 Problem Description

Dynamic probabilistic risk assessment (DPRA) is an extension of traditional PRA methods that allows for inclusion of time dependence and phenomenological modeling of system transients. DPRA methods require extensive computational resources to fully evaluate risk and often suffer from state or combinatorial explosion. The consequences of state explosion are an increase in computational costs for DPRA methods that are prohibitive outside of a high-performance computing (HPC) environment. These methods require both investments in computing equipment and resources to develop and analyze data. Optimization methods can reduce computation costs and allow for more efficient modeling of risk.

1.2 Purpose and Scope

DPRA is an extension of traditional PRA methods that allows for inclusion of time dependence and phenomenological modeling of system transients. DPRA methods require extensive computational resources to fully evaluate risk and often suffer from state or combinatorial explosion. This dissertation documents the research in use of the Branch-and-

Bound algorithm to optimally search Dynamic Event Trees (DETs) to identify scenarios and timing of events that result in the highest probability of failure. A review of the literature has identified few optimization methods for DETs and none that have used the Branch-and-Bound method. The use of optimization algorithms in evaluating DETs allows for significant computational cost savings. The optimization allows us to utilize DPRA, in particular DETs as a useable for probabilistic risk analysis.

During the creation of DETs, many of the trees branches results in a success or in the case of a nuclear power plant, neither core damage nor release. The branches that are of greatest concern are failure branches or branches that have resulted in core damage. In addition, some of the failure branches have a significantly lower probability (i.e., several orders of magnitude lower) than the branch resulting in the highest probability of failure. It is the success branches and low failure probability branches that do not provide meaningful or useful results. Optimization algorithms employed for DETs should include the capability to discard or prune these branches. The higher probability branches resulting in core damage are the contributors to risk and determine the operating limits for nuclear power plants.

The use of DETs relies on system modeling using simulation codes such as RELAP and MELCOR. These codes rely on user-generated models that may or may not have any degree of validation. Modeling uncertainty contributes to the uncertainty in the risk analysis and should be included and addressed in any risk analysis performed.

The advantages of using the optimization algorithm are demonstrated in this research by performing a Sensitivity Analysis and Uncertainty Quantification (SA/UQ) on accident sequences generated from the DET that have resulted in the highest probability of failure. The

SA/UQ methodology is used to develop a Phenomenological Identification and Ranking Table (PIRT) of modeling parameters that can be used to evaluate epistemic uncertainty as well as aleatory uncertainty. The PIRT is developed based on a risk-informed decision process rather than expert knowledge of the system and can be used to support validation experiments as well improvements in system modeling. This methodology provides a risk-informed decision process to improve safety margins allowing for nuclear power plants. Safety margin improvement is beneficial to the not only the existing fleet of reactors, but to future reactors. Power uprates and life extension are two examples of the benefits of safety margin improvement.

1.3 Summary of Probabilistic Methods

Risk assessment has been a fundamental tool in evaluating various processes that contain significant hazards. Many tools have been developed for evaluating for processes, which include HAZOPS, FEMA, what-if, and probabilistic risk assessment (PRA) [1]. PRA has been the preferred method for evaluating the risk associated with operating nuclear power plants. The first initial evaluations of a nuclear power plant are documented in the WASH-1400 report [2]. Prior to the development of WASH-1400, reactor safety analysis was focused primarily on the design basis accidents, most notably a large break loss of coolant accident (LOCA) [3]. The report concluded that transient, small LOCAs, and human error were the greatest contributors to risk.

The WASH-1400 report was commissioned to estimate the risks associated with operating nuclear power plants. The intention was to estimate the risk as a function of fatalities and potential property damage from potential accidents at a nuclear reactor. The report used fault tree and event tree analysis originally developed by the Department of Defense (DOD) and National Aeronautics and Space Administration (NASA). The report concluded that the individual fatality risk from 100 operating nuclear power plants was 1 in 5 billion per year [2]. Criticism of the WASH-1400 report included an understatement of the uncertainty associated with the frequency related to the consequences of an accident. The criticism of the WASH-1400 report has led to the development of NUREG-1150, addressing severe accident risks [4].

NUREG-1150 was considered a major improvement in WASH-1400 as it applies to risk-informed decisions within the regulatory complex. The analysis evaluated the risk for 5 specific operating plants, addressing a criticism of WASH-1400 that did not account for plant specific design and construction. However, unrealistic conservatism had been applied in the study [5]. The traditional PRA methodology due to limitations in computing technologies relies extensively on overly conservative assumptions. Though powerful in evaluating reactor transients and the adequacy of the safety systems, traditional PRA techniques still have limitations. As cited by J. B. Garrick in Reference [3], “PRA is not perfect, because is depends on many imperfect factors such as theories, hypotheses, assumptions, scope, the handling of information, and people.”

The traditional or static PRA utilizes Fault Trees (FT) and Event Trees (ET) to characterize transient conditions. Branches in ET represent a success or failure of a system. The probability of each branch is determined by the solutions of the FTs, which utilize Boolean algebra to solve the probability of each top event in the ET. The sequence of the ET branches is typically predetermined by the PRA analyst based on expert knowledge of the system and procedures, as well as thermal hydraulic simulations as in the case for a nuclear power plant. In addition, the timing of events and the necessary mission time are also predetermined by the analyst. This determination is usually based on educated assumptions from experienced analysts that have detailed knowledge of plant operations and the physical behavior of a system. However, due to the complex nature of nuclear power plants and the inclusion of human interaction, specific scenarios or branching conditions may not be fully evaluated. The assumption of the operators performing an action and the timing of those actions may be fully understood and incorporated into the analysis. An example such as operator actions with regards to loss of feed water. The analysis may assume that a plant would scram on a low steam generator level. In reality, a partial loss of secondary or feed water may delay the automatic scram from the reactor. The operator actions for manual trip may delay actual the actual scram, in which case significant amounts of energy can be added to the system prior to scram.

Traditional PRA has been a very powerful tool in evaluating the risk of a nuclear power plant. With improvements in computational resources, the risk associated with changes in operations of a NPP or maintenance activities resulting in the unavailability of systems can be evaluated relatively quickly (e.g., a few minutes to a few hours). The classical ET/FT approach does have limitations. Classical methods do not treat time-dependent interactions between the plant and physical processes. The methods are also limited in the treatment of interactions between humans and the plant [5]. Additionally, the failure rates of components do not take into account the physical stresses that may be experienced due to the nature of the transient events. This leads to uncertainty in the analytical results obtained. Additionally, the traditional PRA methodology does not address circular logic within a fault tree. This is essentially a chicken and the egg the problem, where analysts have to decide the exact order of events, where in a plant, the ordering may depend on the transient and the plant state. As such, a DPRA methodology allows for addressing these issues, as well as a more rigorous treatment of uncertainties as will be discussed in this dissertation.

Uncertainty can be categorized into two groups: 1) epistemic uncertainty and 2) aleatory uncertainty. Epistemic is essentially the systematic uncertainty or uncertainty in the lack of modeling detail or knowledge of a particular phenomenon. Aleatory uncertainty is the statistical uncertainty or variability in process models such as the roughness of a pipe or the uncertainty in the failure rate of a component.

The assumed uncertainties, both Aleatory and Epistemic, used in risk quantification in a nuclear power plant typically leads to tighter operating restrictions that inhibit a plant from operating to its full capacity. As described above, the NUREG-1150 analysis, though an improvement over WASH-1400, contained many conservative assumptions, that led to limiting the potential operating capacity of NPP [5]. Identification and quantification of uncertainties is the first step in increasing safety margin and allowing plants to operate near their full potential. An increase in safety margin can lead to an increase in the licensed operating power; this can result in increased revenues for a utility.

Risk Informed Safety Margin Characterization methodology is currently under development and aims to quantify and reduce uncertainties associated with risk analysis, as well as provide operating utilities a means to make risk-informed decisions associated with safe operation, license renewal, and extended operation. The focus on RISMC methodology is characterizing “margin.” Margin is essentially defined as the difference between the capacity and the load. The capacity can be considered as the ability to withstand some sort of event or transient, while load is the amount of stress applied to the system during the event. The margin is the difference between the load and the capacity. Figure 1 depicts qualitative distributions of load, capacity and margin. Each curve in the figure represents a probability distribution of the load and capacity, with the margin being the difference between the curves. The vulnerability within a plant can be associated in the region where the two curves intersect.

The uncertainty in the load probability distribution is the focus of this research. By reducing uncertainty in the load distribution, the safety margin is increased and the intersection between the load and capacity curve is decreased. By reducing the uncertainty, the load can be increased to the right closer to the capacity curve maintaining the desired safety margin for operation, thus allowing for plants to continue operation past their original 60-year life and potentially at higher operating powers.

By considering the dynamics of an event, the uncertainty in a specific transient can be better quantified. The method of continuous event trees was developed in the early 90's. Devooght and Smidts presented the first papers introducing the Theory of Continuous Event Trees and a companion paper providing a case study was documented in References [7] and [8].

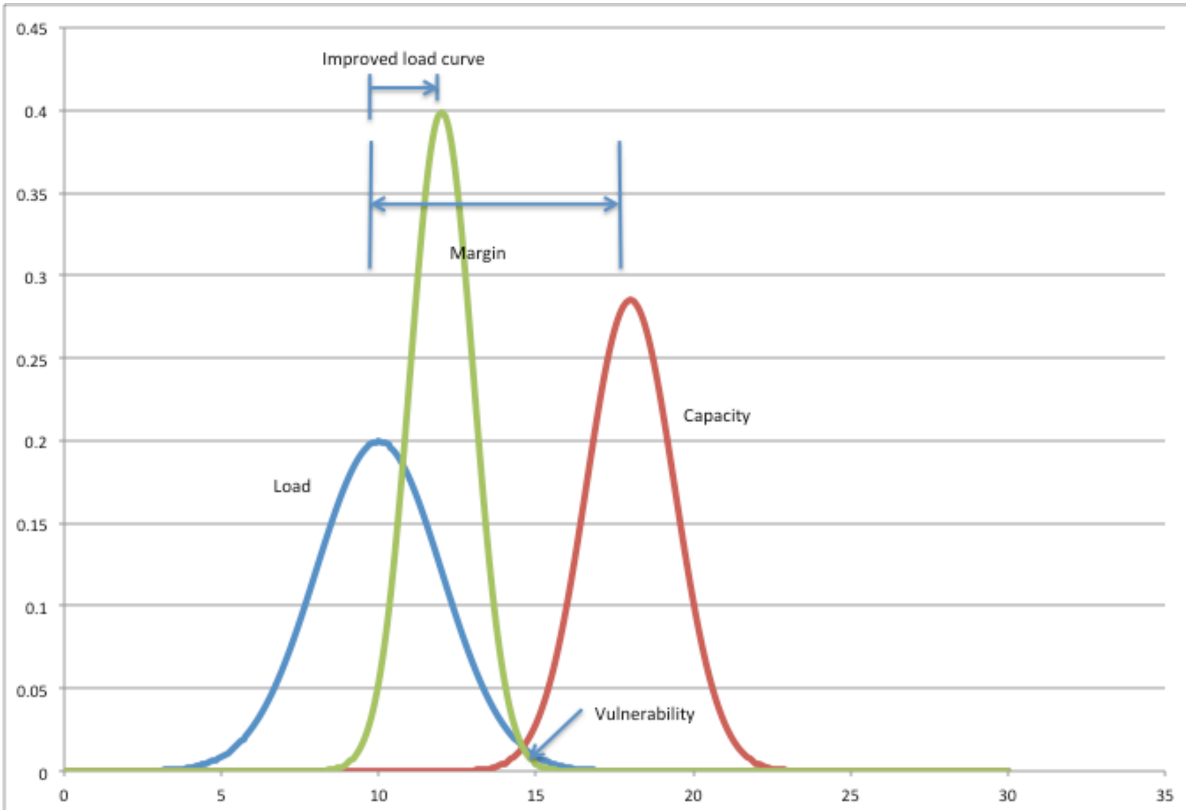

Figure 1. Diagram of the RISMC Methodology.

Probabilistic reactor dynamic is derived from the evolution of the changes of states of the reactor. The changes in states are governed by the probabilistic laws. The reactor dynamics can be governed by the following equation:

$$\frac{dx}{dt} = f_i(x, t)$$

Probabilistic reactor dynamics is assumed to be Markovian in the theory of CET. That is to say that the state of the system at time t+dt is only conditional upon the state at time t and is not conditional by the past evolution. By assuming a Markovian system, the probability density of the system can be described by the following differential equation [7]:

$$\frac{\partial}{\partial t}\pi(x,i,t\left|x_o,k,t_o\right.)+div\left(\pi(x,i,t\left|x_o,k,t_o\right.)f_i(x,t)\right)+\lambda_i(x)\pi(x,i,t\left|x_o,k,t_o\right.)$$
$$-\sum_{j=i}p(j\rightarrow i\left|x\right.)\pi(x,i,t\left|x_o,k,t_o\right.)=0 \tag{1}$$

Where:

$\pi(x,i,t)$ = the probability density of state (x_i) x is a process variable and i is the component state

$f_i(x,t)$ = describes the evolution of the state vector x for a given component state i at time t

$\lambda_i(x)$ = transition probability to leave state i in the interval Δt when the state vector is x

$p(j\rightarrow i|x)$ = probability of transitioning from state j into i given state vector x

The above equation is also known as the forward Chapman-Kolmogorov Equation. By solving for π(x,i,t), the probability density for the reactor dynamics is obtained, which corresponds to the solution for the load within the RISMC methodology. An assumption that is made in the above equation is that the system is modeled deterministically [9]. In other words, the uncertainty in physical parameters of the system is not taken into account. The uncertainty in the physics of the system can be taken into account by adding an additional term as shown below:

$$\frac{\partial}{\partial t}\pi(x,i,t\left|x_o,k,t_o\right.)+div\left(\pi(x,i,t\left|x_o,k,t_o\right.)f_i(x,t)\right)+\lambda_i(x)\pi(x,i,t\left|x_o,k,t_o\right.)$$
$$-\sum_{j=i}p(j\rightarrow i\left|x\right.)\pi(x,i,t\left|x_o,k,t_o\right.)+$$
$$\frac{1}{2}\sum_{m,n}\frac{\partial^2}{\partial x_m\partial x_n}(B_{m,n}(x,t)\pi(x,i,t\left|x_o,k,t_o\right.))=0 \tag{2}$$

where $B_{m,n}$ represents the covariance matrix for x. The inclusion of this second term complicates the solution of the equation and is more difficult to obtain a solution. It is also imperative for including the term in considering uncertainty quantification of the physical models.

The significant problem with solving the above equation, deals with the potential for state explosion. As the state of the reactor evolves in time, the number of possible states grows exponentially. Reference [7] suggests that above methodology does not replace classical event trees, but rather, supplements the solution in situations where timing of events or the reactor dynamics is critical to the state of the system. The solution to the above equation with very explicit assumptions results in the solution with classical event trees. By neglecting phenomenological effects (i.e., thermal-hydraulic solution to x) and assuming a pre-selected transition time, the equation reduces to a simple probabilistic equation related to the probability of changing of plant states and directly related to the distributions associated with λ.

One of the objectives of this research is to provide a method for quantifying uncertainty and develop a quantified phenomenological identification and ranking table (QPIRT) that is based on risk-informed decisions. These parameters can then be used to better understand the effects of modeling uncertainty and experimental validation data can be used to improve the safety margin. High fidelity modeling of thermal-hydraulic systems can be computationally expensive and human resource intensive. Validation of high-fidelity models can also be costly in experiment design and performing experiments. Providing a risk-informed methodology for developing high-fidelity models and validation experiments will result in cost savings in support of an increase in safety margin.

This research examines the solution to DETs and proposes a methodology for optimizing the solution to the equation for the conditions resulting in the highest probability of failure as well as a methodology for developing a QPIRT for an accident transient that is based on risk significance. This will allow for sensitivity analysis of physical parameters that are quantified with importance to risk rather than expert-based knowledge. The methods are not intended to replace expert-based knowledge, but rather to leverage the knowledge base in existence, to enhance the knowledge of experts and confirm their opinions as well as identify the possibility of conditions that experts may not have discovered. In many instances, the time-domain sequence of events within a PRA analysis, may not receive the attention that major accident scenarios have revealed. The expert-based knowledge, when combined with human interaction, may not fully understand the time scales required to prevent core damage during a reactor transient.[1]

Several methodologies have been used to solve Equation 1 above. Each solution method has its own advantages and disadvantages. Reference [10] provided a summary of the mathematical methods that have been employed to solve Equation 1 and are briefly summarized here. Methods that have been employed, consist of analytical solutions, Marginal Distributions and Interpolation Schemes, Neural Networks, Cell-to-Cell Mapping Techniques, Monte Carlo methods and Discrete Dynamic Event Trees.

Analytical methods provide an exact solution to Equation 1. Analytical methods are very limited in the ability of solving systems that are very complex. These methods do however,

[1] Based on the ANS Fukushima Report and other related post-accident analysis, human response had a significant impact on the eventual outcome.

provide for a solution to simple systems that can be used for analytical benchmarks and can be used to validate other more complex numerical methods.

Marginal distribution and interpolation schemes are based on solving Equation 1 for the moments. The solutions are based on expanding Equation 1 in terms of Taylor Series Expansions to obtain the 0^{th}, 1^{st}, and 2^{nd} moments [11]. The advantage to this method is that instead of solving a system of N (number of component states) PDE for M+1 (number of physical variables) variables, it is solved for M systems of N PDEs with respect to one process variable and time. As the complexity increases, the system of equation expands and becomes cumbersome to maintain the accounting of the expansion of equations, which results is a significant disadvantage. Additionally, the method has limitations with regards to transition of states on demand.

Monte Carlo methods have been employed for solving Equation 1. In a companion paper to Reference [7], Reference [8] provides the method of solution for a fast reactor transient using Monte Carlo Methods. Analog Monte Carlo methods are not practical for a solution of reliability problems, especially for system that are inherently safe. The transition probabilities for failures of components are relatively low and sampling in the failure region does not provide for an adequate solution in a reasonable amount of time.

Variance reduction techniques have been employed to improve the computation efficiency. Most notably, methods that force a transition and biasing towards failure of a component are typically employed. The results are then weighted based on the biasing to produce a relatively accurate answer.

Recent advancements have utilized an adaptive sampling algorithm that employs a learning algorithm to generate a response surface. The algorithm utilizes few samples to create an estimate of the response surface and then relies on sampling near the surface for the remainder of the simulation. Significant efficiency has been achieved using these algorithms for complex system [13].

The methods proposed in this research utilize both Monte Carlo methods as well as dynamic event trees. Monte Carlo sampling provides a significant improvement in sampling the physical parameters with some known uncertainty and distribution. Failure states or state transitions are better suited for dynamic event trees, where the transition may or may not occur based on some probability. They inherently characterize time-dependent system behaviors.

Discrete dynamic event trees have been extensively used for solving Equation 1. Equation 1 can be discretized in time, where each time step represents a branching condition. The main advantage is that all possible branching of a system is considered. The data and computing resources required is a limitation. Additionally, time discretization needs to be considered. One of the latest tools for discrete dynamic event tree, is called ADAPT [11]. ADAPT was developed to interface with different simulation tools that have a stop/restart feature, where control modules can be modified at the stopping of a solution, and restarted with minor changes to the control variables. ADAPT does not explicitly solve the continuous event tree equation, however, simulations of dynamic event trees satisfy the equation.

In ADAPT, the user provides branching rules that determine the probability, and the change to the simulation if a specific condition is reached during simulation such as the pressure set point of a Power Operated Relief Valve (PORV). The discrete dynamic event tree currently has several limitations [13]. The primary limitations are associated with combinatorial explosion of states. The greater the complexity of the system, the greater the number of possible branching conditions. This limitation also exists in other methods such as Monte Carlo. DETs do have an advantage of Monte Carlo methods in the fact that each simulation does not have to begin at the initial start. Rather, the simulation branches into two or more new simulations at a branch condition restarting from the branch rather than at the initial time. The limitation with regards to the timing of branching conditions is relied upon the user to specify when to create a branching condition and how many branching conditions within a distribution function need to be sampled.

Two major disadvantages that are the focus of this research deal with time discretization and the effects of sensitivity and uncertainty quantification on risk. With regards to time discretization, the intent of this research is to optimize solutions resulting in failure of the plant such as reaching the Zr/water interaction temperature. Numerous solutions can be obtained that do not result in failure and result in conditions of success. Due to the fact that most failures have low probability, it would stand to reason that most simulations should end in success. These conditions from a risk point of view, are not of interest. Additionally, it can also be seen that some scenario conditions simply reach failure rather quickly and though interesting, due to either an extremely low probability of failure or condition where large uncertainties in the model will not effect the result adds to the computation of the experiment and do not address the potential for risk reduction. As an example, the failure of emergency battery power at the time a scram and station blackout (SBO) occurs, can result in core damage relatively quickly. The probability of immediately loosing battery power upon SBO is low. Evaluating uncertainty associated with emergency cooling pumps can be costly and the major impact on the event is the timing of loss of battery power. Pruning these types of events from the tree do not necessarily impact the safety margin of the plant.

Another type of method for solving dynamic systems is referred to as Cell-to-Cell Mapping Techniques [15]. The state variables are broken down into discretized grids. The probability of transition from grid to grid is determined based on clustering of the state of the system in state space. The limitations for CCMT methods lie in the restriction that only a small number of state variables can be considered. When dealing with large systems, CCMT has an advantage in solving problems where combinatorial explosion can occur, however, the limitation of the number of state variable considered is a major disadvantage [9].

Optimization methods have been evaluated for DPRA methods. References [18] and [19] have proposed a method for developing a structured planned simulation based on a combination of engineering judgment and advanced learning algorithms to develop and execute a plan for performing the simulation. The method involves utilizing Shannon information entropy to provide a measure for information gain and branches within a tree containing higher values are explored.

Hidden Markov Models (HMM) have been shown to provide promising results for identifying failure scenarios [20]. The method utilizes a learning algorithm to train the simulation and verifying the results for a test set. The algorithm has been shown to provide 55% time savings in identifying failure scenarios.

1.4 Organization of this Dissertation

This dissertation is organized to provide a brief overview of the Branch-and-Bound optimization algorithm used to optimize DETs (Chapter 2), provide an overview of the methodology to develop bounding functional relationships for the Branch-and-Bound algorithm using what is referred to as LENDIT Metrics and S2R2 set theory (Chapter3), provide a discussion of the implementation into the RAVEN framework (Chapter 4), summarize the SA/UQ methodology to create a PIRT for a reactor transient (Chapter 5), describe and present the results for two case studies for SBO for a PWR and BWR reactor (Chapter 6 and Chapter 7), and summarize the results of this research (Chapter 9).

Chapter 2: Branch-and-Bound Algorithm

The primary intent of PRA is to identify vulnerabilities within a nuclear power plant. Classical event trees as discussed in Section 1 have been used extensively to identify known vulnerabilities and identify the probabilities of core damage or release of radioactive material. Dynamic event trees allow for inclusion of system dynamics that can lead to unidentified failures that are difficult to identify. The unidentified failures are not the result of unidentified transients, but rather a lack of knowledge of the transient progression coupled with the complexity of human interaction. Experts experienced in reactor transients are not able to identify every possible sequence of events. DPRA methods, in particular DETs, have the ability to identify these sequences. The disadvantage of dynamic event trees is the issue with state explosion, which results in a significant increase in computational cost and leads to large amounts of data that requires significant efforts for mining the data.

It is proposed in this research to use an optimization search algorithm to manage the creation of the dynamic event trees. The intent is to optimize the solution of the event tree to guide the simulation to conditions of failure. In other words, the intent is to find the highest probability of failure for a given plant state. In this research we utilize the Branch-and-Bound algorithm [15] to find the solution resulting in the highest probability of failure.

The Branch-and-Bound algorithm is a method to optimize the best potential outcome for a mathematical model. The intent is to optimize an objective function or response function such as [18][22]:

$$\min_{x \in S} f(x)$$

where *f(x)* is the objective function over variables (x_1, x_2, $x_3 \ldots x_n$). Within the Branch-and-Bound algorithm, the objective function is minimized (or maximized in the case of DET) over a region of feasible solutions, *S*. Possible solutions to the f(x) exists in P, which contains S, with S being a subset of P. In other words, the minimum (or maximum) solution is contained in S where P is subdivided into subsets. A bounding function, *g(x) ≤ f(x)* is contained in S for all x. The problem is solved as *g(x)−>f(x)*. A diagram of the branching and bounding process is shown in Figure 2. The diagram is shown for an objective function to minimize *f(x)*. The maximization of *f(x)* is similar except the bounding function *g(x) ≤- f(x) [22]*.

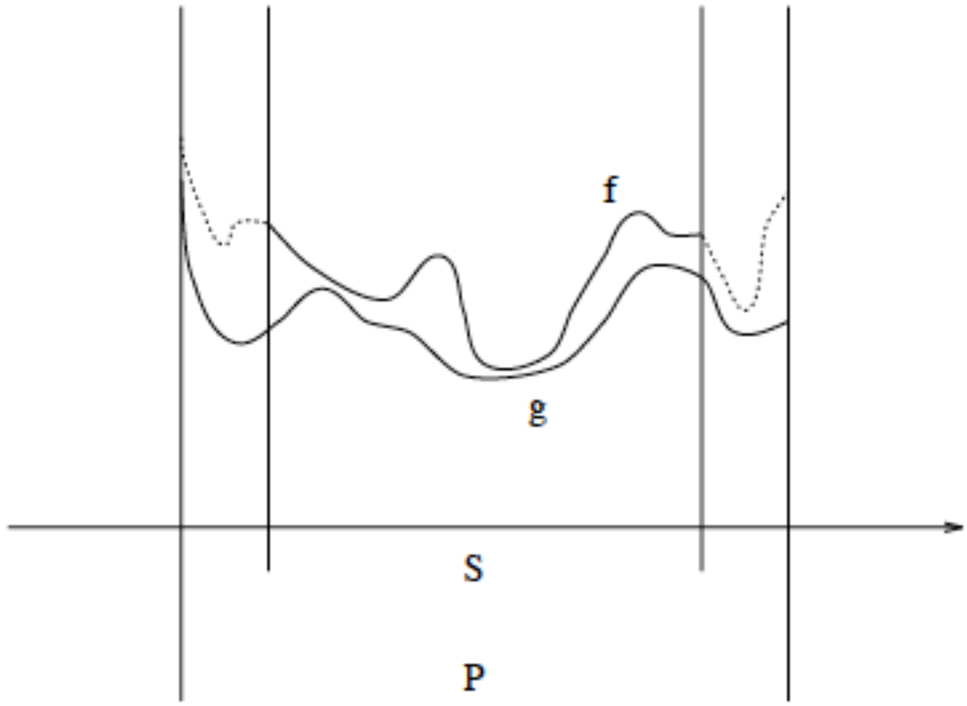

Figure 2. Diagram of the Branch-and-Bound subset.

Optimization methods have many applications such as manufacturing, where costs need to be maximized. A classical example of a linear problem is the traveling salesman problem, where it is desired to optimize the path a salesman takes to minimize the time and distance a salesman has to travel between customers [22]. Within this research, the Branch-and-Bound algorithm is used to identify the highest probability of failure or release in a nuclear power plant as evaluated using DETs. The solution of the DETs satisfy Equation 1, in which the solution provides the load curve for the risk-informed safety margin characterization.

The Branch-and-Bound algorithm can be applied to both linear and non-linear problems. Non-linear problems present a challenge with regards to finding maximum or minimum values. Linear problems are much easier to evaluate, as it is easier to find minimum and maximum values associated with linear functions. With regards to this research, we are interested in identifying the failure conditions of a power plant that is modeled and simulated with a set of non-linear thermal-hydraulic equations. Since we are interested in only the probability of failure, the solutions of Equation 1 in the integral form is linear. Complexity of the solution of Equation 1 is introduced in the solution of the constraining variables (e.g., x=cladding temperature, liquid mass, etc). With regards to solving equation, 1, variables are selected, to support bounding functional relationships as discussed below. The selection of these variables is critical in ensuring the solution of the optimization function is not pruned during the search (e.g., construction) of the DET. Within the Branch-and-Bound framework, subsets of the feasible solutions P, may be neglected or pruned if they are determined to not contain the optimal solution. We have discovered that care must be taken to ensure sufficient number of variables (x) are identified to not over prune the DET. Selection of too many variables results in “less optimization” or less pruning. The consequences of this condition are that the optimal solution is still found, but the simulation time will take longer. The weakness of the algorithm is associated with selecting too few of variables, which can lead to pruning the optimal solution. Therefore, we have developed a set of metrics, which will be discussed in Chapter 3, which will support the decision process for selecting variables. Additionally, the use of this method should include testing for specific transients to ensure the appropriate variables are selected.

Within the Branch-and-Bound algorithm, the space S can be split into a subspace. The branching of the space S into a subspace is a node within the DET. The intent is to divide the potential solution space into smaller subspaces and analyze each subspace to find a solution to the objective function. The Branch-and-Bound algorithm is treated as a search algorithm of a DET. Optimization is provided by developing the constraints and bounding function g(x) over P to optimize the solution f(x). Subdividing the problem allows for comparison at each node to the bounding functional relationships, which is restricted to the following conditions [22]:

$$g(P_i) \geq f(P_i) \text{ for all nodes } P_i \text{ in the tree}$$
$$g(P_i) = f(P_i) \text{ for all leaves in the tree}$$
$$g(P_i) \leq g(P_j) \text{ if } P_j \text{ is the father of } P_i$$

The above set of conditions can be seen that during the optimization of the solution, the bounding function g approaches the optimal solution of f until g=f at leaf nodes. In the case of DETs, the bounding functional relationships and objective functions are related to the probability of the node with the constraints that the leaves for the optimal solution be greater than some failure conditions. The final condition ensures that the bounding functional relationships is approaching optimal conditions as the solution approaches an optimal condition. Within the DET, it is not feasible for $g(P_i) > g(P_j)$, since the probability of a child node must be equal to or less than the probability of the parent node. The probability of the child node is simply the probability of the parent multiplied by the branching probability, which must be less than or equal to unity. With regards to the risk analysis for a nuclear power plant, the intent is to maximize the probability of failure such that the f(x) is the probability of x such as identified in Equation 1. The problem is further constrained by x exceeding some value such as the peak clad temperature is greater than 2200 °F.

The Branch-and-Bound algorithm requires two tools for implementation. One is the branching condition where S_1 and S_2 is a subset whose union covers S. Branching conditions or methods to branch the subspace into S can vary by problem. Additionally, searching the space S using a Branch-and-Bound algorithm can involve both depth and breadth searches. Within this research, both depth first and depth and breadth search have been considered. Initial indications identified that a breadth and depth search is more efficient in identifying the solution to the DET, though the depth search approach is easier to implement. The use of the RAVEN framework as described in Chapter 4, allows for massively paralyzed capabilities, which allows for significant breadth type searches. Depth first searches are typically easier to implement, as it involves recursively-evaluating nodes of a tree down through the depths and back out. The decision on which branch to follow can effect the efficiency of the algorithm.

The second tool for the Branch-and-Bound algorithm is the bounding function, which sets the limits for *f(x)* in subset S_i. The initial selection of *g(x)* can effect the ability to optimize the solution. In typical application of the Branch-and-Bound algorithm, the functions for *g(x)* are well defined. Ideally, one would prefer the solution *g(x)* to be close to *f(x)* as feasibly possible. Within the DET framework, it is difficult to identify a bounding function close to *g(x)*. By utilizing LENDIT metrics and S2R2 set theory, we define a bounding functional relationship such that if g(x) lies within f(x) for subspace S_i than S_i contains a feasible solution and should be pursued. The LENDIT metrics and S2R2 set provide a heuristic approach to defining the bounding functional relationships g(x) and are described in Chapter 3.

2.1 Branch-and-Bound Example

For a demonstration of the Branch-and-Bound problem, lets consider the case of a reactivity insertion accident with the reactor power increasing exponentially in time. A reactor scram results in decrease in reactor power. For this simple example, it is assumed that the peak clad temperature is directly proportional to reactor power. Therefore, the cladding temperature is also increasing exponentially and is represented by the following equation (see Figure 3):

$$T = T_o e^{w_1 t} \tag{5}$$

where T=temperature at time t, and w_1 is the time constant associated with the reactivity insertion, and T_o is the initial temperature. Following reactor scram, the temperature is represented by the following equation:

$$T = T_o e^{(w_1 + w_2)t_o - w_2 t} \tag{6}$$

where w_2 is the time constant associated with reactor scram and t_o is the time of the transition. The probability of reactor scram is represented by the following equation:

$$P = (1 - e^{-\lambda t}) \tag{7}$$

If the problem were to be discretized similar to what would be performed in a dynamic event tree, the probability of the peak clad temperature at time t from Equation 5 and Equation 6 can be determined. The CDF used to simulate to sample branching conditions is shown in Figure 4. The intent is to maximize the probability of the temperature exceeding some specified value. A simplified dynamic event tree for this simulation is shown in Figure 5. By evaluating the branching conditions on the cumulative distribution function (CDF) as shown in Figure 4, there would be approximately 24 nodes. Using the Branch-and-Bound method, the nodes are evaluated and ranked by highest probability. By following the path with the highest probability, we are able to neglect the final 7 nodes in the simulation. The algorithm would skip several branches if evaluated only on the condition of probability (1, 3, 5, 7) until it has reached branch 8. The simulation would come back to and evaluate nodes, 5, 7, then 10, 9, 3 1 and continue evaluating the remaining nodes in order until the failure condition is reached at node 17. Greater efficiency can be considered by using a heuristic approach and knowing that if a failure has not occurred later in time, then earlier nodes can be pruned. In this case, the simulation would completely skip nodes 1, 3, 5, 7 and 9 resulting in greater efficiency.

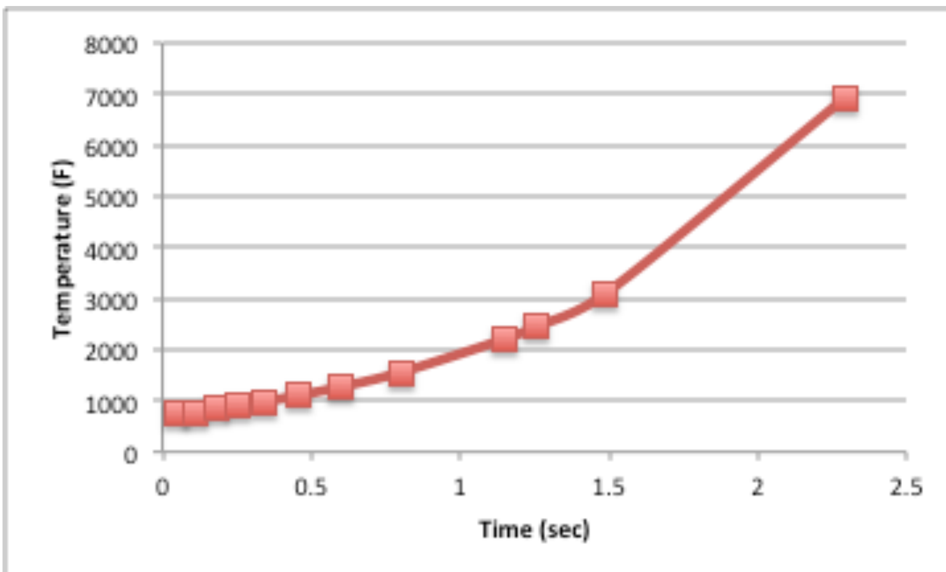

Figure 3. Reactivity transient example

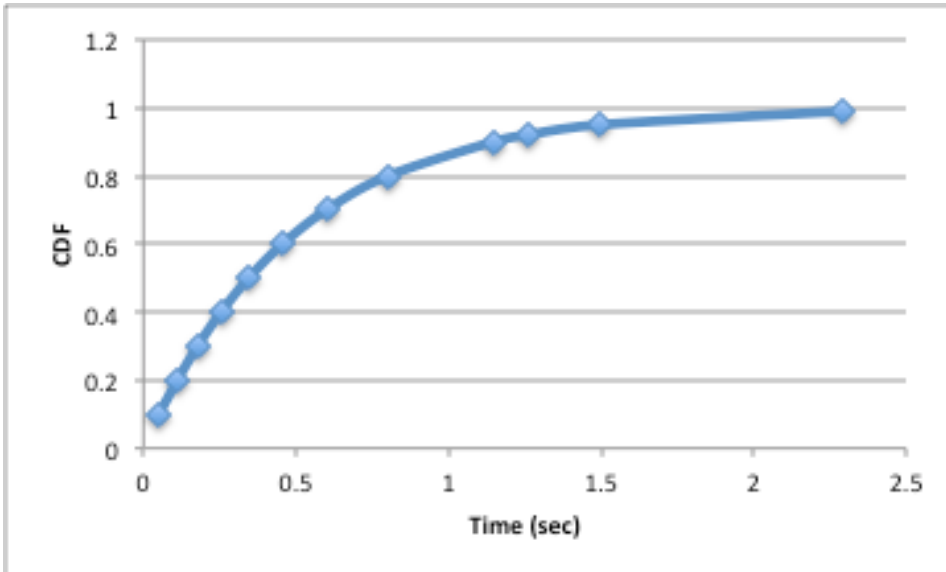

Figure 4. CDF for reactivity transient example.

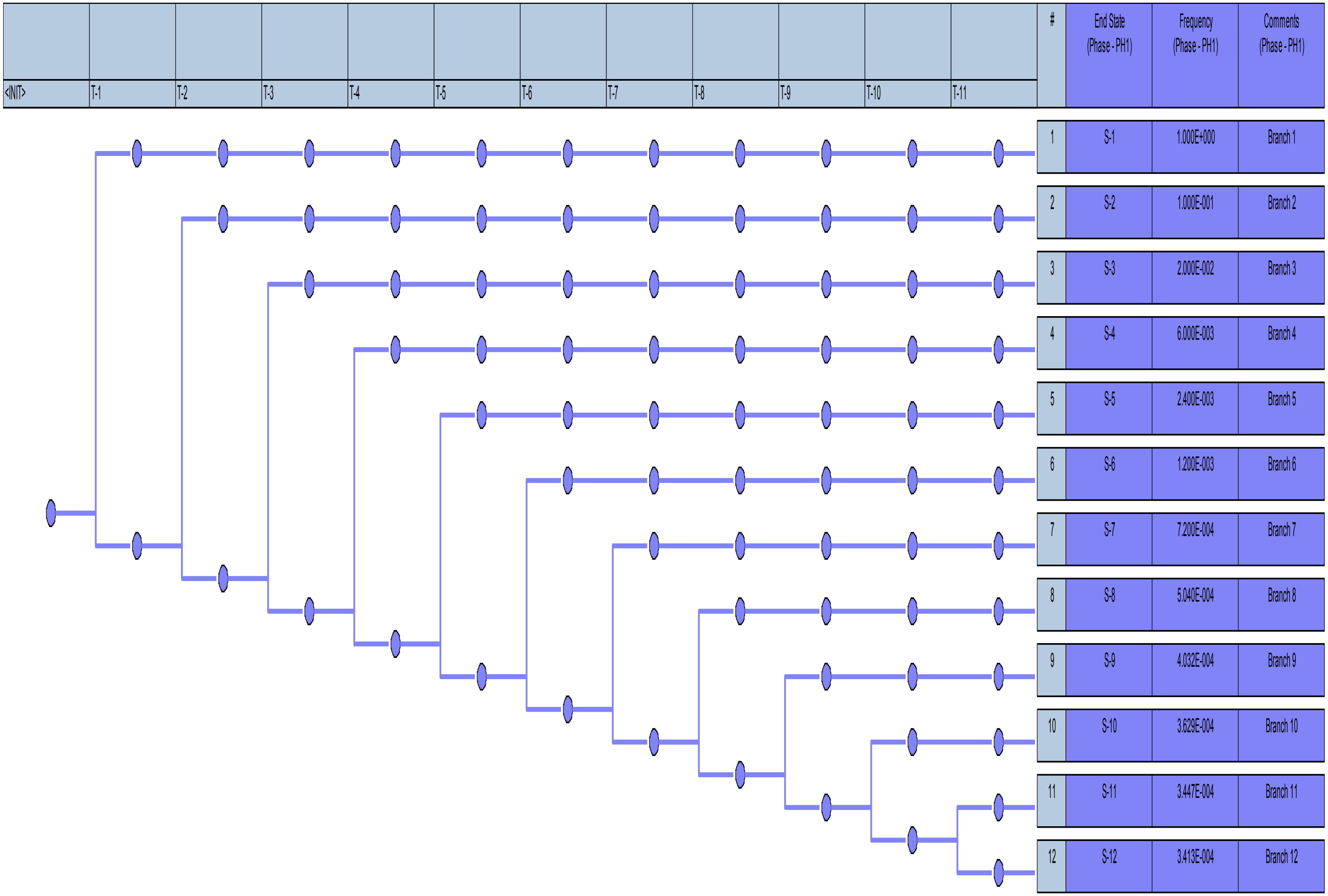

Figure 5. DET for simplified reactivity transient with no optimization.

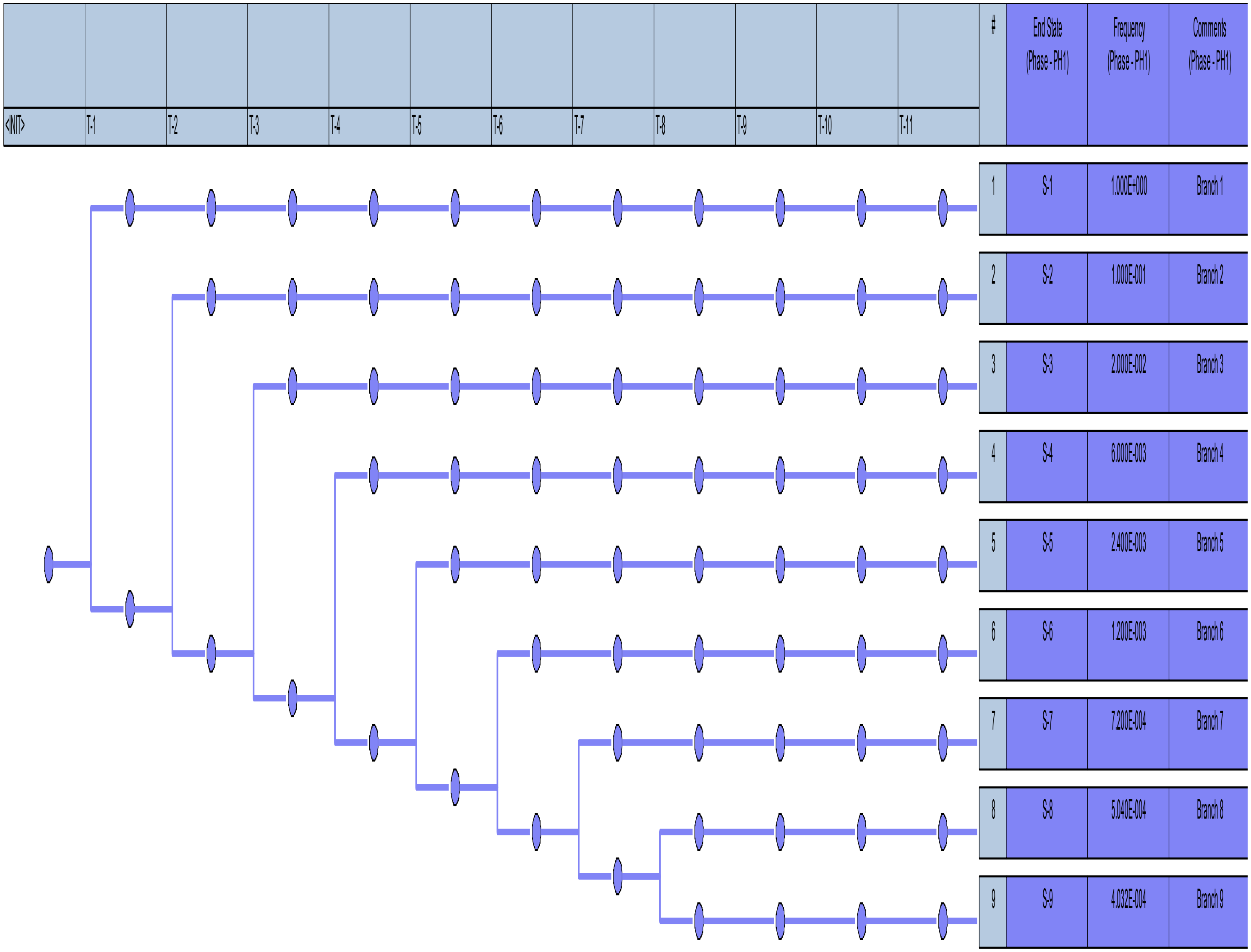

Figure 6. DET with optimization for simplified reactivity transient.

From the above example, several nodes are found based on the fact that they have a lower probability of failure than currently analyzed. Others can be pruned on the basis that they were determined by previous cases to not result in a failure and thus removed from consideration. The above example exemplifies the complexity of nuclear power plants. While evaluating nuclear power plants, the thermal-hydraulic effects and potential changes in plant states are extremely difficult to evaluate. When using the Branch-and-Bound algorithm for dynamic event trees, the selection of branches to explore can be considered based on probability alone, in which case, improvement in efficiency can be expected. However, using knowledge on thermal-hydraulic system behavior, pruning of the tree based on plant states and achieve a much greater efficiency in the finding the branches resulting in failure.

2.2 Implementation of the Branch-and-Bound to Dynamic Event Trees

As discussed above, the key to achieving significant amount of efficiency in the Branch-and-Bound algorithm is to identify the branches with the highest probability followed by evaluating those conditions that will yield a potential failure or if they have been previously enveloped by a condition where failure has been shown to not occur. The first condition for selecting which node to search is relatively straightforward by simply placing the branches in a queue where the branches with the highest probability are evaluated first. The problem is subdivided into subsets of the previous node until a failure condition is reached. The second step is to determine whether the branch will yield a success (i.e., no core damage) and can be pruned. This second step can be more difficult to determine. Due to the non-linear equations used to model the system and changing plant conditions, pruning trees can become difficult. However, using expert based knowledge of thermal-hydraulic performance of reactor transient, we can use engineering judgment to determine and rank which parameters are important.

During a reactor transient, the primary function is to remove the amount of stored energy in the system and establish a path to cold shutdown or acceptable quasi-steady conditions. In other words, it is desired to achieve a condition where energy removed is equal to or greater than energy generated from decay if the reactor is scrammed. Parameters such as reactor power, liquid mass, pressure, liquid level, and decay heat are examples of parameters that indicate how much energy is or can be stored in the system. The idea behind the Branch-and-Bound method as implemented here is to prune branches that have been shown to have the ability to remove energy at a rate greater than created from radioactive decay. An increase in internal energy, pressure and decay heat with concurrent decreases in liquid mass and core liquid level indicates a trend towards a thermal-hydraulic state that can lead to core damage. Higher pressures for example in the reactor prohibit emergency cooling capabilities, while higher decay heats allows for energy to be added to the system. In the event that these state properties are shown to be completely enveloped by previous simulations, the nodes can be pruned as these states will end in a system success (reaching a safe condition) and with regards to risk analysis of little value.

Pruning of the dynamic event tree also relies on knowledge of the process of a transient. For example, there are specific sequences of events that will occur and transition from one state to another may not be possible. Following reactor scram, it is not considered possible for the reactor to be brought critical, assuming the safety rods can maintain the required shutdown margin. Additionally, the activation of the emergency cooling system is extremely unlikely to occur unless it is called upon either through automatic activation or operator action. Though some conditions such as inadvertent operator action may occur, each case needs to be evaluated on a cases-by-case basis.

Prior to running any dynamic event tree simulation, the analyst needs to identify potential conditions or possible transition points from plant state to plant state. The conditions and transitions provide the initial constraints for the simulation. The timing of events can vary greatly and the effects of the timing of events are the determined in the simulation. However, the knowledge of the distribution of the timing of events and the sequence or potential sequence of events should be included in each simulation. The following section provides a discussion of the LENDIT metrics and the S2R2 sets used to construct the constraining and bounding functions for the Branch-and-Bound algorithm. The use of these scales, the defined sets and the reactor thermal-hydraulic states parameters associated with a given time-dependent analysis provide the optimization approach for the solution to the problem.

Chapter 3: LENDIT Metrics and S2R2

The LENDIT metrics are a collection of relevant physical quantities such as time, energy, and length for which thermal energy systems and certainly nuclear power plant operator-action depends. These scales reflect, for example, the length (*L*) of the liquid level in the core; the amount of (thermal) energy (*E*) in the reactor; the number (*N*) of NPP operators; and approximate anticipated time (*T*), for core damage, under insufficient cooling of the decay heat. Although all LENDIT scales apply to a system under scrutiny, some metrics are less relevant simply because of the scales apply across many of the systems' function. As an example, the *a-priori* emergency preparedness includes prompt initiation of designated 'team' response (consisting of '*N*' members), information (*I*) from critical instrumentation, controls and hardware needed to address the post-event, and the distribution (*D*) of possible component states or probabilities of being in several physical states. Taken together these quantities are represented as a tuple of scales denoted by (*N, I, D*). The utility of LENDIT is that the concept can be applied consistently.

The use of the LENDIT scales helps establish the bounding constraints and functional relationships for a simulation. The bounding functional relationships are needed to optimize the Branch-and-Bound algorithm as described above. For each simulation or transient, the analyst should become familiar with the transient process using available resources. These resources include plant safety documents, procedures, and scoping thermal-hydraulic analyses (LENDIT Metrics 'I,E,T'). A classical PRA for the specific plant and similar plants can also be used to help identify potential (static) states and probabilities of entering a distribution of states (D).

The procedures can include very valuable information with regards to the necessary response and resources (N) needed to address a transient as well as an estimate of the time to complete the necessary actions (T). The dynamic simulation can be initially seeded by this information. As an example, immediate activation (i.e., seconds to a minute) of feed-and-bleed may not be possible in a station blackout (SBO) condition. Since the transition time to initiate feed in bleed is in minutes, sampling on branching conditions on the order of seconds, would not be prudent; thus it would be better to sample initiating of feed and bleed on the order of minutes to hours. The branching conditions should be considered with regards to timing of events. Inclusion of highly improbable heroic actions by the operators can still be included in the DET simulation; however, they may add little value in determining plant failure states and results in longer simulation times. Besides it would be inappropriate to rely on heroic operator actions. Value is added though if the heroic actions of operators are the only path to success, then possibly the number (N) of operators available to respond may increase the probability of success. The opposite condition may also exist in having an insufficient number of operators, which may decrease the probability of success.

The procedures and safety documents also provide insight into the analysis that is used to support the plant. In addition, thermal-hydraulic models for a small subset of cases can be used to evaluate the properties important to the Branch-and-Bound algorithm. These items might be specific system measures (information from sensors) such as core liquid level, energy, liquid mass, and pressure (L,E,I,T). By evaluating these properties, one can determine for example the increase in parameters that might precede core uncover or fuel clad melting. The PWR SBO case summarized in later sections demonstrates for example, how the increase in internal energy (E) precedes the decrease in core liquid level (in time) leading to core uncovery.

In addition to the physical parameters, one can make some conclusions with regards to the timing of events (T) and how a delay for example in SBO allows for an increase in time for operator action to recover off-site power and initiate appropriate actions.

The LENDIT scales importantly allows for the analyst to set up the simulation by incorporating trip settings into the simulation to create branching conditions, as well as asking questions with regards to guiding the simulation. As an example, once the transient begins, questions can be asked such as; “has reactor scram occurred?” and “is emergency cooling available?”. A diagram of a LENDIT flow chart is provided in Figure 7. The Figure is used to show how the SBO example described in later sections was developed.

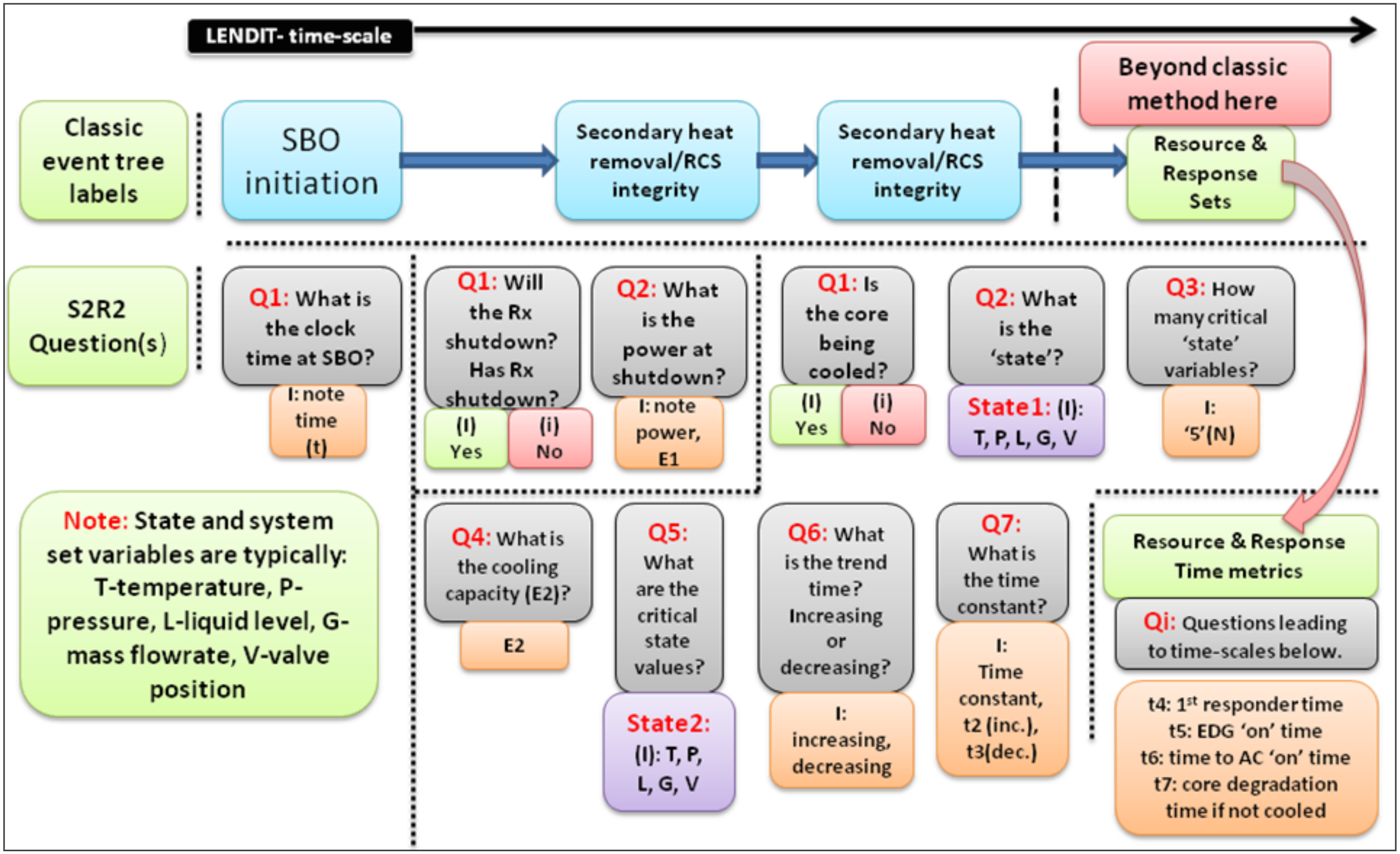

Figure 7. Diagram of the LENDIT flow chart for a PWR SBO.

3.1 S2R2 – State, System, Resource and Response Sets

The LENDIT-scales are used in conjunction with a set theoretic approach to system analysis. Four ‘sets’ called, ‘state, system, resource and response’ or ‘S2R2’ describe key system operations that systematically describe the descriptive use of LENDIT-scales. The LENDIT-scales in combination with S2R2 can be used to characterize off-normal reactor events and plant operators' (first responders) capabilities to intervene. Steady-state and normal operations are also defined by the S2R2 formulation. The S2R2 sets follow basic set operations. The response set is well defined in the algebraic sense. That is to say that the response set considers the Boolean operation based on state, system and resource set to create possible branching conditions for each node within the dynamic event tree. An example would be if the system set consists of SBO AND SRV closed AND the state set consists of Pressure>7.58 MPa, AND the resource set includes SRV available. The resulting response set would be OPEN SRV. Additionally, using set operations, S2R2 elements provide linear constraint on the Branch-and-Bound algorithm, where a linear programming method is used. A brief description of each ‘set’ follows.

State Set

The State Set depythscribes the thermodynamic state of the reactor and as such, refers mainly to instrumentation and controls (I&C) sensors that define the state of the reactor. The state of the reactor of course changes in time. The state is described by LENDIT information scales defined by: temperature, pressure, liquid level, mass flowrate and valve position or function. There are additional LENDIT scale describing the number and distribution of sensors (*N,D*), time response of sensors (*T*) and lastly the physical location of the sensor (*D,* *L*) if, under emergency response, a responder has to physically attend to the sensor unit (that is, go from the control room inside the containment).

With regards to DETs, the state set is provided by the simulation program such as RELAP5-3D. The analyst uses the information from plant procedures to identify the appropriate plant and operator actions with regards to the state of the system. A loss of off-site power for example would cause an automatic scram as the result of loss of primary cooling pumps and a drop in primary pressure as well as loss of secondary flow. This type of information (I) is provided to the event tree tool from the simulation program.

Outside of risk analysis, the same methodology of LENDIT can be used to help operators understand the necessary action to take during a transient. Formalization of LENDIT within an operating plant can help guide the development of operating procedures. The procedures can be developed such that the subset of parameters that are important to a specific transient are considered. The operators would only have to focus on the physical parameters important to the transient rather than the entire plant. Control systems can be designed to improve human performance with regards to operator actions.

System Sets

The System Set describes the state of hardware-based subsystems and components such as the primary system, but since our focus is on off-normal events, two examples are the emergency core cooling system (ECCS) or gravity driven cooling system (GDCS). These subsystems are typically called upon to mitigate off-normal conditions and activate based on State Set LENDIT scales (e.g. temperature, pressure etc.) but are described by their own LENDIT scales. For example, the GDCS has certain volume (L^3) and emptying time (*T*). Of special importance under off-normal conditions, such as a SBO, is the start-up time of emergency diesel generators and coast-down time of the primary coolant pumps and steam turbine (both *T*).

The state of the system is typically controlled in the simulation tool. RELAP5-3D contains control features and trips that allows for components to start and stop based on the State Set and operating procedures. With regards to DETs, the simulation is stopped when a component transition is required. The probability (D) of the component changing states is provided and a branching condition models allows for a change of state (e.g., EDG started or fails to start). The state set includes component states as well as possible transitions of component states. The development of the state sets incorporate the LENDIT scales by utilizing distributions of component transitions (D) and the number of components (N). The state of the components is used in the Branch-and-Bound algorithm to establish constraints for the simulation. This is used to limit state explosion into unfeasible states or solutions.

Resource Set

The LENDIT scales here pertain to existing safety systems, including those engineered to be used under hypothetical emergencies. However, this set also pertain to resources per beyond design basis or unanticipated events that are not part of the engineered safety system. For example, the most important resources may concern human factors; that is, operators as an available ‘resource’. Resource can also be in terms of ‘tools’ such as flashlights and walkie-talkies; these are needed resources under many emergency situations. Perhaps most important is that all involved in the response have common information; a matter of information and distribution (*I, D*).

Within a DET framework, the simulation tool is limited to the capabilities of modeling the resources to physical plant components used in the thermal-hydraulic analysis. However, indirect resources such as tools for communication eventually lead to providing input into engineered resource set elements. Therefore, the DET tool needs to include the capability to address resources such as the number of operators and human factors. The resource set within a DET tool can be expanded with the other simulation tools into a dynamic fault tree framework. Traditional fault trees rely on a Boolean algebra framework to solve for the top events in an event tree. This would allow for inclusion in plant states to model phenomenological effects to be taken into account for specific components. The physical stress on some components can have a significant effect on the ability to perform its intended function. Traditional ET/FT analysis does not have the capability to account for physical stresses on components. The DET framework utilizing S2R2 sets can include the affects on the distribution of the components from phenomenological conditions (e.g., pressure stress on a pipe).

Response Set

The LENDIT scales here refer to metrics describing the combined systems and human (1st responder team) response, recognizing the relevance and significance of the above Sets. Given that the 1st responder team is present (a Boolean '*Y* or *N*'), 1st responders must uniformly understand the situation at hand (*I*, *D*) or one generates two 'paths' based on differing levels of understanding. Further, from practice the team members (and institution) should know the average availability time of the emergency generator (*T*) and time when the core degrades (*T*) if the core is insufficiently cooled. These are typically considered within the emergency response procedures for the plant.

The response set is used to create the branching conditions within the DET. The branching conditions represent changes in plant states as the result of automatic or operator actions. The response set is used to provide input into the changes to the simulation input deck to create the branching conditions. Two or more input decks are created for each branching condition that represents the branches of a node. The response incorporates information from the resource set, state set and system set to obtain the desired condition. The response set is typically developed from operating procedures and plant manuals. As an example, when the reactor power exceeds some predetermined limit (State set), the scram system (Resource), will consider insertion of the safety rods (State set) and the Response set will result cause a condition within the plant to insert safety rods.

3.2 Summary of LENDIT metrics and S2R2 Set Theory

The concept of the LENDIT metrics and S2R2 set theory is a new approach to establishing the criteria for DETs. This approach is based on common sense practices developed using expert based knowledge. DET simulations have used similar but informal processes to establish the simulation boundaries. As an example, the branching conditions for the ADAPT code must be identified by the user and are typically based on input from plant safety manuals, operating procedures, and discussion with experts. The intent of the LENDIT metrics and S2R2 set theory is to formalize the process of developing the simulation boundaries.

The use of LENDIT metrics is also instrumental in developing the bounding functions for the Branch-and-Bound algorithm. Expert based knowledge with respect to plant transients can assist the analyst in determining the appropriate state set parameters to track to create the bounding regions to prune the DET and improve computational efficiency. As will be discussed, the selection of parameters is crucial in prevent over pruning of a DET and maintaining computational efficiency.

Chapter 4: Implementation in RAVEN

Development of DET involves two primary tools. The first tool is a simulation tool to replicate the thermal-hydraulics of a transient in a nuclear power plant. The second piece is a tool or framework to drive the simulation tool by providing modifications to the input deck as well as read in the parameters from the output of the simulation and determine the next branching step. The Idaho National Laboratory (INL) code RAVEN (Reactor Analysis and Virtual control Environment), which is part of the Multiphysics Object Oriented Simulation Engine (MOOSE) framework provides the necessary tools to couple the simulation tool to a risk analysis framework [13][23][25] .

The RAVEN package was initially designed as a control module for RELAP7, but was expanded into a probabilistic risk analysis tool capable of handling various methods for dynamic probabilistic risk assessment [13][23][25]. The RAVEN package contains the capabilities to do both Monte Carlo and Dynamic Event tree simulations. The framework is code agnostic, meaning that it can be modified to handle a variety of simulation tools. For this research, we chose to use RELAP5-3D, as RELAP7 is still in development. The following section provides a summary of the mathematical framework for the RAVEN methodology with regards Dynamic PRA.

4.1 Mathematical Framework for RAVEN

The mathematical framework for RAVEN was developed initially by solving Equation 1. The controlling state transitions can be evaluated using an operator splitting technique as follows:

$$\begin{cases} \frac{\partial \bar{x}}{\partial t} = \bar{F}(\bar{x}, \bar{v}, t) \\ \bar{C} = \bar{G}(\bar{x}, t) \\ \frac{\partial \bar{v}}{\partial t} = \bar{V}(\bar{C}, \bar{v}, t) \end{cases} \tag{8, 9, 10}$$

where C represents a monitored vector of the physical states, and V represents the controlled variables. Both C and V have lesser dimensionality than x.

As the transients reach a quasi-steady-state, the discretization of time steps for solving Equations (9,10) can be increased as a function of the system. Additionally, the number of control variables that dictate the transition conditions can be greatly reduced from that of the start of the transient. As the number of control variables is reduced, the probabilistic dynamics can be quantified using more of a heuristic approach where LENDIT scales and S2R2 sets can be used.

The mathematical framework developed for RAVEN is documented in Reference [23]. As stated above, RAVEN utilizes an operator splitting technique to as shown below:

$$\frac{\partial \bar{x}}{\partial t} = \bar{F}\left(\bar{x}, \bar{v}_{t_{i-1}}, t\right) \tag{11}$$

$$\bar{C} = \bar{G}\left(\bar{x}, t\right) \tag{12}$$

$$t_{i-1} \le t \le t_i = t_{i-1} + \Delta t$$

$$\frac{\partial \bar{v}}{\partial t} = \bar{V}\left(\bar{C}, \bar{v}_{t_{i-1}}, t\right) \tag{13}$$

where $\bar{x}$ is the unknowns solved using the simulation engine such as RELAP5-3D or RELAP7 where as $\bar{\upsilon}$ are the RAVEN regulated variables. There are a few reasons why an operator splitting technique is preferred. First, there is an inherent time lapse after which control systems react. Second, the control system reaction can shift the system among two distinct discrete states where there will be first order numerical errors, especially if the discontinuity has not been handled appropriately.

The simulation tool is responsible for handling Equations (11, 12) in order to find $\overline{C}_i$. Also, Equation (13) receives $\overline{C}_i$ from Equations (11,12) and finds $\bar{\upsilon}_{t_i}$, which it then sends to Equations (11,12). Figure 8 shows a flow chart assuming the RELAP-7 interface. With respect to implementation in RELAP5-3D, the flowchart is nearly identical with the MOOSE framework block replaced by RELAP5-3D. The RAVEN control logic provides the necessary changes to support a DET. The framework for RAVEN allows for use of different simulation tools and can support additional simulation tools such as MELCOR. By the nature of RAVEN, when defining the input framework for RAVEN, the user defines the controlling parameters $\bar{\upsilon}_{t_i}$ in the input deck. Within RELAP5-3D, the controlling variables can be self-contained within RELAP5-3D or included outside of RELAP5-3D as is done in the DET methodology. RELAP5-3D allows for control variables to be monitored within the simulation and trip functions to be defined based on the values of the control variables. With respect to DETs, the RELAP5-3D simulation can be stopped and an external wrapper used to modify/change conditions allowing for restart of the simulation from the last available time step. The external wrapper is a file containing information on which parameters need to be changed as the result of branching condition reached in the DET simulation. The external wrapper creates a '.xml' file that can be read into RAVEN which in turn interacts with the RAVEN Code Interface class and creates the new input file. The external wrapper in this research contains the S2R2 set information. This importantly provides the means to undertake a time-based thermal-hydraulic simulation.

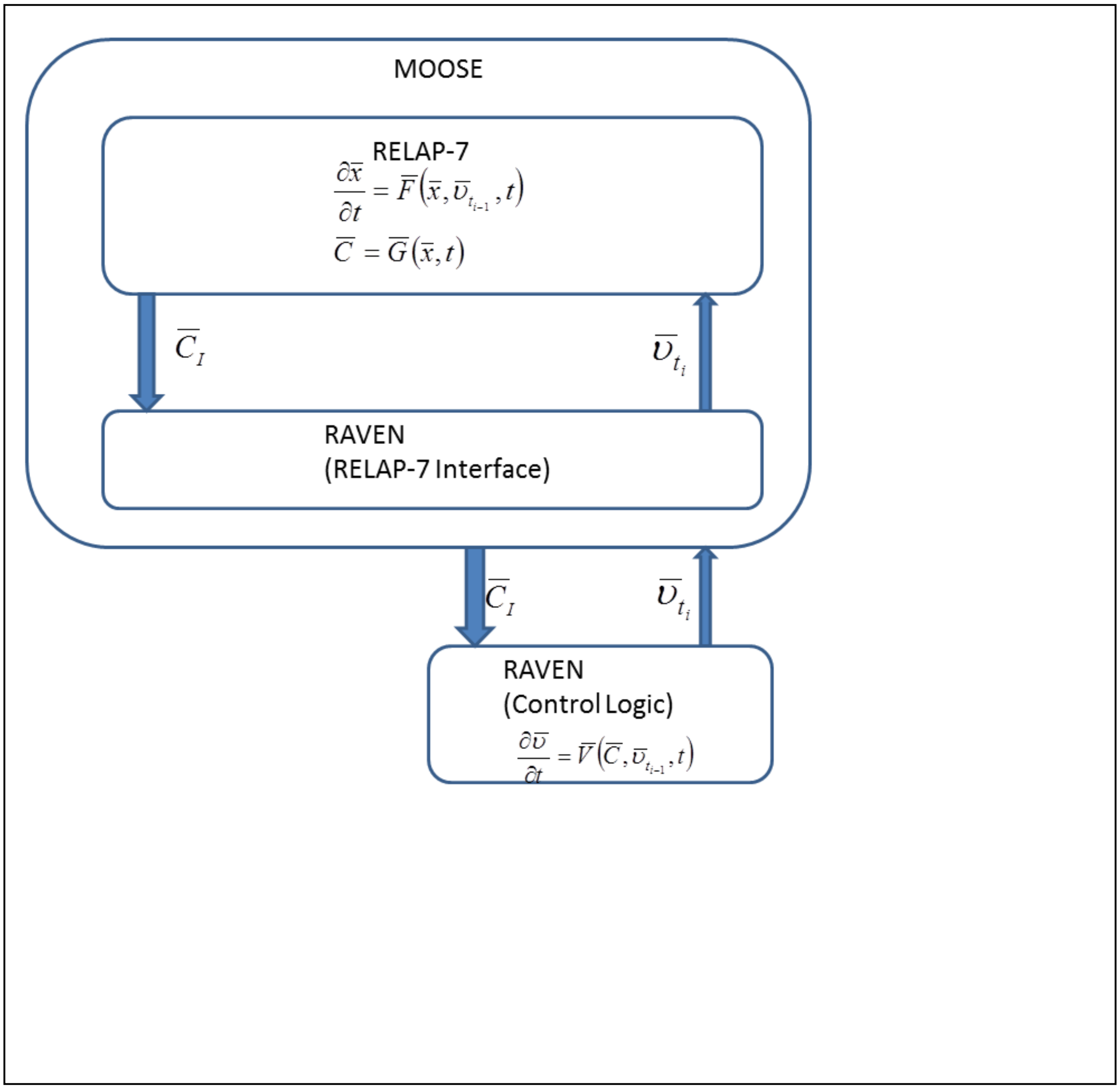

Figure 8. RAVEN Framework as implemented with RELAP7.

Reference [23] provided a more refined operator splitting technique, by adding auxiliary variables to the set of differential equations [12]. The main purpose of the auxiliary variables is to act as an effective and useful means to support the control system. Also, they can contain additional information beyond the capacity of $\bar{x}$ and $\bar{\upsilon}$. Below is the new set of equations:

$$\frac{\partial \bar{x}}{\partial t} = \bar{F}\left(\bar{x}, \bar{\upsilon}_{t_{i-1}}, t\right) \tag{14}$$

$$\begin{gathered} \bar{C} = \bar{G}\left(\bar{x}, t\right) \\ t_{i-1} \le t \le t_i = t_{i-1} + \Delta t \end{gathered} \tag{15}$$

$$\frac{\partial \bar{a}}{\partial t} = \bar{A}\left(\bar{x}, \bar{C}, \bar{a}_{t_{1-1}}, \bar{\upsilon}_{t_{i-1}}, t\right) \tag{16}$$

$$\frac{\partial \bar{\upsilon}}{\partial t} = \bar{V}\left(\bar{x}, \bar{\upsilon}_{t_{i-1}}, \bar{a}, t\right) \tag{17}$$

The auxiliary variables are intended to address non-Markovian systems that violate the Markovian assumption that the dynamic PRA equations are based. A Markov process is based on the present condition without regards to the history of the process. Auxilliary variables such as time-integrated stress on a component or valve cycling have failure probabilities that are based on the history. This new auxiliary variable allows for tracking history of the components and still maintaining the Markov process for those identified processes and sub-systems where in the history of ‘use’ is not of significance or immediate concern.

Equation (16), which is the new differential equation, contains the auxiliary variable $\bar{a}$.

Just like the monitored variable $\bar{v}$, it also has time steps. Figure 9 shows the process for RAVEN coupled with RELAP5-3D.

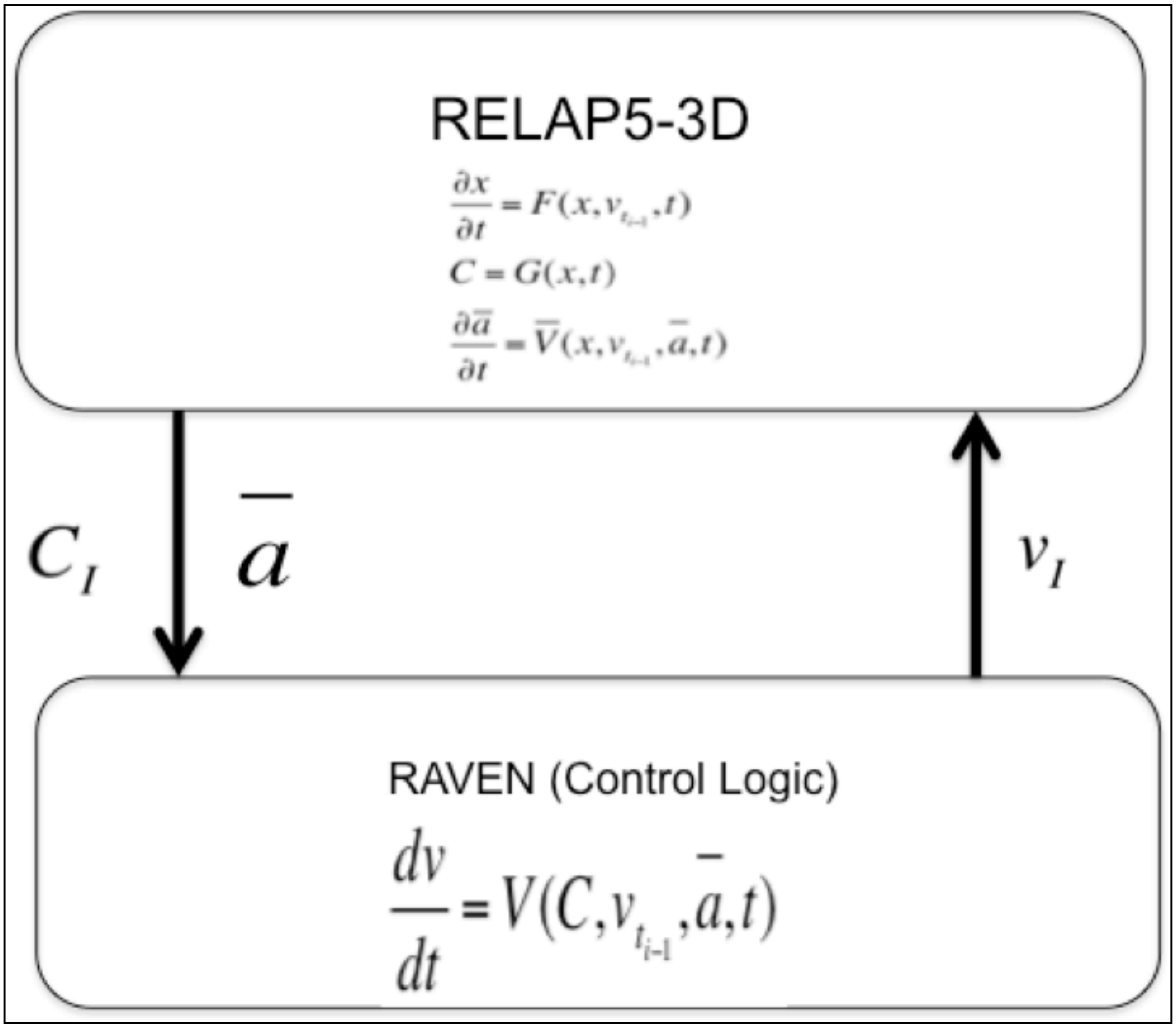

Figure 9. RELAP5-3D/RAVEN control process.

4.2 Description of the RAVEN Framework:

The RAVEN Framework was developed using the PYTHON scripting language. PYTHON has the advantage of allowing for Object-Oriented programming structure. The

RAVEN framework allows a simpler method for coupling various simulation codes without accessing the simulation source code. As discussed above, the methodology was employed in this research with RELAP5-3D.

The RAVEN code utilizes a set of classes to manage the sampling structure, modifying input decks and running the simulation on a High Performance Computing (HPC) cluster. The primary classes of interest within this research are the Samplers class (Samplers.py), Distributions class (Distributions.py), and the Interface class (codeInterface.py).

The sampler class allows for the methods for running the dynamic event tree simulation. It essentially contains the methods for performing dynamic PRA such as Monte Carlo sampling, Latin Hypercube and Dynamic Event Tree. Within this framework we have inherited the dynamic event tree class, which is part of the Sampler class. The dynamic event tree class contains the methods for starting the simulation, determining the event cause for a branching condition, determine the probabilities for each of the branching condition, and restarting the simulation for each of the branching cases. The class does not actually control the start of the simulation, but rather returns instances back to other classes in RAVEN that allow for the actually running the simulation on the HPC cluster.

In order to implement the Branch-and-Bound algorithm in RAVEN, the Dynamic Event Tree class was inherited and modified accordingly. The modification included the addition of a Constraints class. The constraints class is used to evaluate the thermal-hydraulic data as well as probabilities. The constraints class keeps a running list of success parameters to evaluate whether or not a simulation may or may not end in a success. If it is determined that the simulation will end in success, the constraints class returns a Boolean variable of false and thus, the particular branch does not contain a feasible solution. Within the dynamic event tree class, if constraints returns false, the branch is pruned and is not added to the queue. The constraints class is contained in Appendix A.

In order to more efficiently evaluate the dynamic event tree, the dynamic event tree class was modified. The original implementation method for dynamic event trees allowed for the branching conditions to be added to a queue, and the models for those branching conditions returned to RAVEN in the order they were added to the queue. Implementation of the Branch-and-Bound method first involves extracting the node or branch from the queue with the highest probability. The branch probability is compared to previous failure conditions for that particular system set. If it has a higher probability of failure, the state sets of the branch are compared to determine if it will yield additional information (i.e., has not been shown to reach a cold safe shutdown for that system set given the state set). If the branch is pruned, another branch from the queue is evaluated.

The Distribution class within RAVEN contains all the possible distribution functions available. The distribution functions are specified in the RAVEN input deck. For the purposes of the dynamic event tree, the user specifies the values from the cumulative distribution function. The frequency or number of samples is left up to the users discretion. The LENDIT scales and knowledge of the progression of events can be used to help limit the number of samples. As an example, if it is determined that EDG recovery for SBO needs to occur within the first 2 hours following loss of battery power, sampling at a high frequency after 2 hours may not provide much useful information. However sampling at a high frequency below 2 hours may provide more useful information. This type of decision making in setting up the problem helps seed the constraints in place by the Branch-and-Bound algorithm before the simulation even begins and results in a more efficient run times.

Chapter 5: Sensitivity and Uncertainty Analysis

Evaluation of modeling uncertainty within this DET framework was performed by randomly sampling parameters of interest. The parameters were selected based on the ability for energy creation or removal. Energy removal from the fuel and cladding is of tantamount importance. Additional parameters and modeling aspects may be chosen as well. This research limits the selection of those parameters that are inherently important for a cold safe shutdown (i.e., energy removal is less than decay heat energy). The intent is to determine which parameters greatly influence modeling uncertainty within a risk-informed framework. In other words, for accident sequences determined in the DET to result in clad failure, a formal PIRT process is used to determine the results of failure.

The PIRT consisted of a method described in References [26]. The method involves randomly sampling various parameters and then using the correlation coefficients between variables to establish a PIRT ranking. The Spearman Rank Correlation has been chosen as it "is a nonparametric measure of statistical dependence between two variables.[27]" The Spearman Rank correlation applies to both linear and non-linear problems as opposed to the Pearson correlation coefficient, which provides a measure of the linear correlation between two variables. The Spearman Rank correlation coefficient is defined as [27]:

$$\rho = 1 - \frac{6\sum\left(x_i - y_i\right)^2}{n\left(n^2 - 1\right)} \tag{10}$$

A correlation coefficient between two variables is a value between -1 and 1. A coefficient value that approaches 1 indicates a stronger positive correlation between variables. A value approaching -1 indicates a strong negative correlation between variables. As the value of the coefficient approaches 0, correlation between variables weakens. By using this methodology, the correlation coefficients are used to develop the PIRT ranking for the various parameters of interest. The following criteria for the PIRT ranking was used to evaluate the specific parameters against the peak clad temperature in the model:

$$|\zeta| \in [0.01, 0.29] \Rightarrow \text{Weak relationship (PIRT=Low)}$$

$$|\zeta| \in [0.30, 0.69] \Rightarrow \text{Moderate relationship (PIRT=Medium)}$$

$$|\zeta| \in [0.69, 1.00] \Rightarrow \text{Strong relationship (PIRT=High)}$$

By identifying parameters that result in higher correlations to the response functions such as peak clad temperature, their impacts can be better understood such that reconsideration of modeling techniques and experimental validation provides a possibility for improvement in the safety margin of an operating reactor.

Implementation of this methodology was performed using the DAKOTA [29] code coupled with RELAP5-3D [31]. As discussed above, RAVEN is used to guide the DET simulation, while at each branching condition; a DAKOTA simulation is performed to determine the effect of the various parameters at this branching condition. The DAKOTA Latin Hypercube Sampling (LHS) method was used to more efficiently evaluate uncertainties in the models as opposed to an analogue Monte Carlo sampling.

LHS has the advantage of sampling multidimensional variables without the need for additional samples. The samples are taken from a grid or Latin square. LHS are taken from the cube with equal probability intervals. In order to satisfy the criteria for a Latin square, there is only 1 sample in each row and each column. LHS ensures that the real variability in represented by the random numbers. In traditional Monte Carlo methods, the random sampling is performed and there is no guarantee on the variability [30].

Additional sensitivity methods for performing PIRT have been proposed. Zhao and Mousseau [32] have proposed a method utilizing forward sensitivity methods that allows for time-dependent sensitivity analysis as part of the solution of the Jacobian Free Newton Krylov method. These methods are evaluated for incorporation into RELAP7.

Additional methods have been proposed for QPIRT utilizing PI groups. A PI group is defined in a finite control volume model as the fluid particle residence time divided by the characteristic time of the physical transfer process. The higher the PI group for a particular phenomena at the control volume/component level provides a higher degree of importance.

Numerous sensitivity methods have been proposed and can be used as desired based on the codes used for simulation and the applicability to evaluate parameters of interest. For this research, we have chosen to use the Spearman Rank correlation coefficients, as it is relatively easy to implement within this research and into the RAVEN framework. Future work may utilize other sensitivity methods.

Chapter 6: Pressurized Water Reactor Station Blackout

The PWR used in this case study is the reference plant, the Zion Nuclear Power Plant located on Lake Michigan, Illinois. The Zion Nuclear Power Plant is a Westinghouse 4-Loop PWR Design [33]. This design consists of 4 steam generators, each on a separate coolant loop. A single pressurizer is located on one of the loops, designed to control the pressure within the primary coolant system. The pressurizer is equipped with 2 Power Operated Relief Valves (PORVs) and 2 safety relief valves (SRVs). The plant is rated at 3250 MWt. A summary description of the Zion NPP is provided in Reference [33]. A diagram of the Zion Nuclear Steam Supply System (NSSS) is shown in Figure 10. An existing RELAP5-3D "deck" of the plant was used for this work.

For the intent of this research, a SBO is evaluated. The SBO in this analysis is simplified to a Loss of Off-site Power (LOSP) followed by immediate loss of battery power. Recovery from the loss of battery power is assumed to be feed-and-bleed, which involves injection of coolant from the ECCS and removal of energy through the PORVs. Additional recovery options are possible, however, for the intent of this research, the recovery process is simplified to demonstrate the applicability of the Branch-and-Bound algorithm to DETs.

The important features related to the SBO is the reactor scram system, loss of battery power, pressurizer PORV, High Pressure Injection System, and the Charging system. Table 1 provides a summary of the steady-state conditions of the Zion NPP [35]. The engineered safety features of the PWR plant and BWR plant (Section 7) are discussed in such text by Knief [35]and Glasstone and Sesonske [36].

Emergency cooling during recovery of the SBO can be supplied by the high pressure injection system (HPI). The HPI system consists of two charging pumps and two safety injection pumps (SI). The 2 charging pumps are each designed to provide up to 150 gallons per minute (9.46 l/s) of flow at 2800 psi (19.35 MPa). The SI system consists of 2 high pressure pumps designed to provide 400 gallons per minute (25.23 l/s) at 1085 psi (7.48 MPa) [33].

Pressure relief can be provided through 2 PORVs located on the pressurizer. Each PORV has a 64.6 lbm/hr/MWt (29.3 kg/hr/MWt) capacity. In addition to the PORVs 3 safety relief valves each with a capacity of 129.2 klbs/hr (16.3 kg/sec) at the low setpoint value of 2485 psig (17.1 MPa), can provide relief to the primary coolant system in the event the PORVs fail or cannot relieve pressure during a transient [33].

Table 1. Steady-state operating parameters of the Zion NPP [35].

Parameter	**Value**
Reactor Power	3250 MWt
Pressurizer Pressure	15.51 MPa
Pressurizer Water/Steam Volume	60/40%
Total RCS Flow	17,010 kg/s
Cold Leg Temperature	549.9 K
Hot Let Temperature	585.5 K
SG Pressure	4.964 MPa
Feedwater Temperature	493.5 K
Steam Flow per Generator	440.9 kg/s
Liquid Volume in each Steam Generator	52.05 m^3

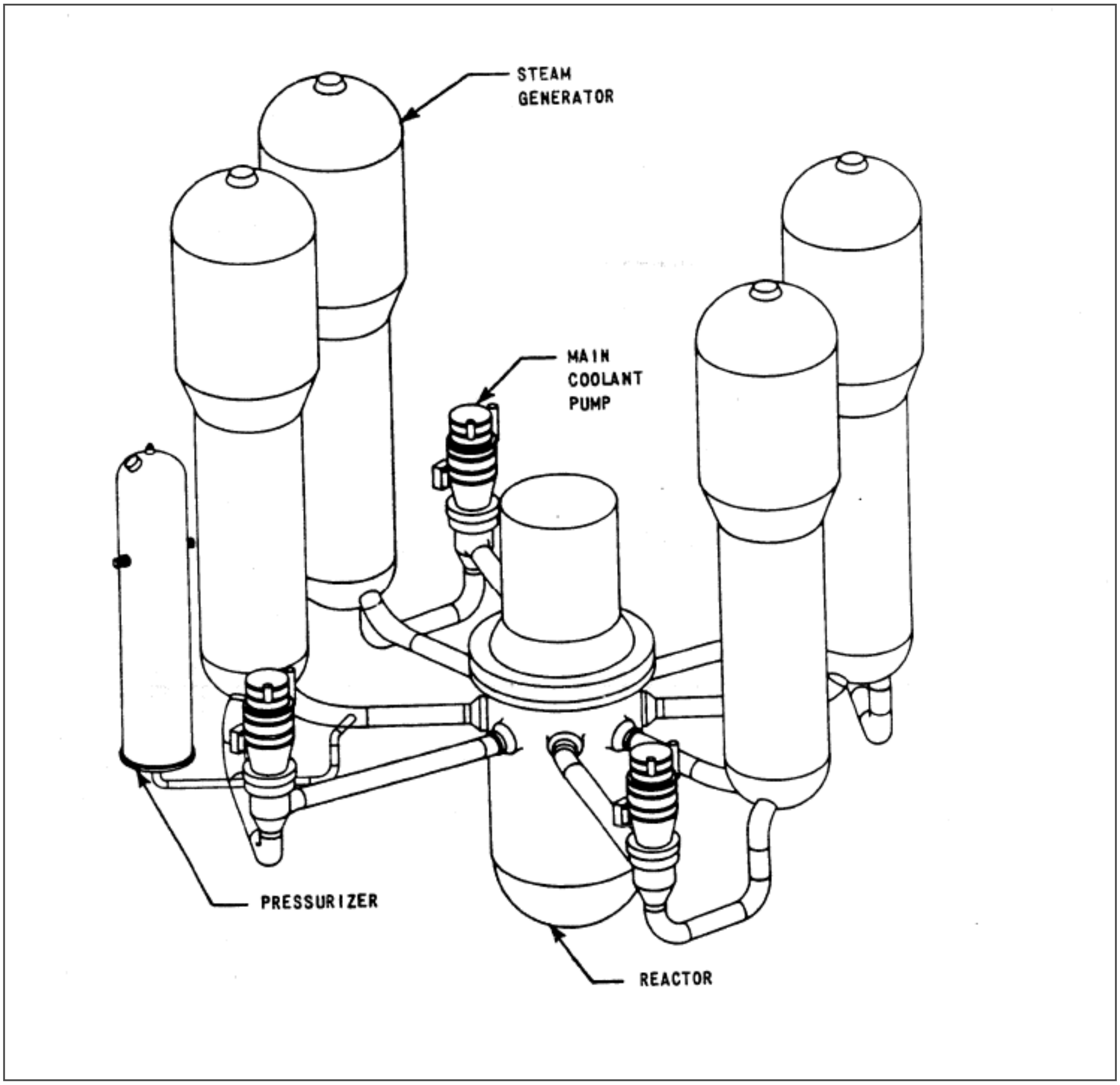

Figure 10. Diagram of a Westinghouse 4-Loop PWR [33].

6.1 Classical Event Tree Model of the PWR SBO

The classical event tree approach to the PWR LOSP is presented in Figure 11 and Figure 12. Table 2 provides a summary of the top events for the classical event tree [38]. The sequence of event associated with a PWR LOSP is as follows:

- LOSP results in an automatic reactor scram due to low primary coolant pressure (System State and Response Sets)
- Auxiliary feedwater provides secondary cooling (System, Resource and Response sets)
- Service water cooling is provided to containment fans, diesel generators, and component cooling (Resource and Response sets)
- Seal LOCA as the result of a loss of component cooling water (System and Response sets)
- Operators attempt to restore AC power as the result of a loss of DG (System, Resource, and Response sets)
- Operators actuate Feed and Bleed (System, Resource and Response sets)

The simplified DET discussed in this section assumes success of the reactor scram (transfer to LOSP-1), followed by a time-dependent failure of auxilliary feed water, loss of service water, component cooling, and success of seals avoiding a LOCA. The simulation then assumes a time-dependent success of the power recovery and success of feed-and-bleed. If feed-and-bleed fail, the end-states are related to core damage and the numbering on the right hand side of the ETs, represent different end-states based on the ability of various safety systems used to mitigate a release. These safety systems are not included in this research. In the classical event tree, the time-dependent modeling is not considered and to occur immediately when challenged. The remaining top events are assumed to be successful. The classical event tree has determined this event sequence to result in success and thus avoids core damage. Many of the initial response actions are performed automatically by the engineered safety features (e.g., reactor scram system) of design certified plants. However, depending upon the timing of events, this may not be the case.

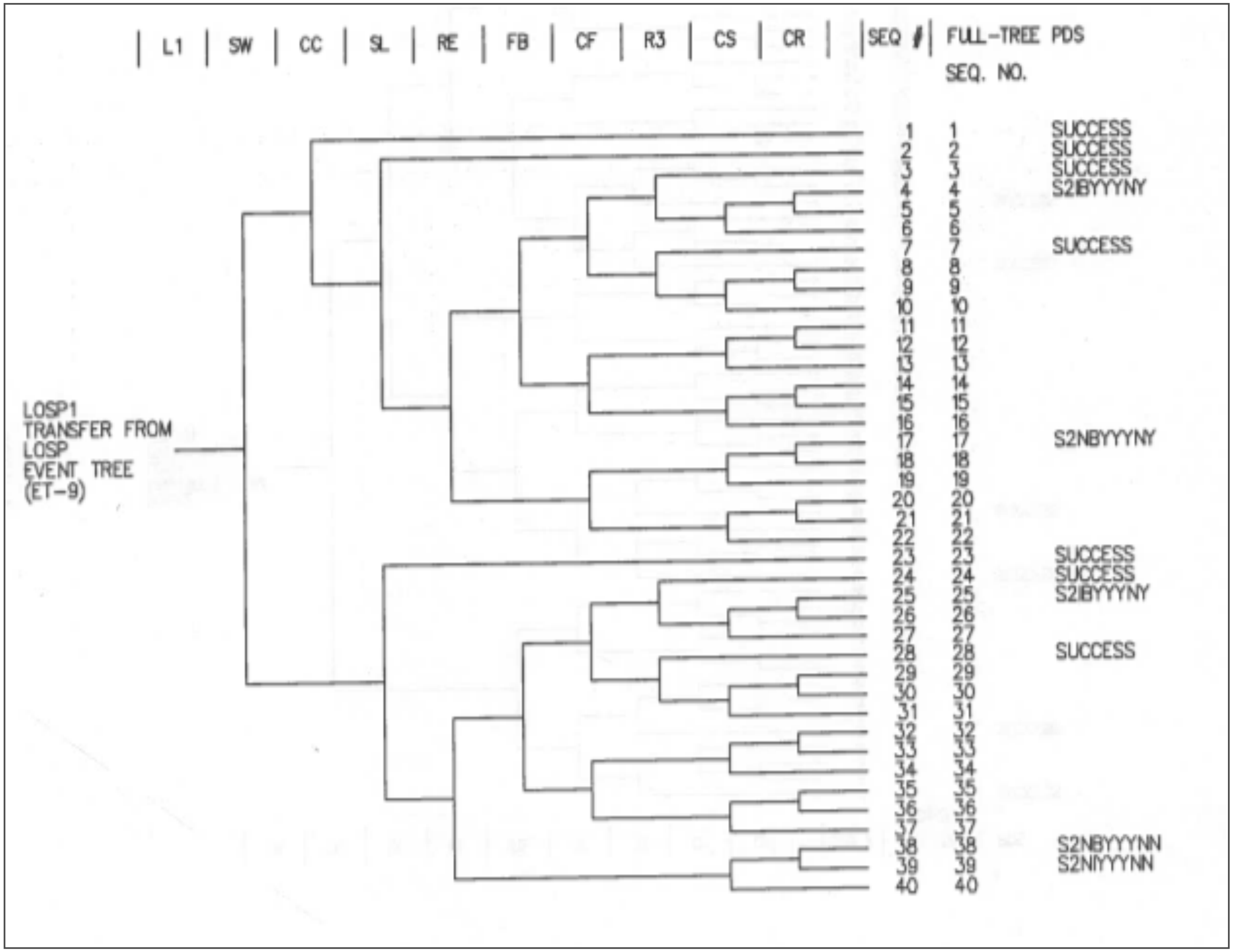

Figure 11. LOSP Event Tree for Zion Nuclear Power Plant (Reference [38]).

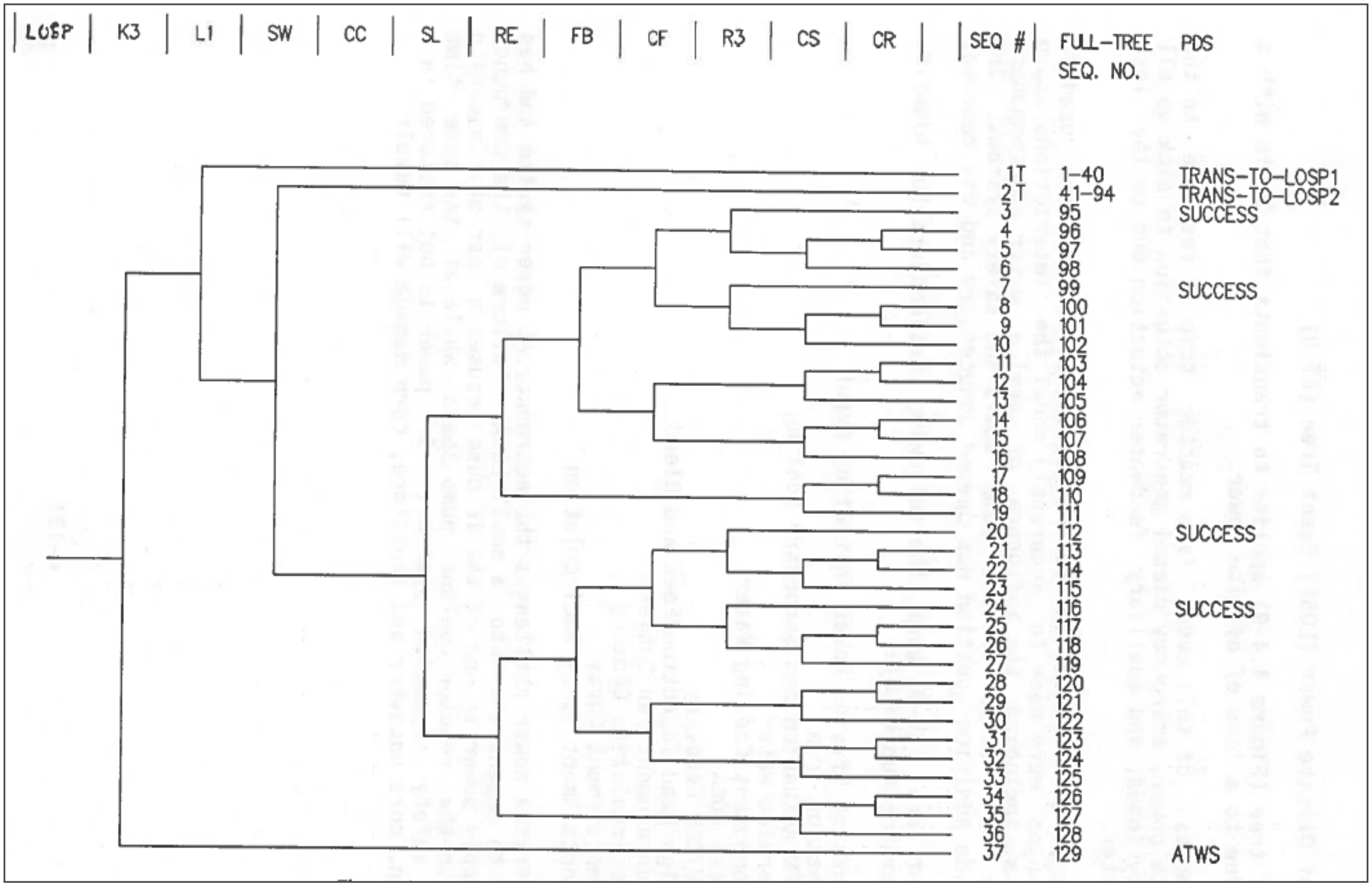

Figure 12. LOSP-1 Event Tree for Zion Nucler Power Plant (transfer from LOSP ET) (Reference [38]).

Table 2. Top events for the Loss-of-Offsite Power.

TOP EVENT	TOP EVENT Description	Probability of Failure
LOSP	Loss of Off-Site Power	7.8E-2/year
K3	Reactor Trip on LOSP	3.0E-6
L1	Aux feedwater system actuation and secondary cooling	3.4E-5
SW	Service water cooling to containment fan, component cooling water system, and diesel generators	2.4E-5
CC	Component cooling water system provides cooling to reactor coolant pump seals	4.1E-5
SL	Seal LOCA given failure of the component cooling water system	7.3E-1
RE	Restoration of off-site power in time to prevent core damage	8.0E-2
FB	Feed-and-bleed Actuation	1.2E-5
CF	Containment fan coolers	9.2E-5
R3	Recirculation cooling	3.8E-4
CS	Containment spray	4.6E-4
CR	Containment spray recirculation	1.6E-3

The primary top events of interest in this example are L1, RE, and FB per Table 2. The RE and FB top events are combined within the DET as simply recovery as the result of the SBO. The timing of the L1 and RE/FB are of interest. It is assumed that recovery of the system is performed within 8 hours following LOSP. It is assumed that complete restoration will be obtained within 8 hours of the start of the simulation. The actions required for recovery of this Generation II plant require a human interface. The design of Generation IV+ will include passive safety systems, reducing the need for human interface.

The classical event tree analysis assumes that for feed-and-bleed with loss of secondary cooling, the operators must manually open both PORVs to allow depressurization to a pressure where the HPI pumps can inject satisfactory cooling. Success can occur with one PORV if a charging pump is available. In either case, one high-pressure injection pump is required [38].

The event tree described above lacks any discussion with regards to timing of events and the timing of operator actions. An additional analysis for a Westinghouse 4-Loop PWR was evaluated to provide some understanding of the transient [39]. The event tree for this analysis is presented in Figure 13. What can be seen is the timing of loss of the secondary system immediately following LOSP or loss in the time frame of 2 to 12 hours. If the secondary is lost immediately, the time to recovery AC to vital systems is much less. If secondary heat removal is lost in the 2-12 hour range, the time to recover AC without core damage is on the order of 24 hours. The uncertainty in the 2-12 hour range and 12-24 hour range is rather large, and the probability of core damage in that range may vary greatly. This information can be used in support of the LENDIT metrics. Sampling of the CDF for loss of secondary should be primarily focused within the first 2 hours with less sampling points after two hours. If the loss of secondary occurs after two hours sampling should be performed for time frames out to 24 hours.

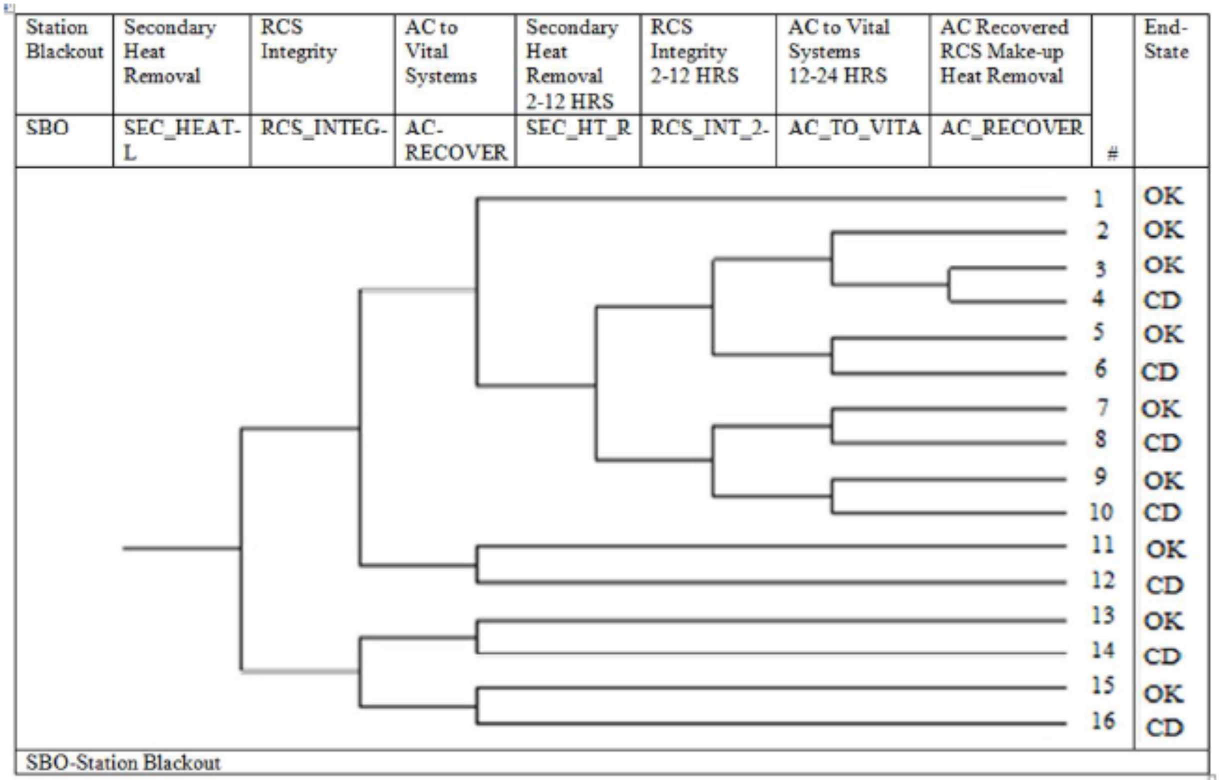

Figure 13. Event Tree Analysis of PWR SBO with timing of event considered.

6.2 Dynamic Event Tree Development

The transient described above involves a loss of off-site power, resulting in a reactor scram. It is assumed that SBO occurs when diesel generators and battery backed power are unavailable to provide cooling for the reactor. Recovery from SBO is provided by feed-and-bleed. Other possibilities can provide recovery such as re-establishing secondary cooling with the primary reactor cooling pumps or activation of the residual heat removal system. The feed-and-bleed method requires the operators to actuate the HPI system and open the PORVs to allow for energy removal. The Westinghouse 4-Loop PWR has two independent trains of each injection system. In other words, there are two SI pumps and two charging pumps. Both systems provide feed into each of the loops in the 4-Loop plant. Bleed is provided by actuation of 2 of the PORVs. For this model the PORVs are modeled as one valve. Failure or unavailability of the different combination of the HPI is however evaluated in this model. Within the S2R2 framework, the SI and charging pumps represent both the resource and response sets needed to prevent core melt. Information regarding the minimum capacity as a function of time can provide operators with I(information) to make a decision about which pumps need to be provided with power first. With an understanding of the reactor pressure (P) and temperature (T), the operators have the ability to rank the importance of which pumps are required to start first.

The probability of a SBO is assumed to be represented by a gamma distribution with a mean of 0.5 and variance of 0.89. Figure 14 provides a diagram of the distribution assumed in this analysis. The distribution assumed for SBO was arbitrarily picked such that sampling is occurring within the first two hours and can be modified according to specific plant conditions. The recovery from SBO by feed-and-bleed is represented by a gamma distribution with a mean of 0.33 and uncertainty of 0.23 [40]. Plant specific data may be used to modify the simulation as needed. The CDF as a function of time is shown in Figure 14. The unavailability of the HPI is summarized in Table 3. The branching probabilities for recovery are determined by the probability of recovery multiplied by (1-unavailability) of the various pump combinations.

The above data and LENDIT metrics, the S2R2 data is used to define the various system, state, resource, and response sets available. A summary of the S2R2 sets is provided in Table 4.

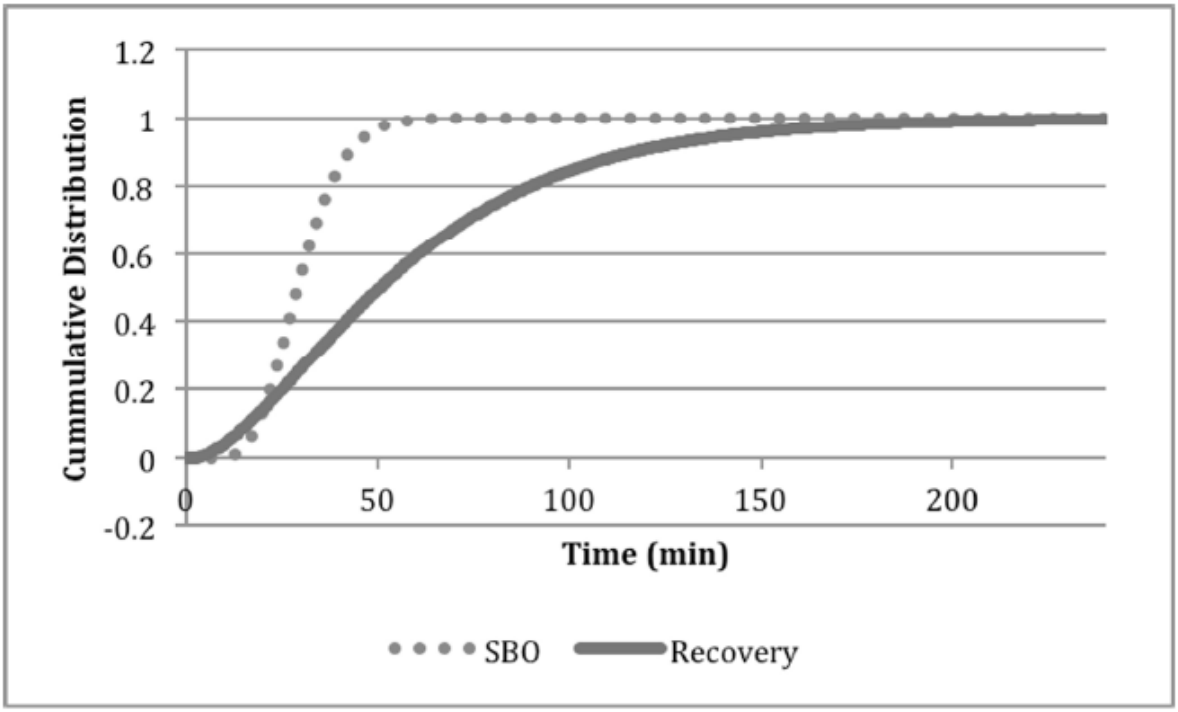

Figure 14. Cumulative distribution for PWR SBO and recovery.

Table 3. Availability of emergency cooling capability.

Emergency Cooling Capability	Probability
2 HPI 2 CCP	9.789E-1
1 HPI 2 CCP	1.000E-2
0 HPI 2 CCP	1.000E-4
2 HPI 1 CCP	1.000E-2
1 HPI 1 CCP	1.000E-3
1 HPI 0 CCP	1.000E-5
0 HPI 0 CCP	1.000E-7

Table 4. Summary of S2R2 sets used for PWR SBO

Set	**Description**
State	Primary pressure Liquid level Liquid mass Internal energy density decay heat
System	Normal Shutdown SBO (no EDG or battery power) Recovery
Resources	Normal shutdown cooling HPI – 2CCP and 2 SI 2 PORVs
Response	Scram Secondary heat removal Feed-and-Bleed

6.3 RELAP5 MODEL OF THE ZION NUCLEAR POWER PLANT

The Zion Nuclear Power Plant RELAP5-3D model was used in this analysis [33]. The Zion plant has been considered a reference plant for many analyses, as it has been decommissioned and represents a typical PWR reactor [33]. The RELAP5 model was based on the “typpwr.inp” model provided with the RELAP5 code. The model was modified to create the steady-state operating conditions listed in Table 1. The “typpwr.inp” model was originally used to demonstrate a loss of coolant transient. Changes to the model include removing the break condition used in the loss of coolant accident, adding a loss of main and

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The steady-state parameters were evaluated in the modified model and compared to those in Table 1. The values are comparable and it is determined that the model is adequate to demonstrate the transient for a loss of heat sink. Additional changes should be made based on real plant data that is currently not available; however, these details will not affect the ability to demonstrate the capabilities of the Branch-and-Bound algorithm applied to DETs.

6.4 Transient Description

The LOSP transient occurs as the result of the loss of commercial power to the plant resulting in a reactor scram followed by decay heat cooling provided by the emergency diesel generators. Heat removal is provided by the secondary system using the Auxiliary Feed Water. The primary reactor coolant pumps continue to circulate cooling through the primary and will be lost upon loss of diesel generators. If the diesel generators are lost, the plant enters a SBO and the auxiliary feed water will be lost. Recovery from this condition, as shown in

Figure 13 requires recovering the diesels or off-site power and cooling through feed-and-bleed in a timely manner. Feed-and-bleed recovery requires human intervention. The classical ET analysis requires that injection be performed using one out of two SI pumps or one out of two CCP for conservatism. This also requires the operators to manually open the PORVs. If only one PORV is opened, one CCP is required. The timing of events as discussed before is not included in the classical ET analysis. In this dynamic event tree analysis, we will examine this assumption, particularly since SBO occurs immediately in classical analysis. In a DET, with coupling to the simulation code, we can examine the effects of energy removal from the core prior to SBO initiation.

6.5 Transient Analysis Parameters

The above RELAP5 model was used to evaluate the dynamics of the LOSP/SBO. Three parameters were considered for this case study with regards to the DET: the time of SBO, time of recovery, and availability of pumps for recovery. The parameters considered for the SA/UQ process included, the PORV capacity, initial reactor power, pump capacity, and reactor scram worth. The parameters for the SA/UQ process were chosen as they have were considered to have a large impact on the overall goal of achieving safe shutdown. These parameters directly effect the deposition of energy into the reactor and the ability to remove energy from the reactor.

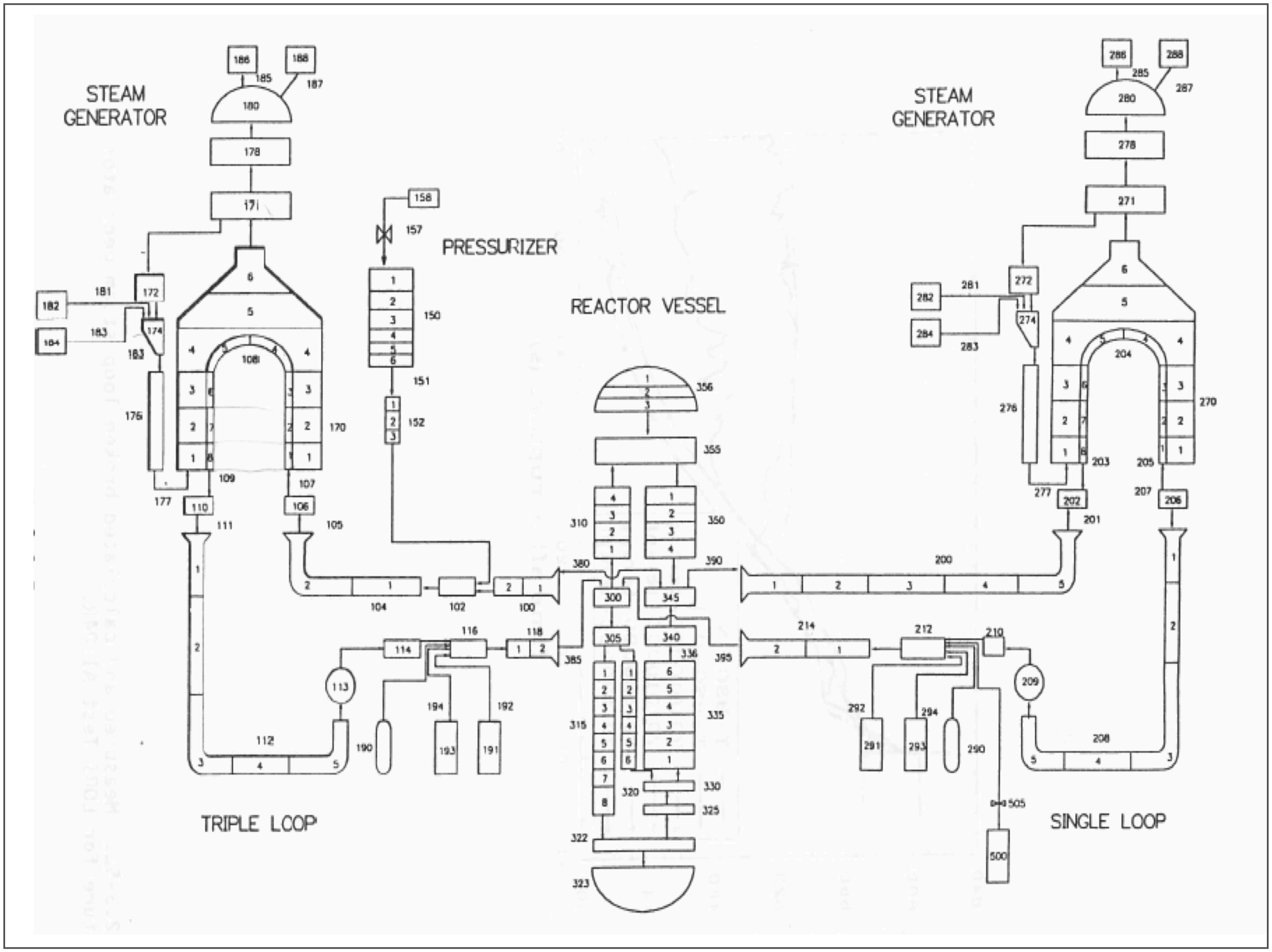


Figure 15. Nodalization diagram of the Westinghouse 4-Loop PWR Reference plant (Zion) RELAP5 Model.

6.6 Dynamic Event Tree Simulation of the PWR SBO

The PWR SBO model was run using the RAVEN interface with RELAP5-3D. Two separate simulations were performed to demonstrate the capability of the Branch-and-Bound algorithm. The first simulation performed consisted of a "brute force" method with no optimization. Using this simulation, a comparison can be made with regards to the maximum amount of efficiency obtained using the optimization algorithm. The simulation for the "brute force" method resulted in over 1500 nodes with approximately 500 leaf nodes. The number of failure nodes was approximately 120 with 380 success nodes.

Several parameters were monitored during the simulations, which were defined by the LENDIT metrics. The parameters that are of most interest are associated with heat removal from the reactor. With regards to optimization, the thermodynamic parameters associated with convective heat transfer are of most interest in defining bounding functions for the Branch-and-Bound algorithm. In particular, the liquid enthalpy (E), pressure (P), liquid mass (M), and liquid level (L) have the largest impact on peak clad temperature. Changes in these parameters can have direct impact on the ability to remove heat from the reactor core. In addition to these parameters, reactor power (E) associated with decay heat is considered as well since the over-arching approach for developing the bounding functions is associated with energy in minus energy out. Figure 16 through Figure 19 provides a time-dependent plot of the parameter considered important for the highest probability of failure cases with 2 CCP available and 0, 1, 2, SI pumps availability. Also shown are a success cases for the same plant state, with recovery occurring prior to core failure. The internal energy density shown in Figure 16 shows that once recovery is obtained the energy density drops steeply. If recovery is not obtained it keep increasing. Similarly (Figure 17), the reactor pressure will drop once feed-and-bleed is initiated as the “bleed” will cause a significant amount of pressure decrease. The pressure remains high until the PORVs are actuated and then decreases rapidly. These argument, as self-evident, are all with respect to time.

The liquid level shown in Figure 18 will continue to decrease as the reactor boils the water off during the SBO. Once feed-and-bleed recovery are initiated, the level returns with the presence of the 2 CCP. The availability of the SI pumps does not have an impact on recovery. This is the result of fact that the operating pressure for SI pumps is below the transient pressure until t=3000-5000 seconds in the transient (transient begins at 2000.0 seconds). The capacity of the CCP can have an impact on the final results as the flow rate from the CCPs may be near the amount of fluid lost through the PORVs.

Figure 20 through Figure 23 provides a similar analysis for the cases with 1 CCP. Similar behavior is noted in these simulations with internal energy density continuing to increase until recovery is initiated. The energy drops to a lower value depending upon the availability of the SI pumps as can be seen in Figure 20 . The reactor pressure as shown in Figure 22, presents similar behavior as seen in in the CCP cases. The liquid level in the case of 1 CCP drops significantly lower than if 2 CCPs were available. It is demonstrated that if recovery does occur, even with core uncovery, cladding damage can be prevented provided the timing of recovery is over a shorter time-scale. Similar behavior is shown with the liquid mass in the primary system, which would be expected as liquid level is directly correlated to liquid mass.

Once recovery has occurred, we note that the pressure fluctuations that is apparent in almost all cases with recovery. Some of them are more pronounced or lag behind others. This may be attributed to boiling in the core followed by collapse of vapor “bubbles.” The overall trend, however, is pressure decreasing in time.

Figure 24 through Figure 27 demonstrate the same thermal-hydraulic parameters as described above without the availability of the CCPs, however, these cases all resulted in failure. What can be seen is the energy density continues to increase until the PORVs are opened and then decrease with a slight increase as pressure begins to build as the result of boiling in the core. Figure 25 shows that for early actuation of recovery with no charging pumps, the pressure decreases and then spikes. This is mostly due to coolant entering in from the SI system, but at the pressure of the transient, more coolant is boiling and escaping the primary system (coolant mass loss) through the open PORVs. As the pressure increases, less coolant is injected into the core. Eventually, critical heat flux is reached and cladding degradation is reached.

As discussed above, success in the traditional PRA assumes that actuation of 2 PORVs with 1 SI pump will result in success. The DET analysis performed in this section examined an initial reactor power of 3600 MWth. Reference [38] PRA was based on the thermal-hydraulics of a reactor operating at 3250 MWth. A reduction in operating power may result in actual success as will be evaluated in the sensitivity analysis section.

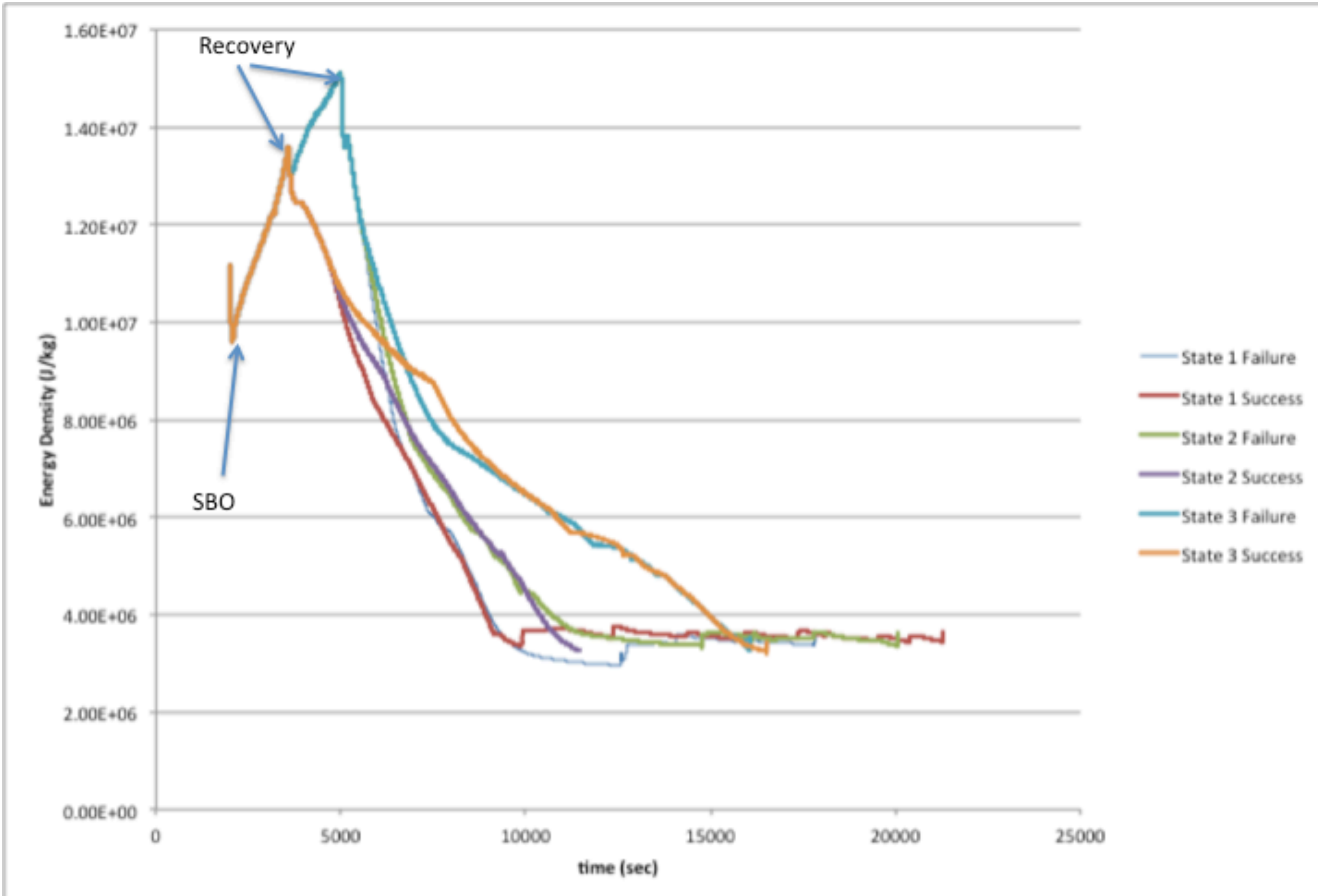


Figure 16. Internal energy density for states 1, 2, 3 (2 HPI, 1 HPI, 0 HPI) with 2 CCP.

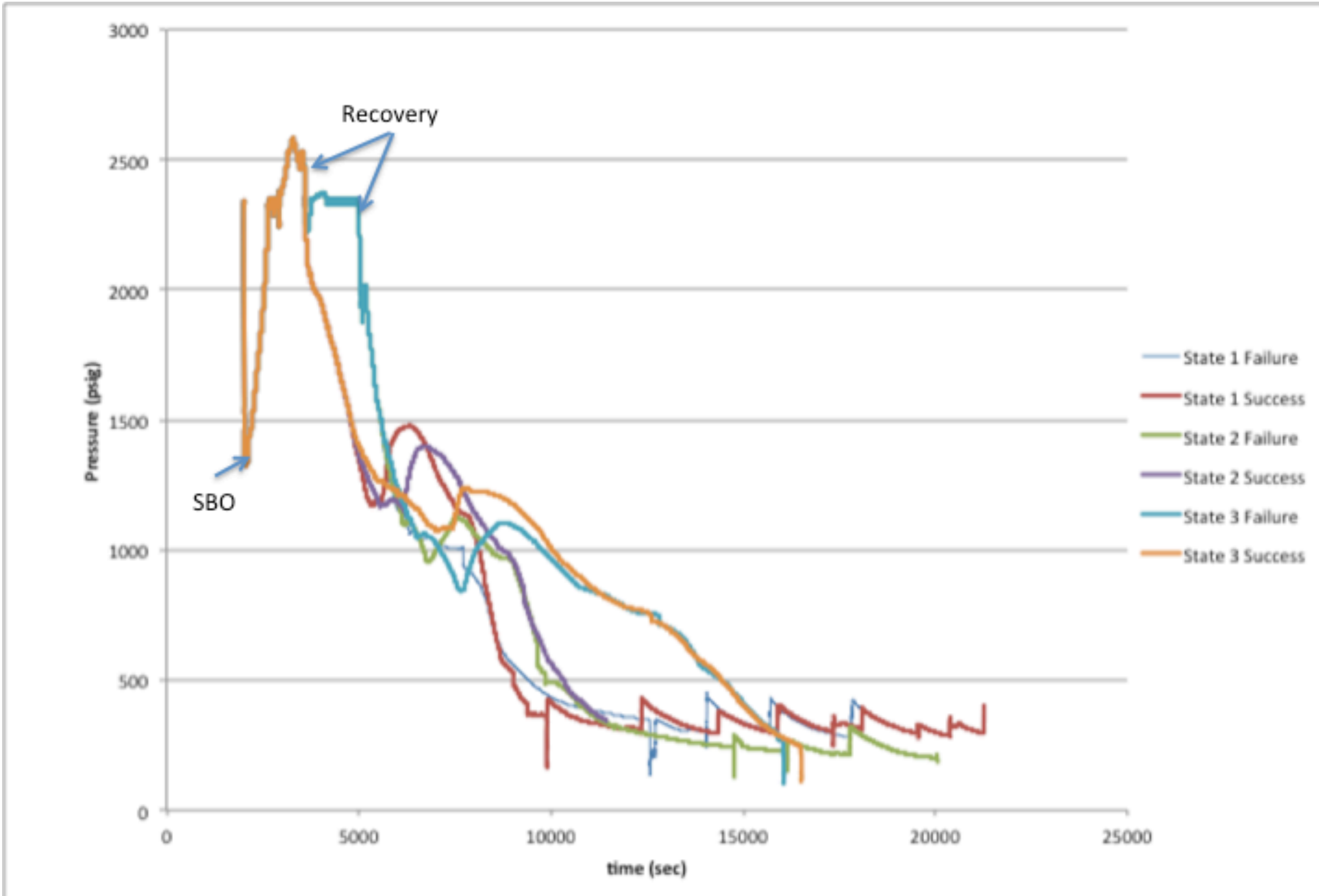


Figure 17. Primary pressure for states 1, 2, 3 (2 HPI, 1 HPI, 0 HPI) with 2 CCP.

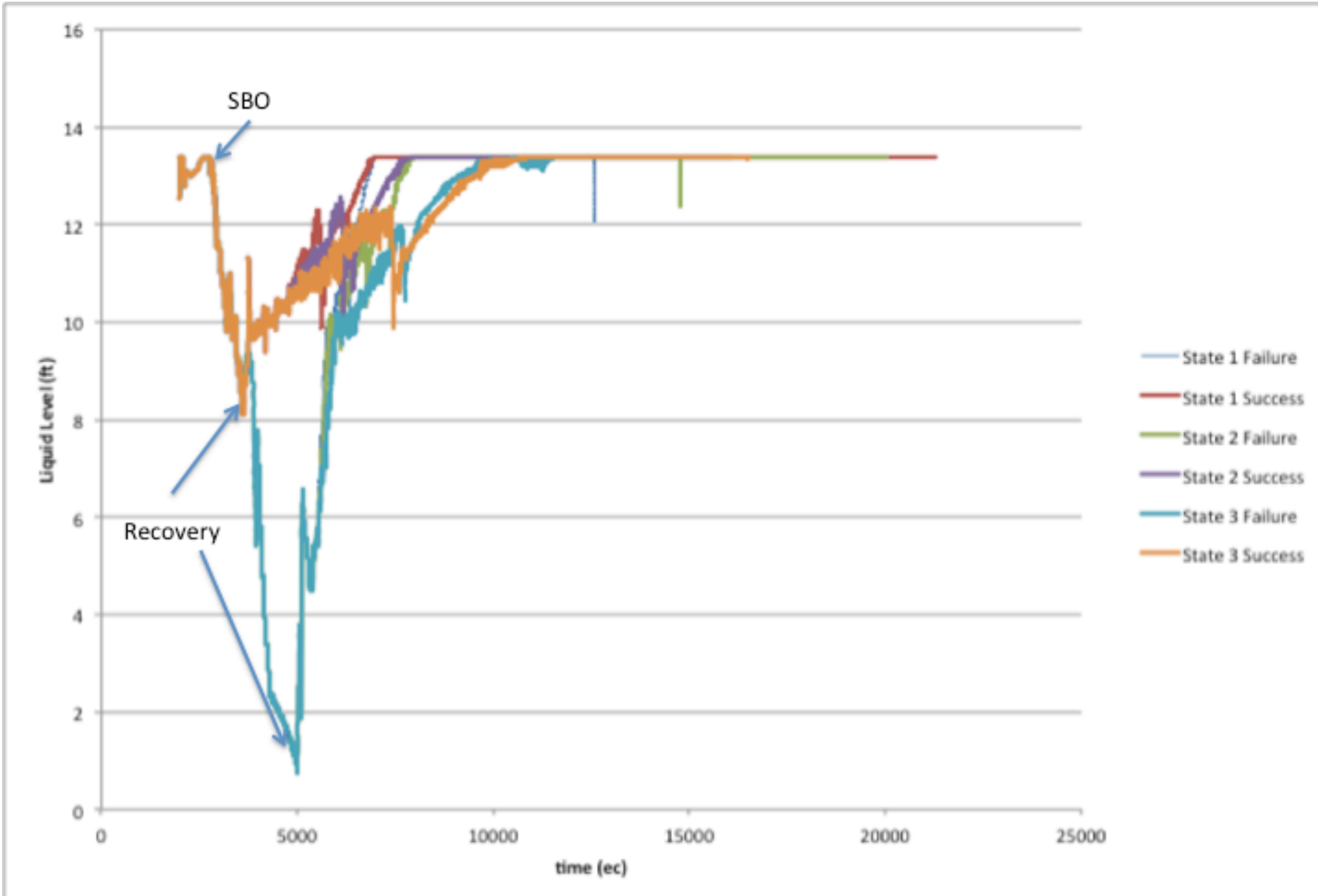


Figure 18. Liquid level for states 1, 2, 3 (2 HPI, 1 HPI, 0 HPI) with 2 CCP.

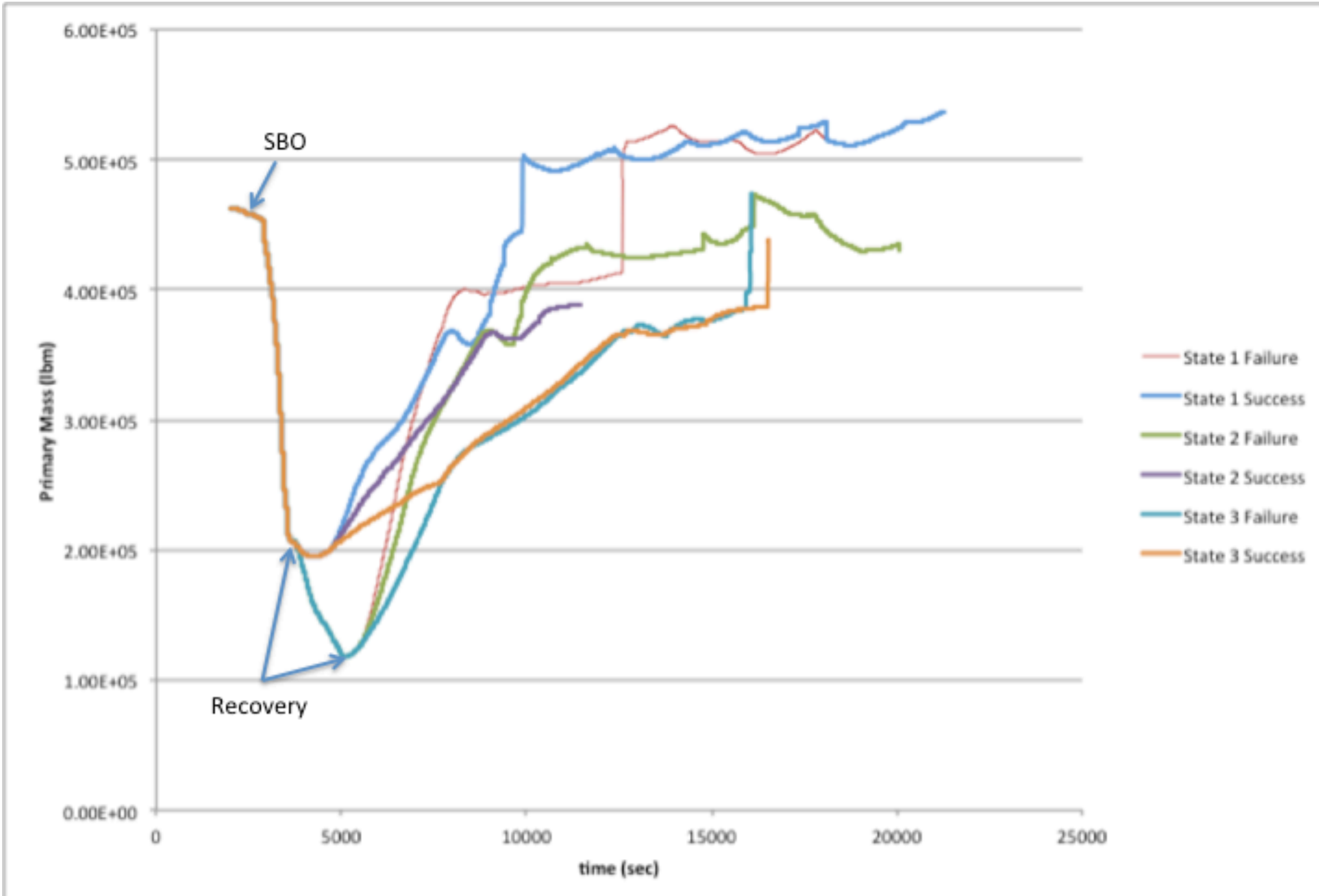


Figure 19. Primary mass for states 1, 2, 3 (2 HPI, 1 HPI, 0 HPI) with 2 CCP.

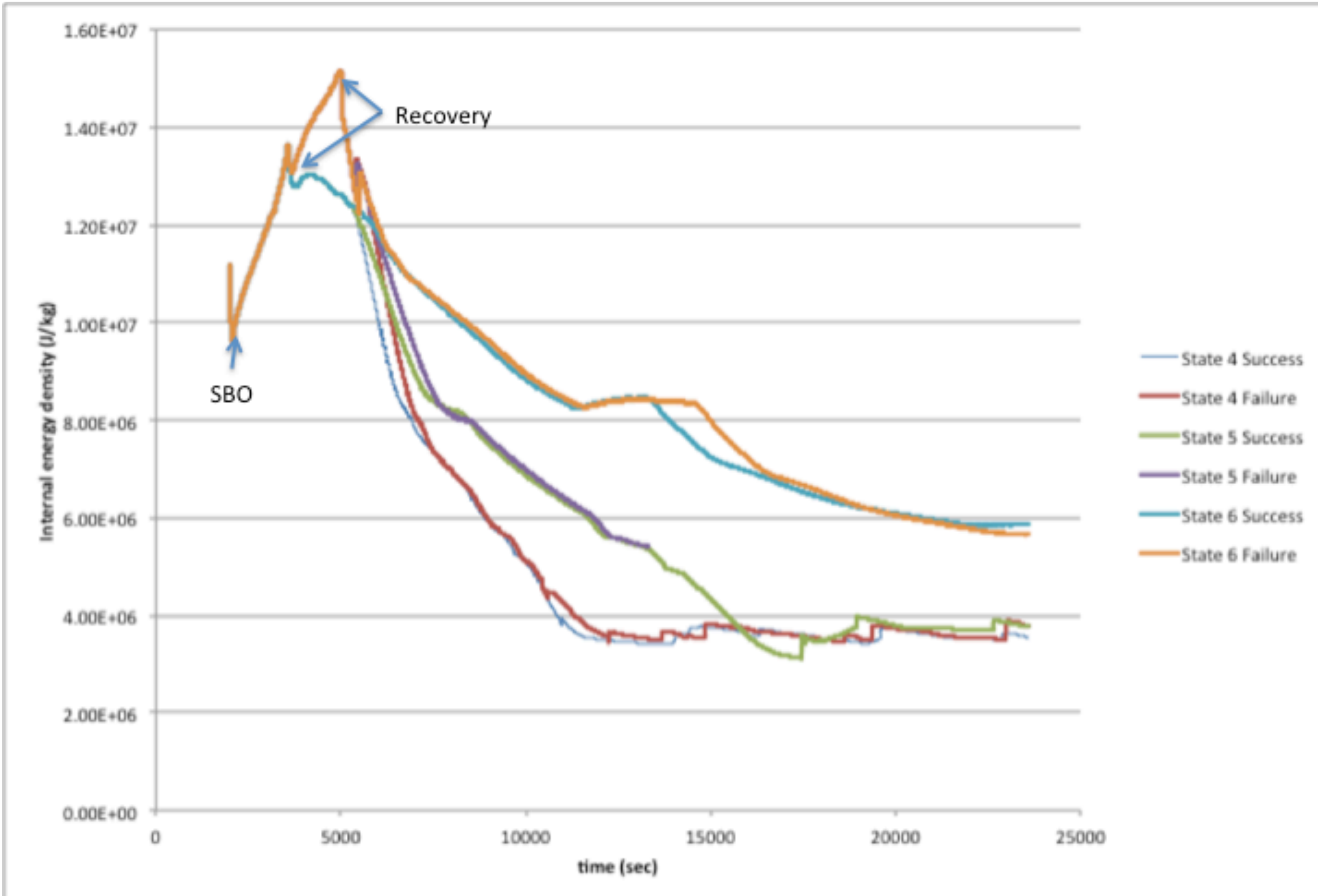


Figure 20. Internal energy density for states 4, 5, 6 (2 HPI, 1 HPI, 0 HPI) with 1 CCP.

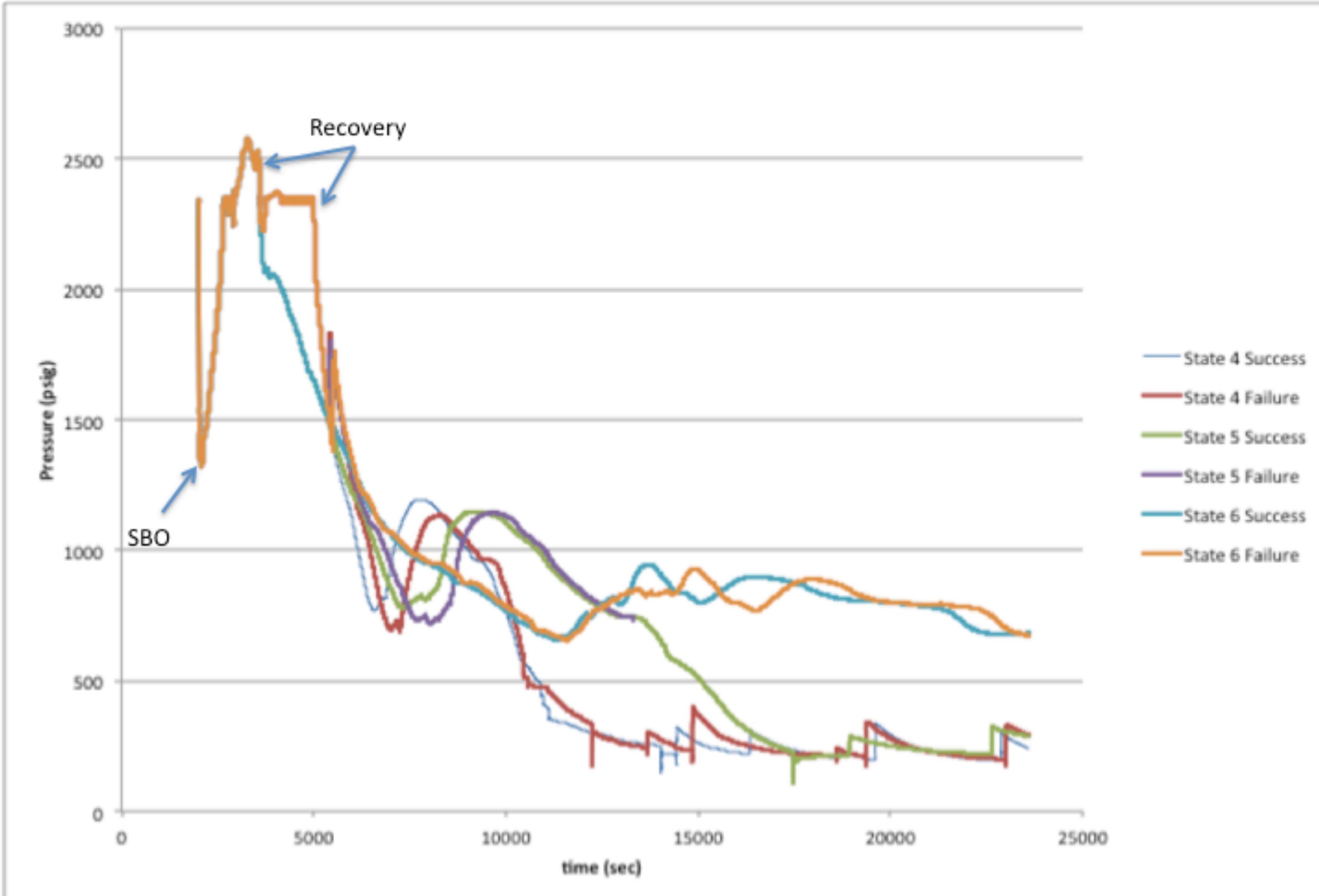


Figure 21. Primary pressure for states 4, 5, 6 (2 HPI, 1 HPI, 0 HPI) with 1 CCP.

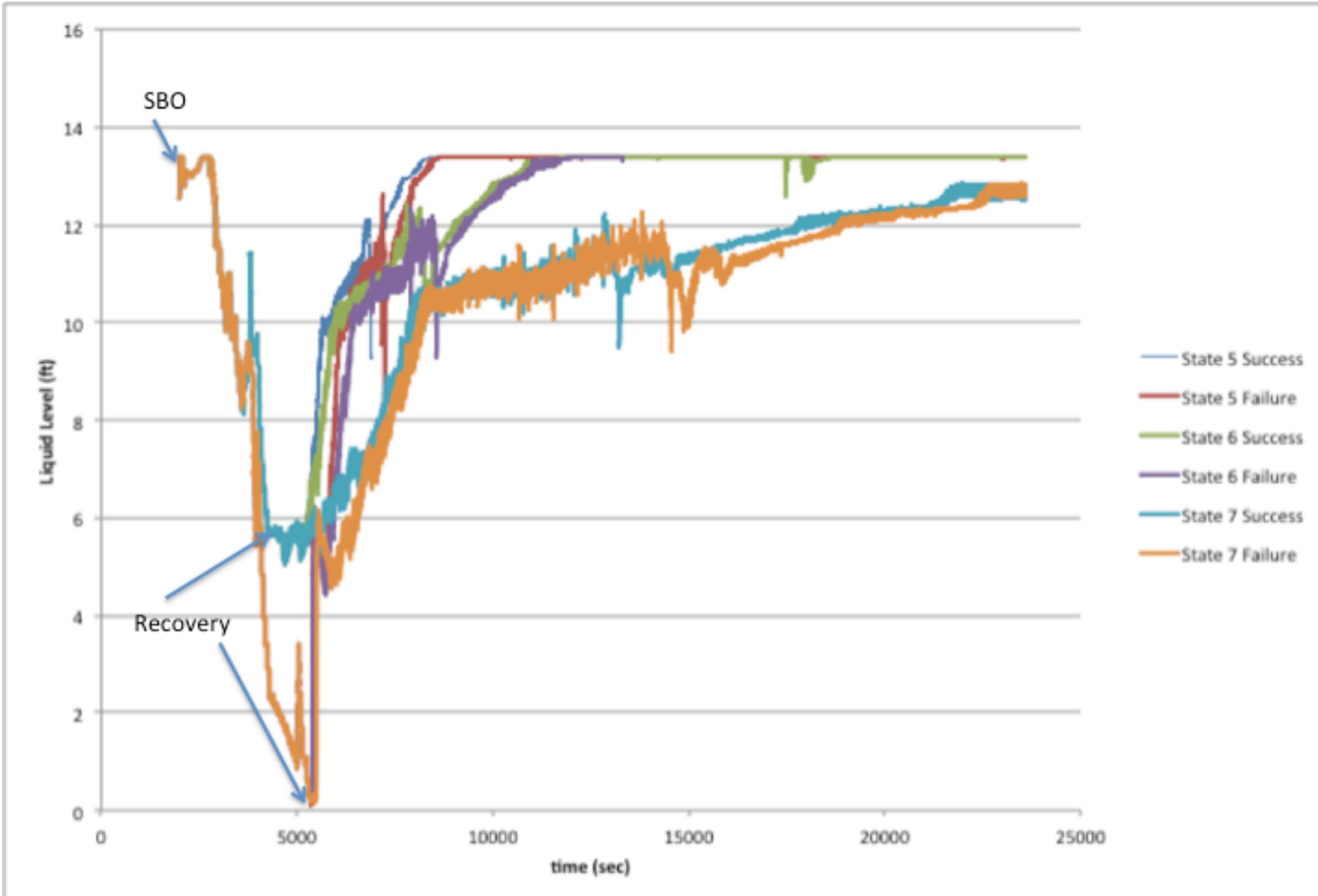


Figure 22. Liquid level for states 4, 5, 6 (2 HPI, 1 HPI, 0 HPI) with 1 CCP.

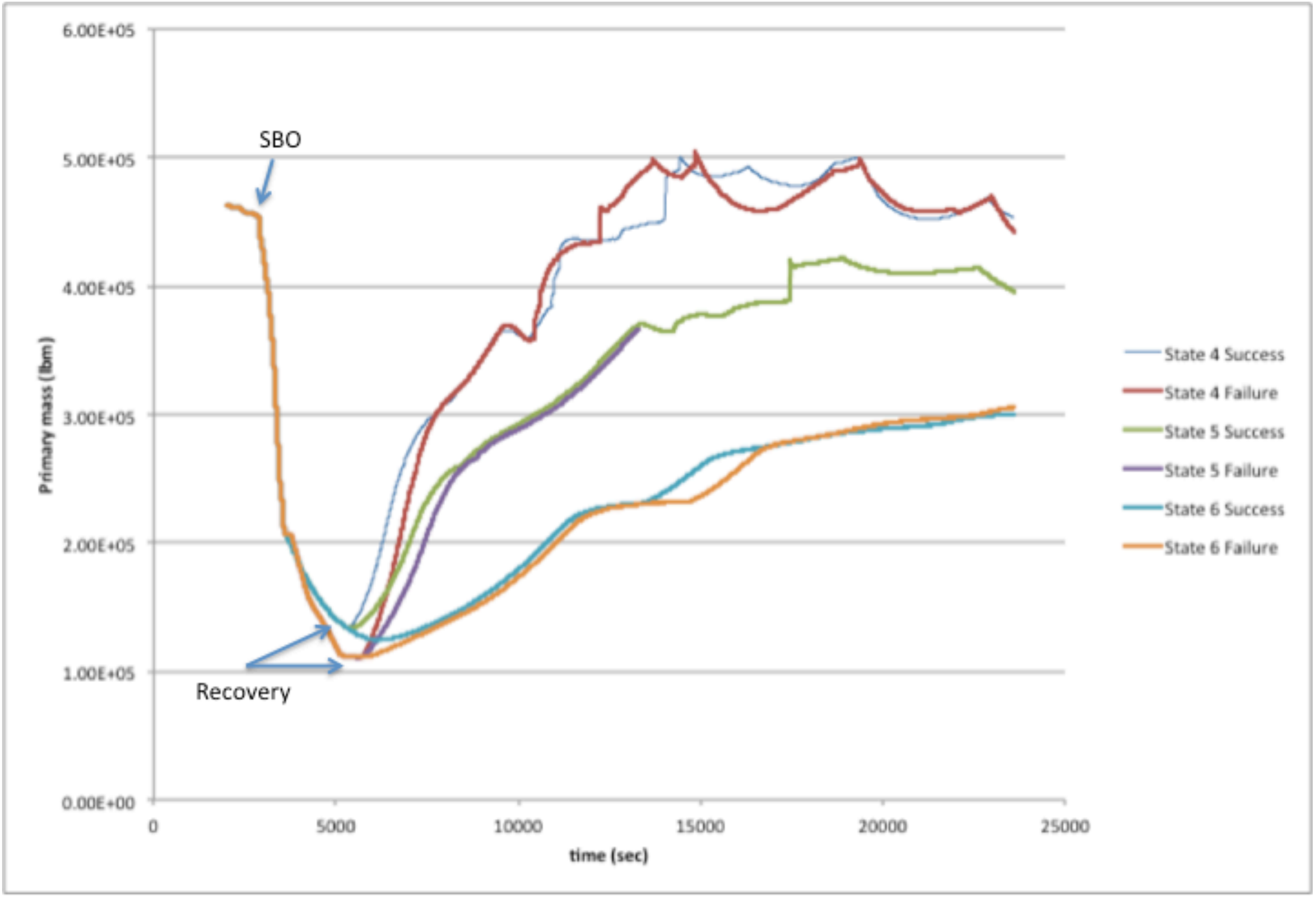


Figure 23. Primary mass for states 4, 5, 6 (2 HPI, 1 HPI, 0 HPI) with 1 CCP.

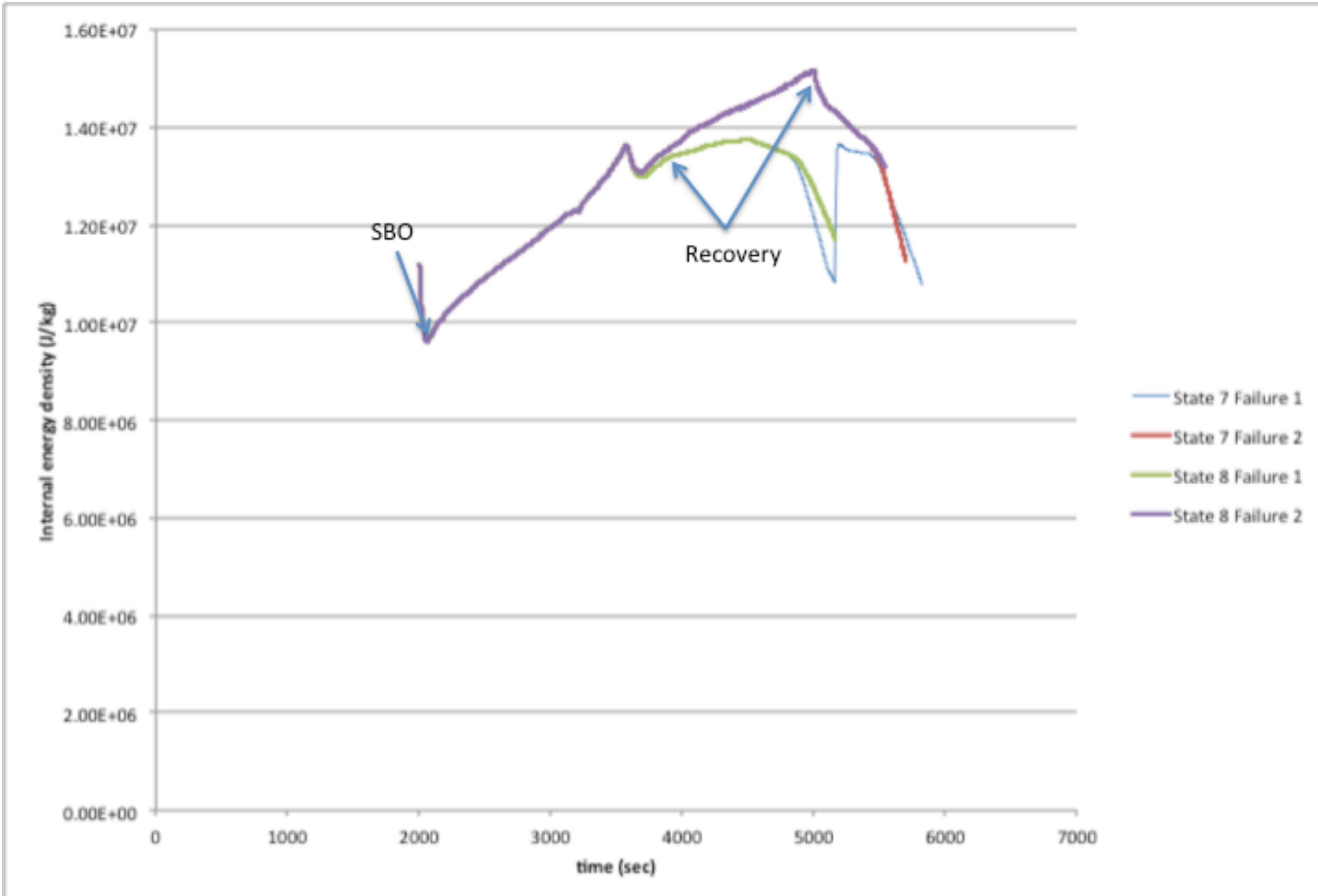


Figure 24. Internal energy density for states 7,8 (2 HPI, 1 HPI, 0 HPI) with 0 CCP.

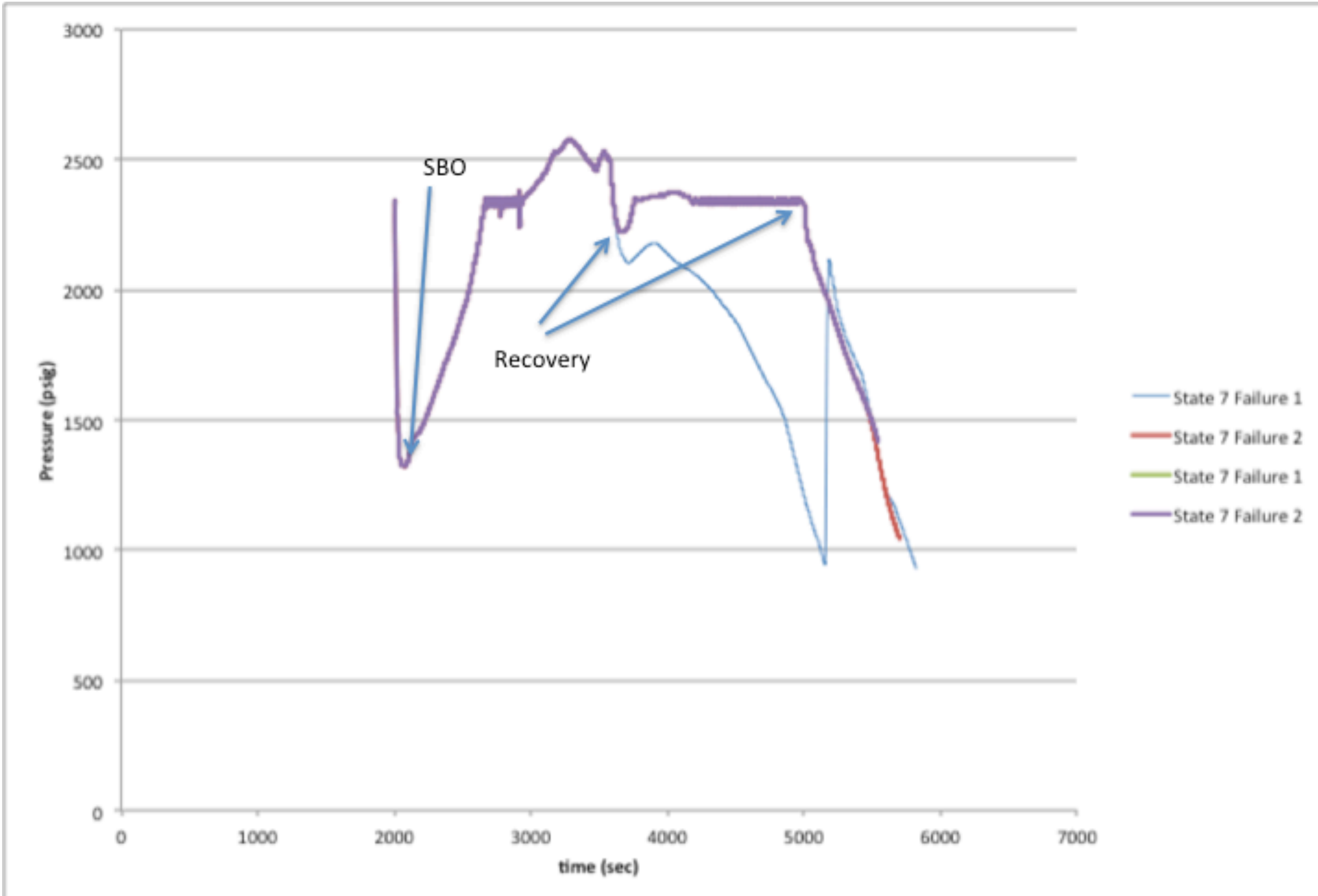


Figure 25. Primary pressure for states 7,8 (2 HPI, 1 HPI, 0 HPI) with 0 CCP.

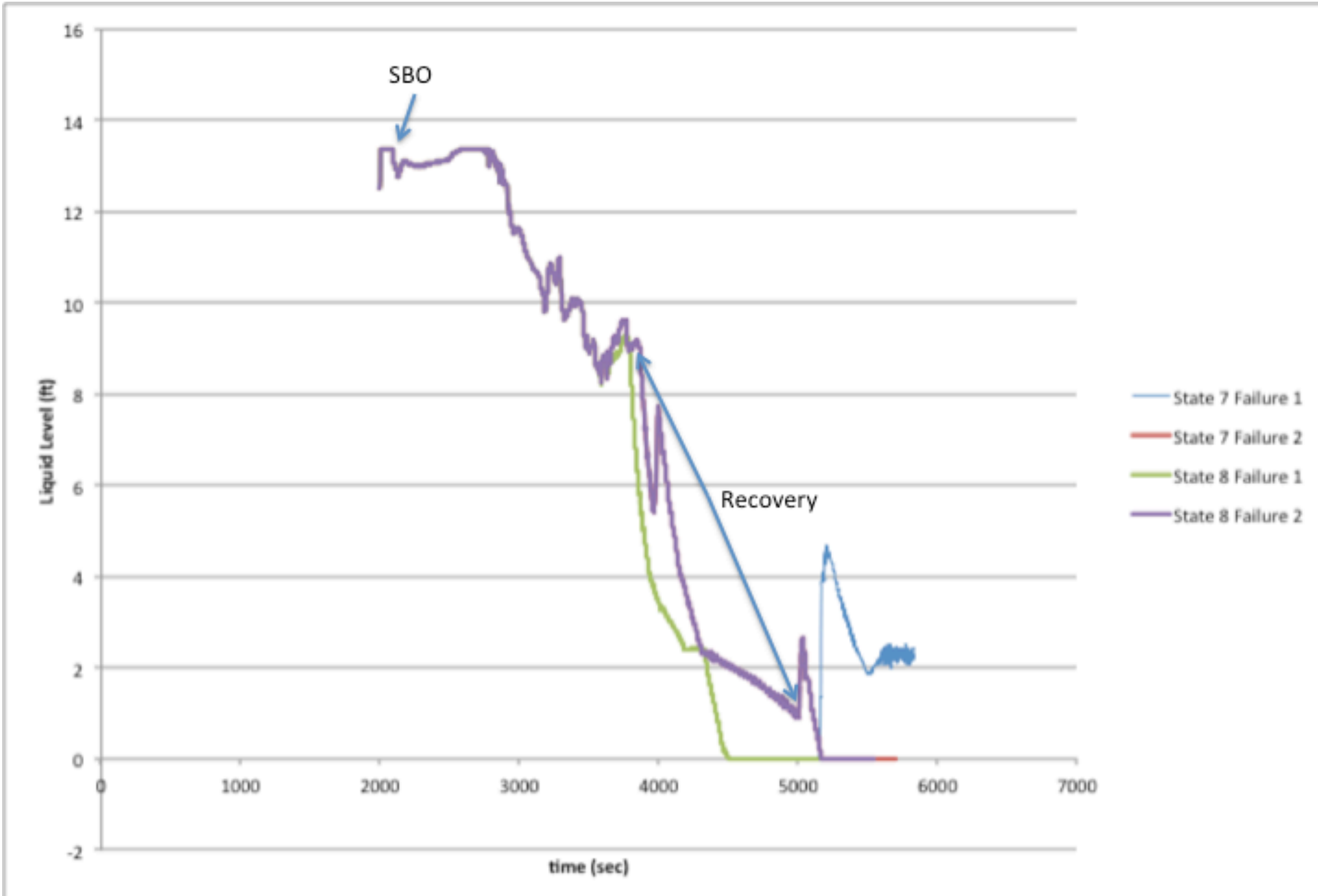


Figure 26. Liquid level for states 7,8 (2 HPI, 1 HPI, 0 HPI) with 0 CCP.

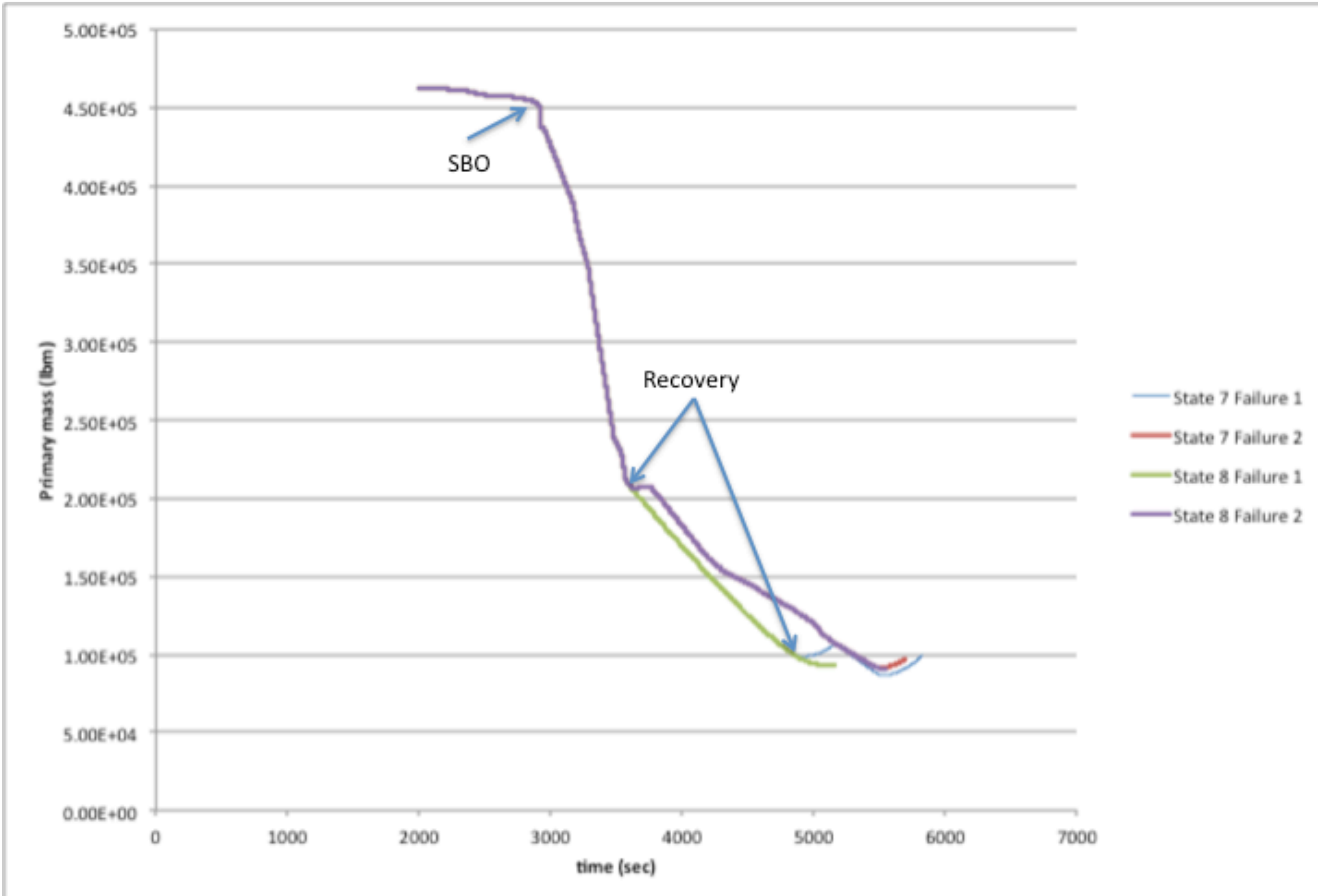


Figure 27. Primary mass for states 7,8 (2 HPI, 1 HPI, 0 HPI) with 0 CCP.

6.7 Optimization of the PWR Dynamic Event Tree

Optimization of the PWR model was performed first by identifying the bounding functions from success (i.e. no cladding damage) leaves that will allow for pruning the tree. As the simulation progresses, the use of parallel computing allows for multiple jobs or branches to be submitted to a processor at a single time. RELAP5-3D is not parallel, however, the RAVEN framework allows for parallel computing where multiple simulations can be performed concurrently [23][25]. If there are more jobs that need to be run than processors available, the RAVEN code keeps the jobs in a queue and submits them in the order in which they are inserted into the queue.

The first step in the Branch-and-Bound DET is to order the jobs to the queue based on probability. Since the intent is to find the leaves with the highest probability of failure, the jobs are inserted from the queue for consideration into the computing cluster based on probability. It is important to note, that these jobs are placed into consideration for the simulating conditions. The next step for the Branch-and-Bound algorithm is to actually determine if the branch contains a potentially optimal solution.

Once the jobs have been placed into consideration, the driving processor will examine the System and State set as defined in Chapter 3 Section 3.1. The process involves examining whether a bounding function exists for the current system set under evaluation. In examining the case against the bounding functions, the system set is evaluated and compared to the list of bounding "functions" previously identified for that particular system set. In the case of the PWR SBO, the potential system sets that would be evaluated are LOSP, total SBO with no battery power, and recovery. Once recovery is reached, the simulation is run until completion with no branching conditions. The bounding functions are developed in this simulation for the beginning of recovery conditions. This results in a set of surfaces for that particular system set to end in success. The State sets are compared to the State sets of the bounding System sets and if the State set is contained within a bounding surface from an identical System set, that particular branch will not result in failure. Therefore, that particular branch is pruned and not evaluated further. If the State set is not contained by a previous bounding function, the probability of that branch is compared with failure probabilities of that system set. If the probability is lower than the failed conditions, the branch will not result in a higher probability of failure and is thus pruned. With respect to the PWR SBO conditions, the bounding functions are simply represented by a “spider” chart and are shown in Figure 28 and Figure 29.

Figure 28 shows the bounding functions for the cases with 1 and 2 CCP available and any number of SI pumps available. It can be concluded that the extra CCP does not present an additional increase in operating margin, however, it does provide additional redundancy reducing the probability of failure. Each line on the figure represents a bounding function State set from a success leaf. During a SBO if the state set parameters are located in any one of the surfaces presented, the recovery with 1 or 2 CCP will reach success.

Figure 29 presents the bounding functions for cases with no CCP and 1 or 2 SI pumps. Comparing the bounding functions between the cases with CCP availability, the pressure, and energy density must be lower while the liquid mass and liquid level in the core must be higher to succeed. This is expected, as the SI pumps need a much lower pressure to inject water into the core while the decrease in energy density is an indication of the heat capacity of the system prior to boiling. The liquid level and liquid mass also provide the indication that a much greater heat capacity exists in the coolant prior to boiling.

Using these bounding functions that are created during the simulation, the total number of nodes was reduced by approximately 85% from 1500 to 225. The estimated time for running this simulation using the Branch-and-Bound algorithm was approximately 2 hours using 32 processors. The failure conditions were created from early failure of power sources. A delay in the SBO occurring resulted in a much greater margin and time to recover prior to clad melt. This reduction in simulation time of approximately 85% provides a significant amount of computational resources for identifying failure cases rather than time spent on running simulations that would result in success and add little to no value to the simulation.

The simulation time for the “brute force” approach was 6 hours. These simulations did not include the sensitivity analysis that is discussed in the next section. By utilizing a LHS approach with 100 samples per simulation, the time is increased by two orders of magnitude from to 200 hours using the Branch-and-Bound and 600 hours using a “brute force approach.” As transients become more complex, the simulation time grows exponentially, and thus, the Branch-and-Bound algorithm provides significant savings.

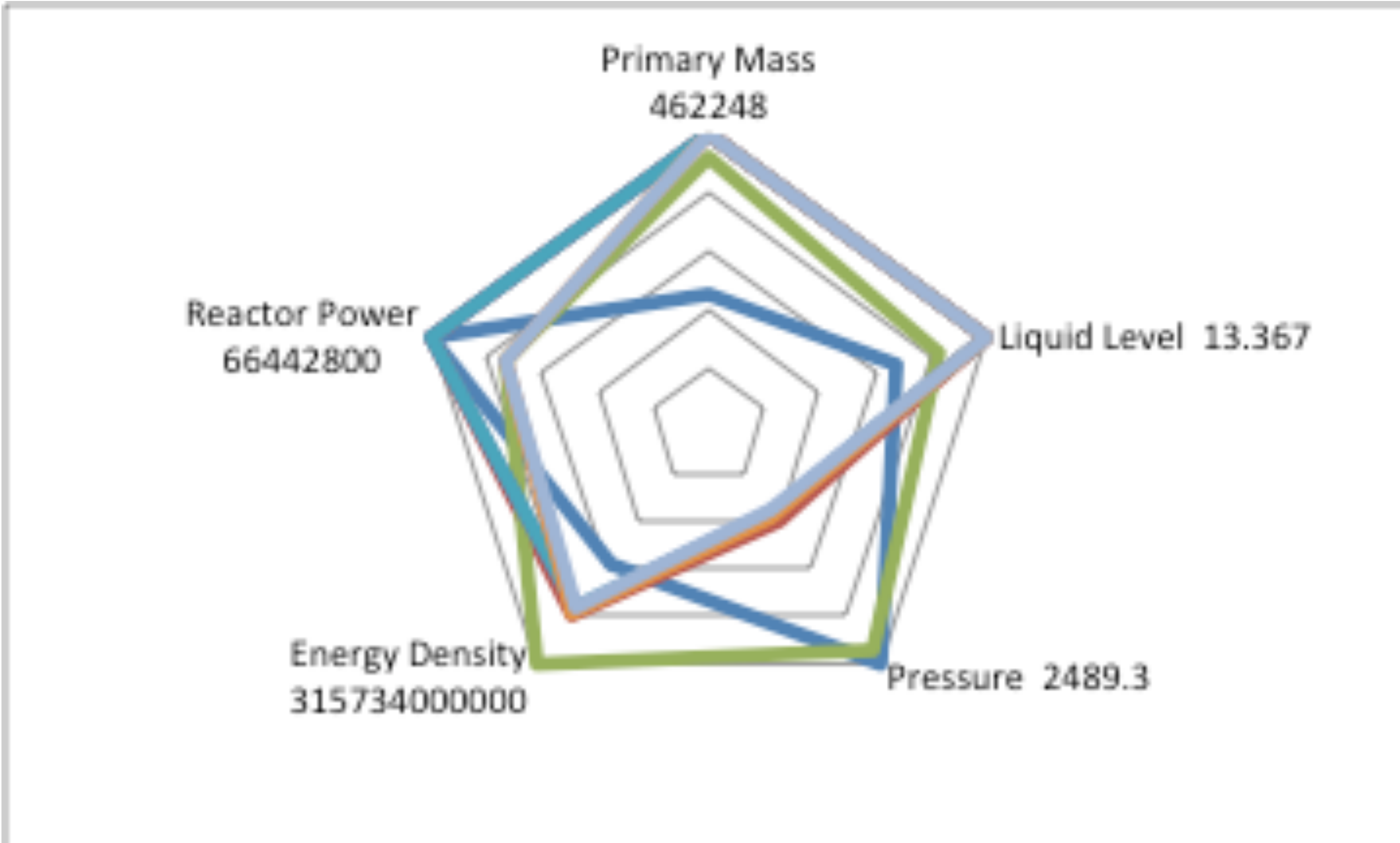


Figure 28. Bounding function for PWR SBO with 2 and 1 CCP availability and 0, 1, 2 SI pumps available.

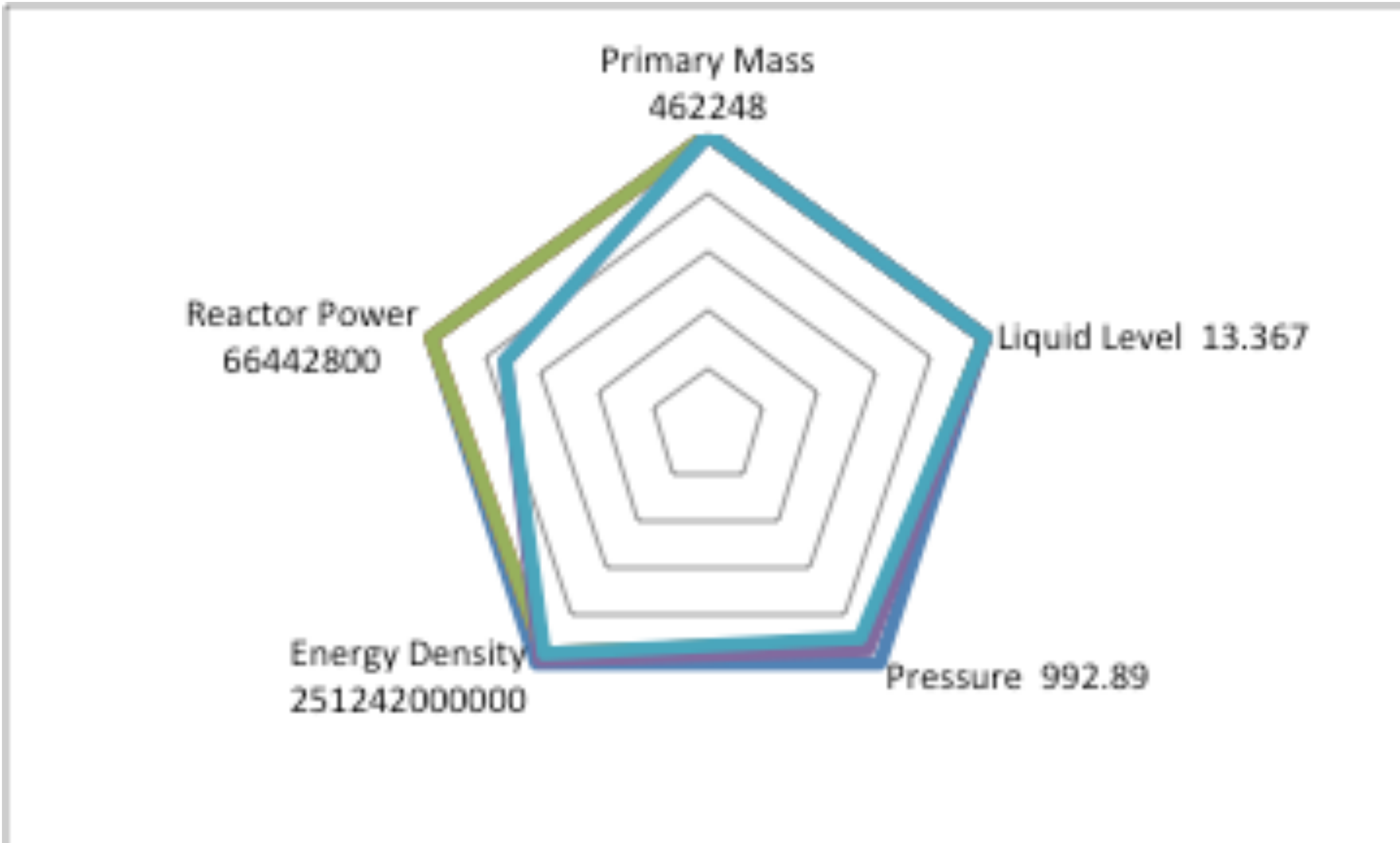


Figure 29. Bounding function for PWR SBO with 0 CCP and 1 or 2 SI pumps available.

6.8 Sensitivity and PIRT Analysis for the PWR SBO

Sensitivity parameter based on the PIRT methodology described in References [26] was performed on the branching cases that resulted in the highest probability of failure. A series of parameters was evaluated for each of the conditions. The parameters chosen based on the ability to either remove energy from the core or add energy to the core. These included initial reactor power, PORV capacity, SI capacity and CCP capacity. Examining the PIRT for a Feed-and-bleed case for SBO [40] additional parameters can be chosen. These are provided to demonstrate the effects of modeling uncertainty on the probabilistic risk assessment and to identify potential candidates for modeling improvement.

The PORVs were modeled assuming a critical flow model based on the capacity documented in Reference [33]. This provides for simple model of the valves without a significant amount of complexity. Adjusting the valve flow area has the potential to change the capacity of the valves. The total capacity of 2 PORVs is 129.2 lbm/sec (58.6 kg/sec) at 2335 psig (1.61 MPa). The corresponding flow area for the two valves is 0.01887 ft^2 (17.53 cm^2). In order to support the sensitivity analysis the flow rate was assumed to be linear within the respect of flow area and the flow area was adjusted assuming a uniform distribution of +/- 10%. For minor changes in flow area through a valve, this has been shown to be a valid assumption.

The capacity of the SI and CCP were both evaluated assuming nominal flow capacity +/- 10%. The RELAP5-3D model of the SI and CCP assumes a time-dependent junction/volume condition for both pumps with fixed flow rates into the primary coolant system. The injection rates are based on reactor pressures on the primary side of the junction. Table 5 provides the flow capacity at several pressures for both types of pumps as well as the maximum and minimum flow parameters. These parameters can then be used to evaluate which region provides the largest uncertainty and can be used to determine if additional modeling has the ability to improve the safety margin.

Table 5. Uncertainty parameters for the PWR SBO analysis.

CCP			SI		
Pressure (psig)	Flow rate (lbm/sec)	Lower/Upper Bounds	Pressure (psig)	Flow rate (lbm/sec)	Lower/Upper Bounds
15.0	29.15	26.23/32.06	15.0	160.92	144.84/177.02
683.0	29.15	26.23/32.06	128.0	34.12	30.71/37.53
2620.0	7.94	7.15/8.74	1418.0	13.21	11.89/14.53
			1529.0	3.30	2.97/3.63

Using the above values and allowing for the DAKOTA package [29] to process the uncertainty data, the sensitivity for each of the parameters was evaluated. Table 6 provides a summary of the parameter as evaluated for each recovery condition. What can be seen, is that reactor power does not have a large impact on the range at which the analysis is examined.

For normal conditions with the 2 CCP and SI pumps available, the correlation coefficients demonstrate the redundancy in the system such that PCT will not be significantly impacted by the sensitivity of the operating components. As the availability of the coolant system decreases (i.e., less pumps), the correlation coefficients become higher resulting in a larger impact on the changing parameters. As an example with 2 CCP and 2 SI, the correlation coefficient has a value of 0.328, which would be considered a MODERATE value in the

PIRT ranking. If 1 CCP is available and no SI are available, the correlation coefficient would be 0.780 or a HIGH in the PIRT ranking.

Figure 30 through Figure 50 provides a representation of the important parameters for all of the cases. It can be seen that as the cooling capacity decreases, the importance on PORV as well as CCP capacity increases.

The system model for the CCP involves a RELAP5-3D time-dependent junction/volume with a specified coolant flow rate. The PORV model consists of a valve modeled using the critical flow model and adjusting the flow area to reach designed parameters. Reliance on these models for a risk analysis case, may demonstrate that additional modeling improvements or validation of the models may yield results with less uncertainty. For models, where credit is taken for both PORVs and CCP, the models may be deemed adequate without additional improvements.

The figures show the effects and trends as the result of varying different parameters. The in objective is to examine the result to evaluate a trend in the data to determine if the sensitivity of one parameter has an impact on PCT. A cluster of data with a flat trend indicates no correlation while a positive (or negative trend) indicates a positive (or negative correlation). There are some outlying data points, which upon inspection of the output files are attributed to stability issues in the specific RELAP5-3D simulation. Thermodynamic property errors were seen in some cases that resulted in excessively high calculated temperature prior to a simulation crash. It is important for one to examine these cases and evaluate if they could impact the trend. Provided the number of erroneous cases is small <6, the results should not be impacted. Figure 40 and Figure 41 provide an example of a

MEDIUM to HIGH correlation. As PORV capacity and CCP capacity increase, the PCT is reduced.

Table 6. Sensitivity analysis for the PWR SBO case.

Parameter	**2 CCP 2 SI**	**2 CCP 1 SI**	**2 CCP 0 SI**	**1 CCP 2 SI**	**1 CCP 1 SI**	**1 CCP 0 SI**	**0 CCP 2 SI**	**0 CCP 1 SI**
Initial Power	0.025	0.079	0.144	0.291	0.041	0.024	0.088	0.149
Safety Rod Worth	0.035	0.108	0.054	0.011	0.159	0.024	0.064	0.038
PORV	0.161	0.212	0.018	0.544	0.203	0.666	0.625	0.805
CCP	0.328	0.313	0.548	0.460	0.498	0.780	N/A	N/A
SI	0.129	0.178	N/A	0.244	0.179	N/A	0.190	0.122

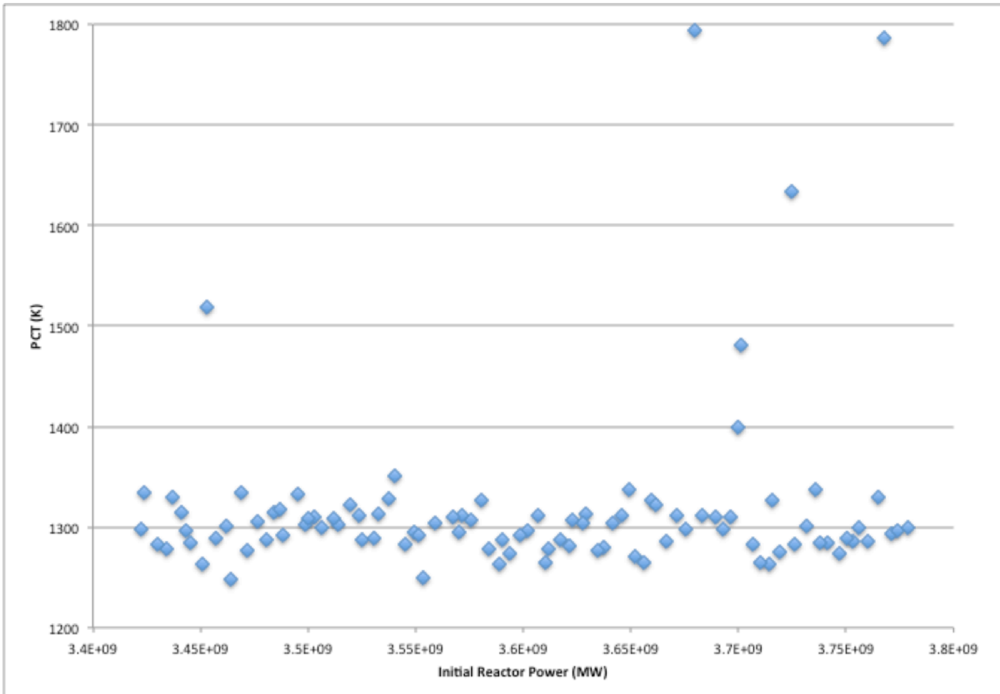


Figure 30. Sensitivity analysis of 2 CCP 2 SI with respect to initial reactor power.

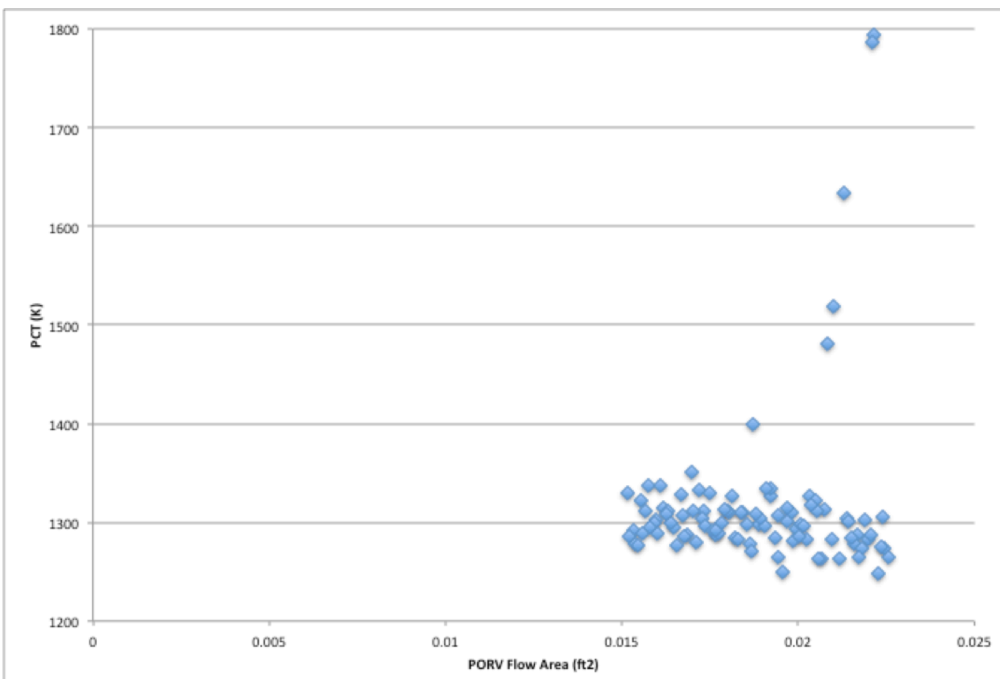


Figure 31 Sensitivity analysis of 2 CCP 2 SI with respect to PORV capacity.

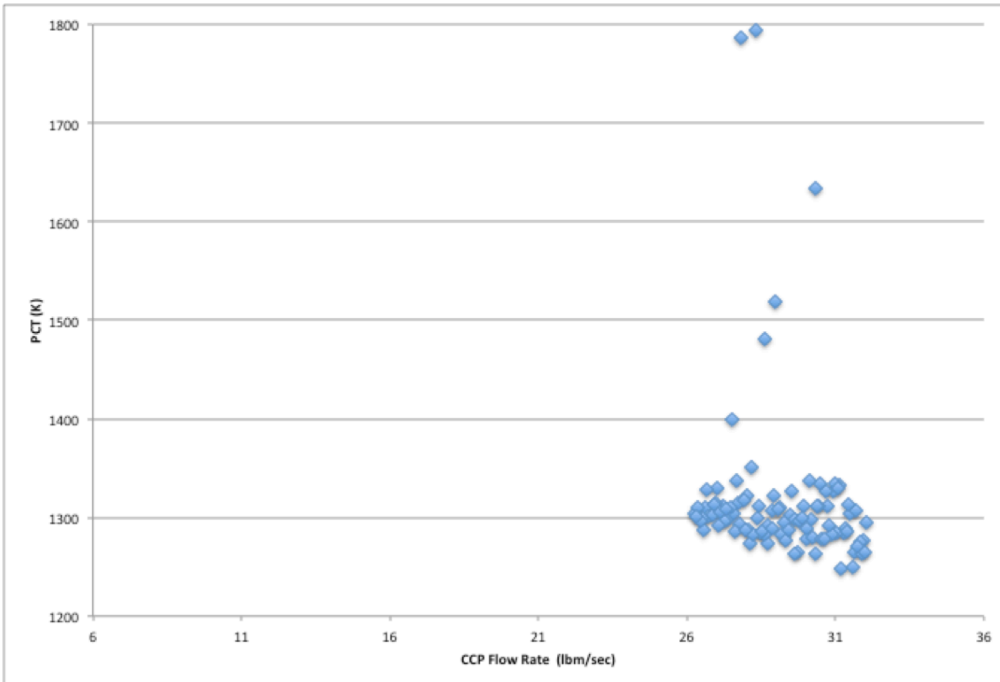


Figure 32. Sensitivity analysis of 2 CCP 2 SI with respect to CCP flow rate.

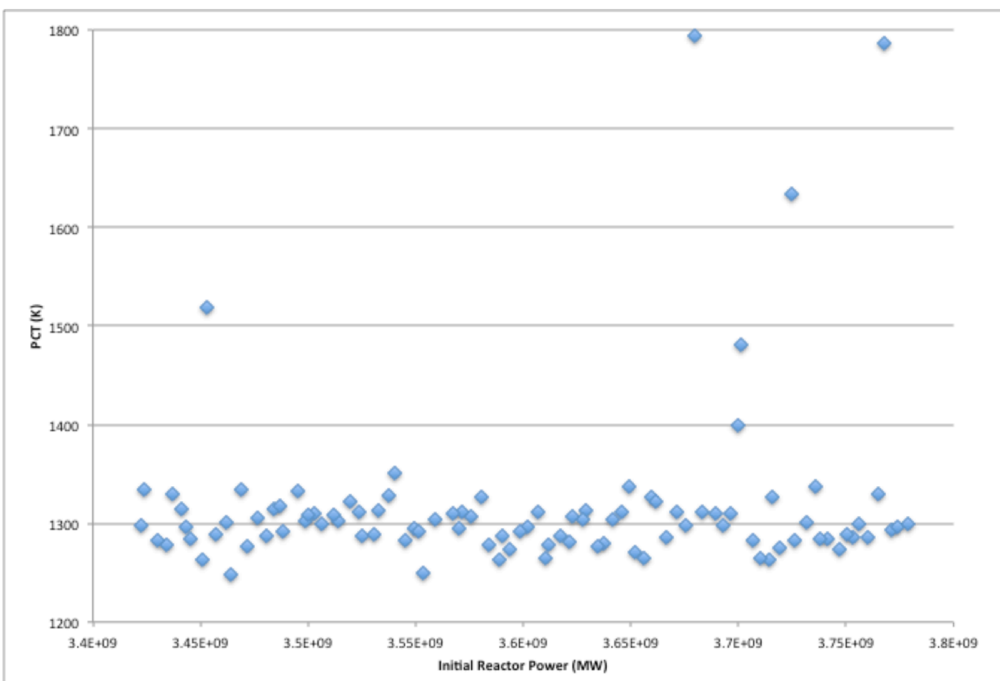


Figure 33. Sensitivity analysis of 2 CCP 1 SI with respect to initial reactor power.

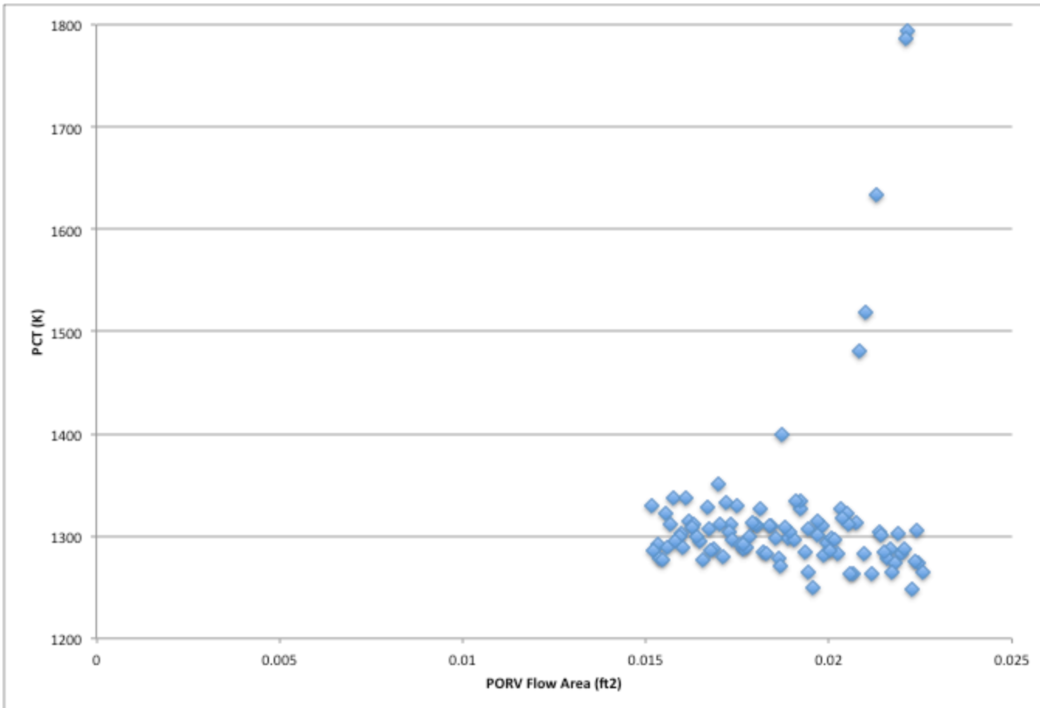


Figure 34. Sensitivity analysis of 2 CCP 1 SI with respect to PORV capacity.

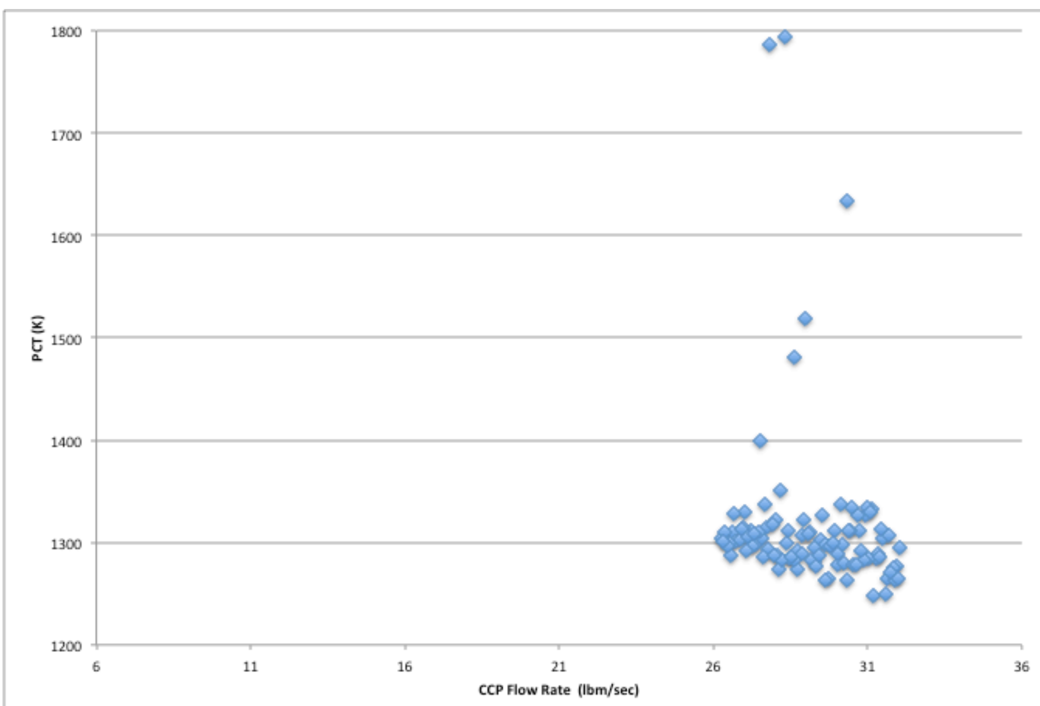


Figure 35. Sensitivity analysis of 2 CCP 1 SI with respect to CCP flow rate.

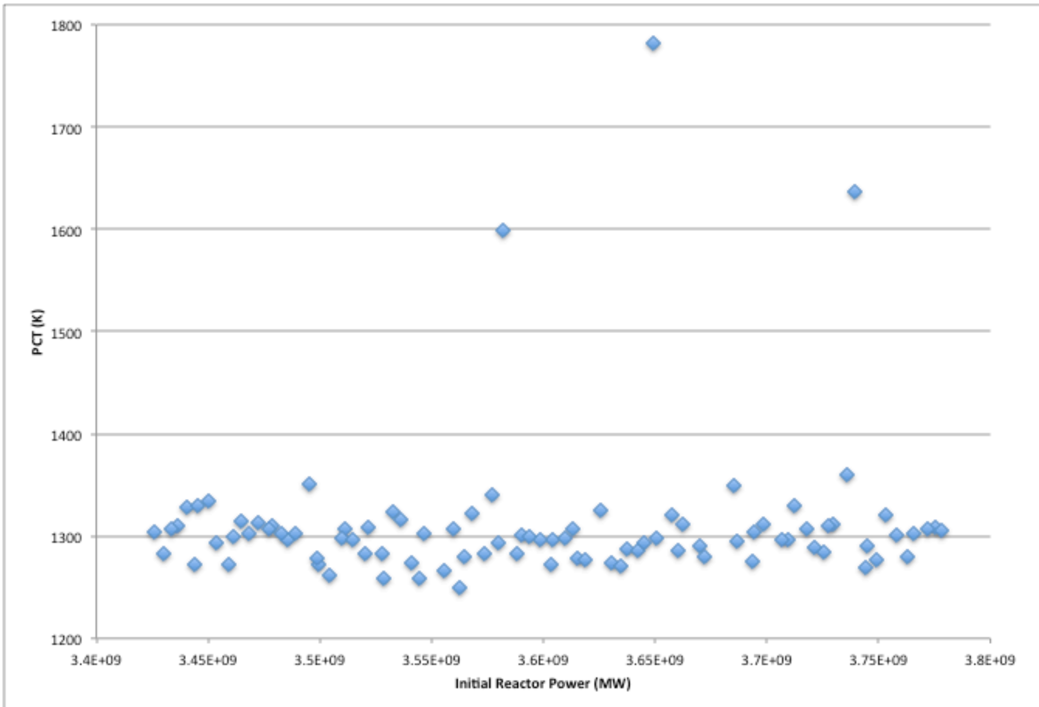


Figure 36. Sensitivity analysis of 2 CCP 0 SI with respect to initial reactor power.

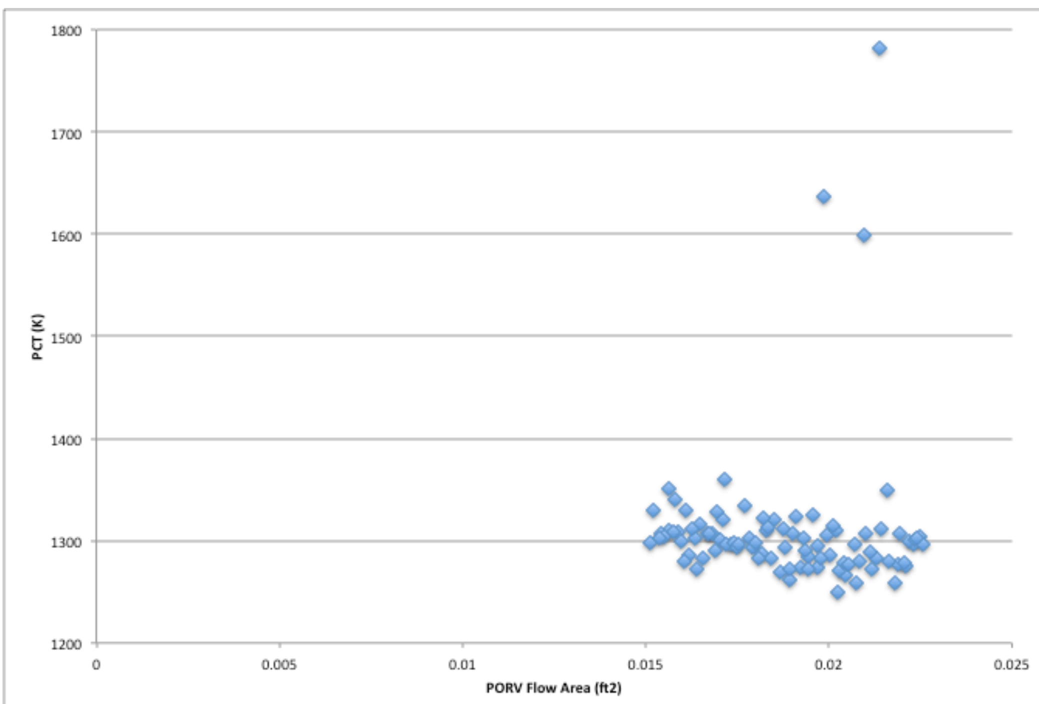


Figure 37. Sensitivity analysis of 2 CCP 0 SI with respect to PORV capacity.

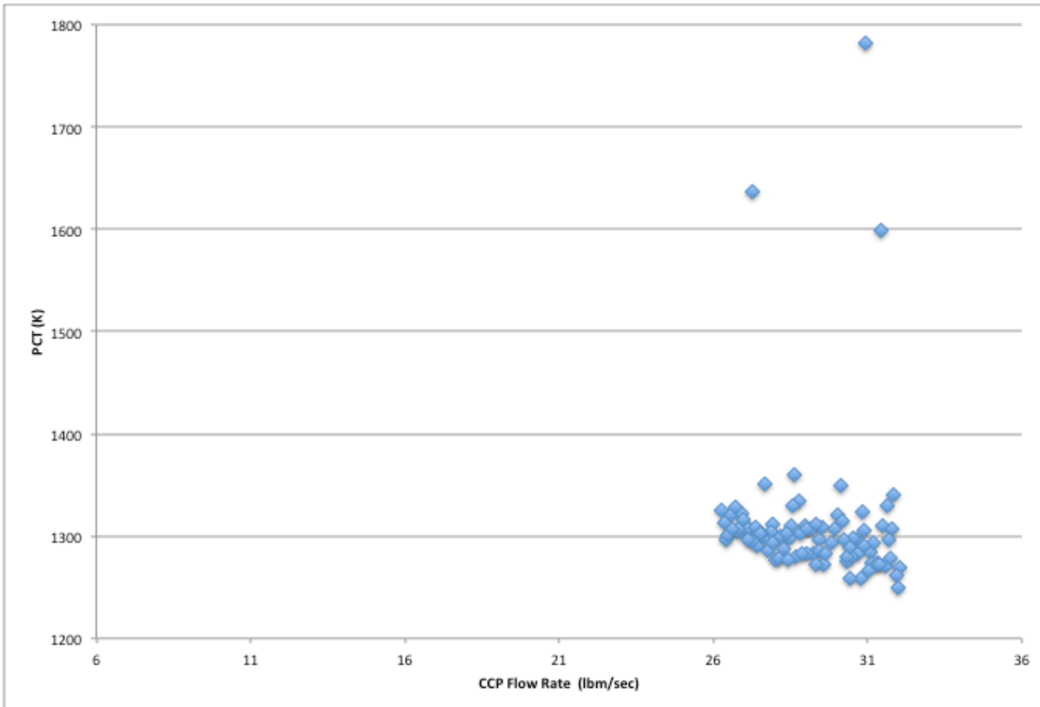


Figure 38. Sensitivity analysis of 2 CCP 0 SI with respect to CCP flow rate.

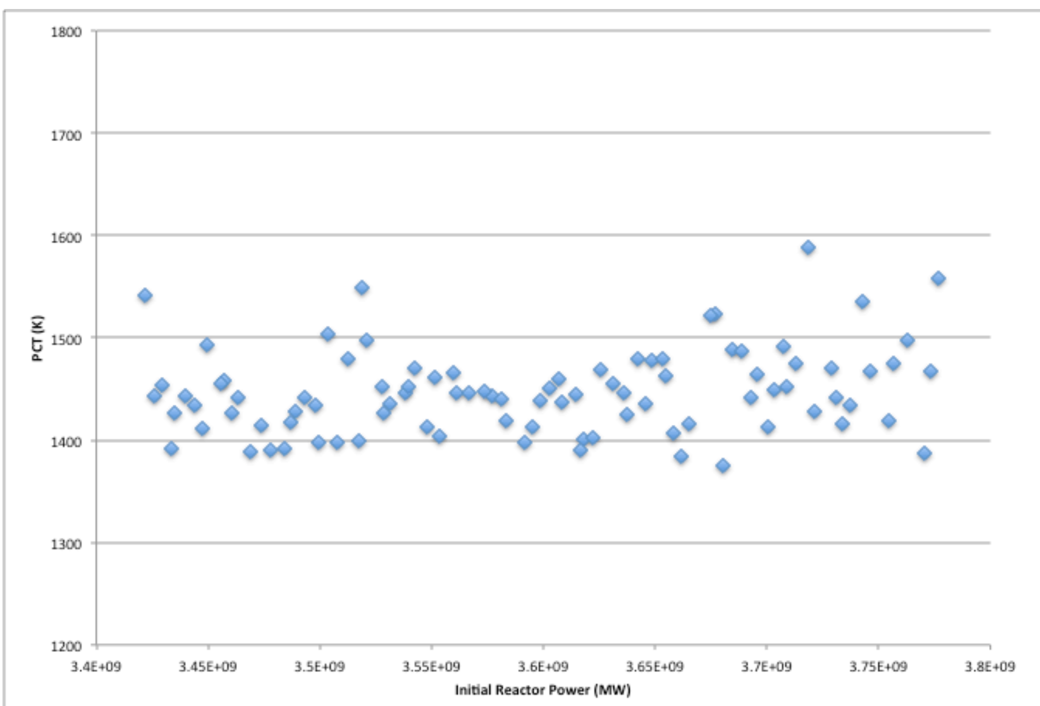


Figure 39. Sensitivity analysis of 1 CCP 2 SI with respect to initial reactor power.

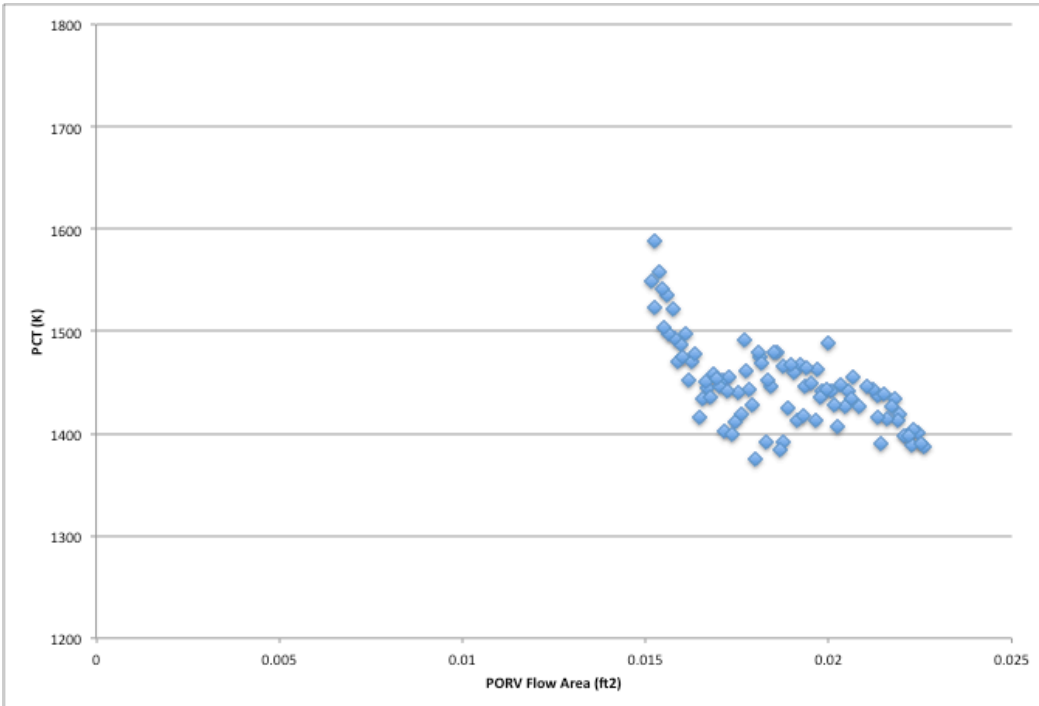


Figure 40. Sensitivity analysis of 1 CCP 2 SI with respect to PORV capacity.

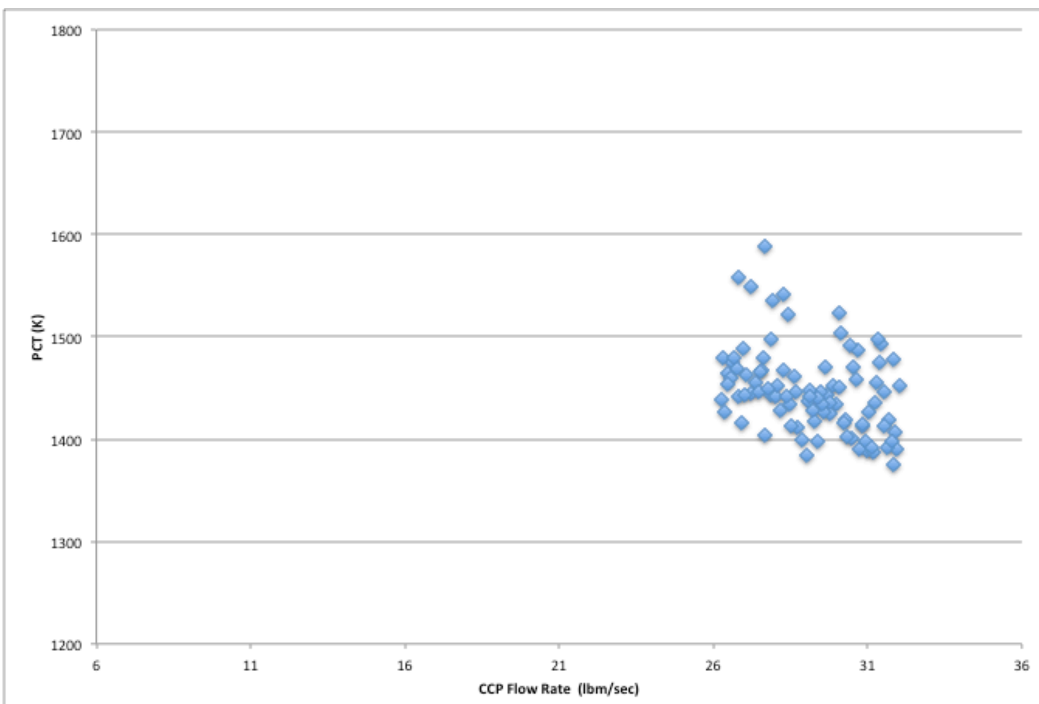


Figure 41. Sensitivity analysis of 1 CCP 2 SI with respect to CCP flow rate.

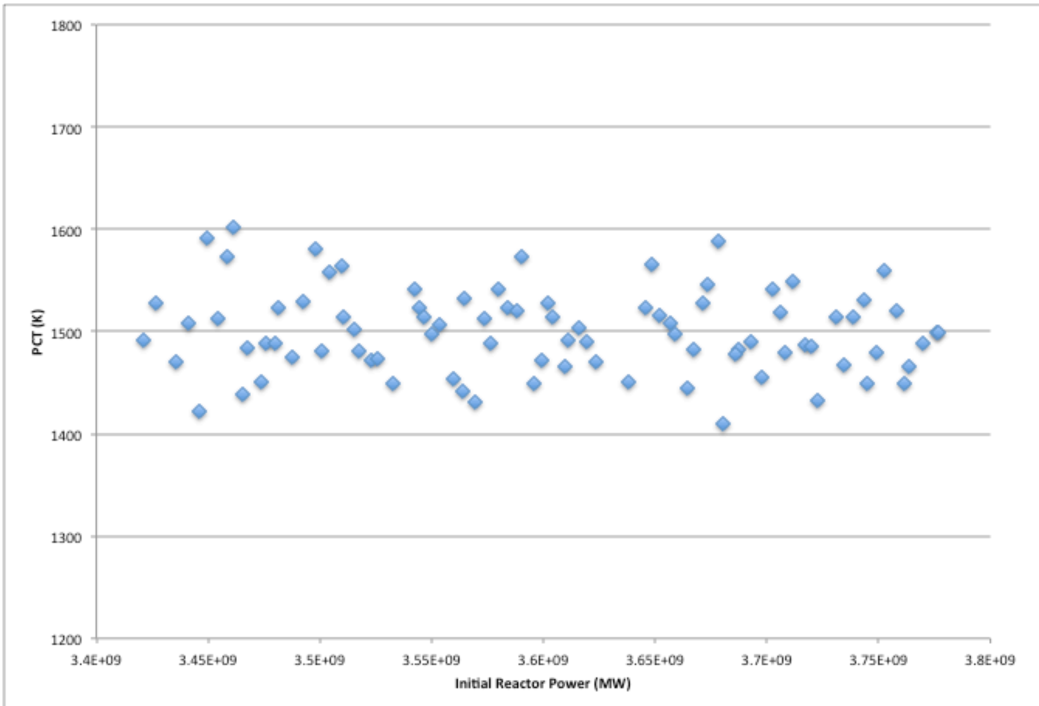


Figure 42. Sensitivity analysis of 1 CCP 1 SI with respect to initial reactor power.

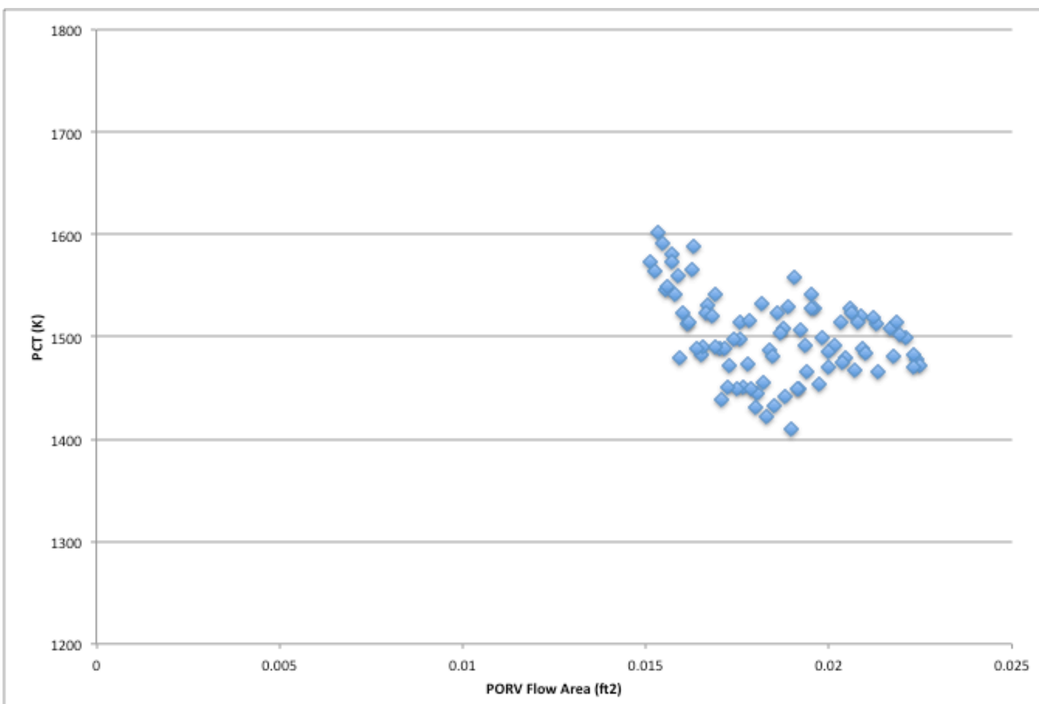


Figure 43. Sensitivity analysis of 1 CCP 1 SI with respect to PORV capacity.

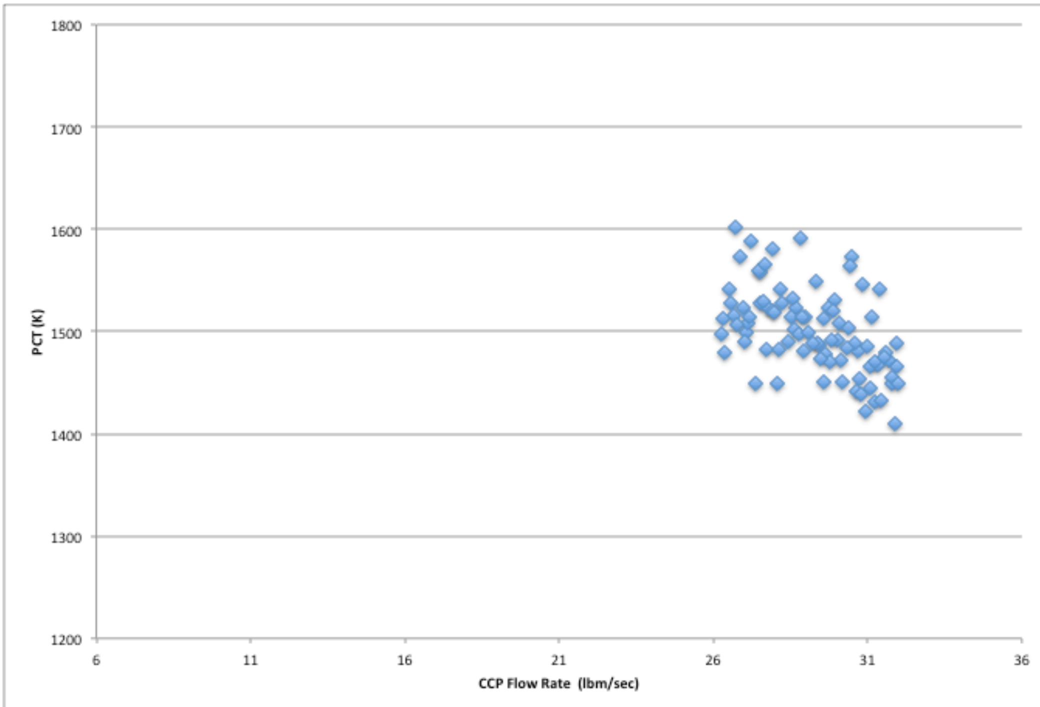


Figure 44. Sensitivity analysis of 1 CCP 1 SI with respect to CCP flow rate.

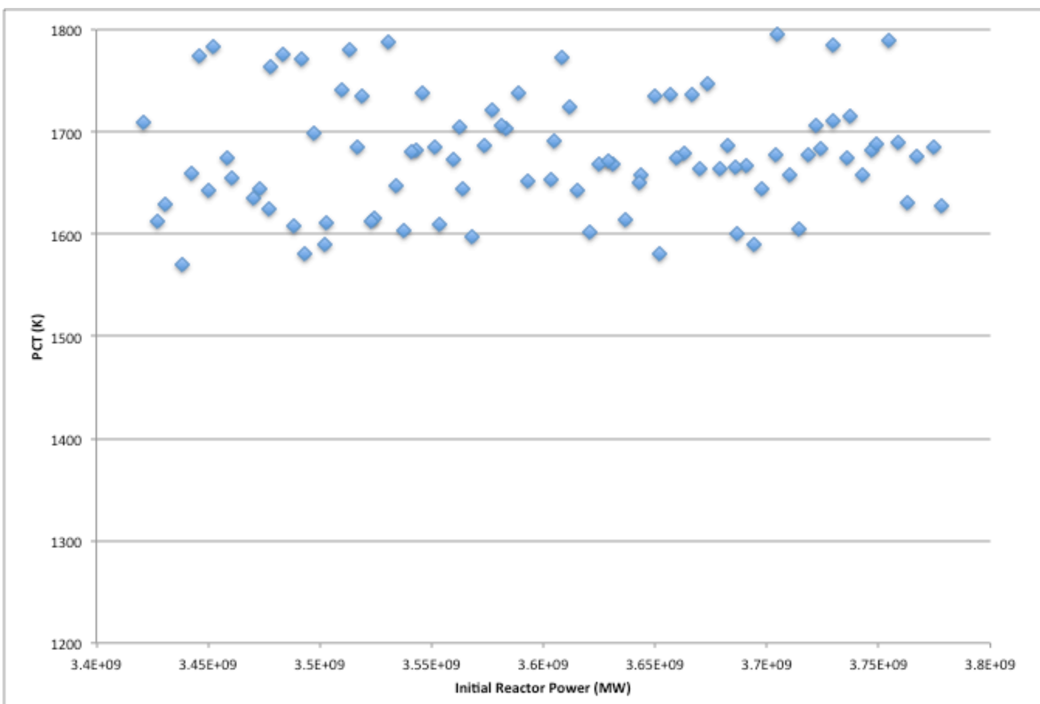


Figure 45. Sensitivity analysis of 1 CCP 2 SI with respect to initial reactor power.

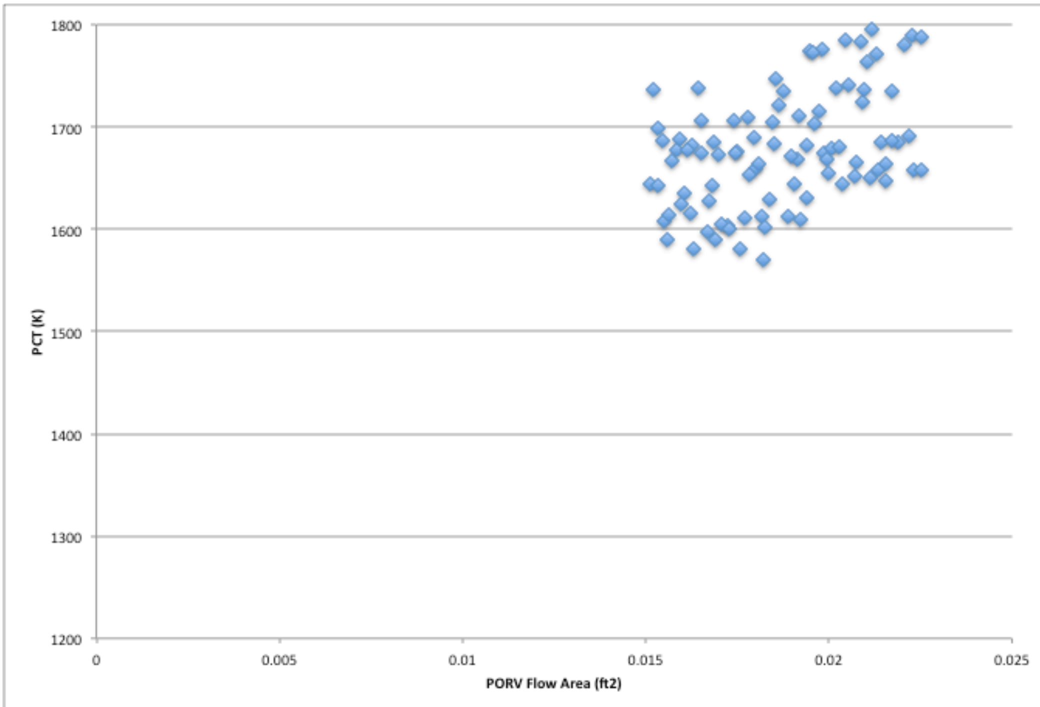


Figure 46. Sensitivity analysis of 1 CCP 2 SI with respect to PORV capacity.

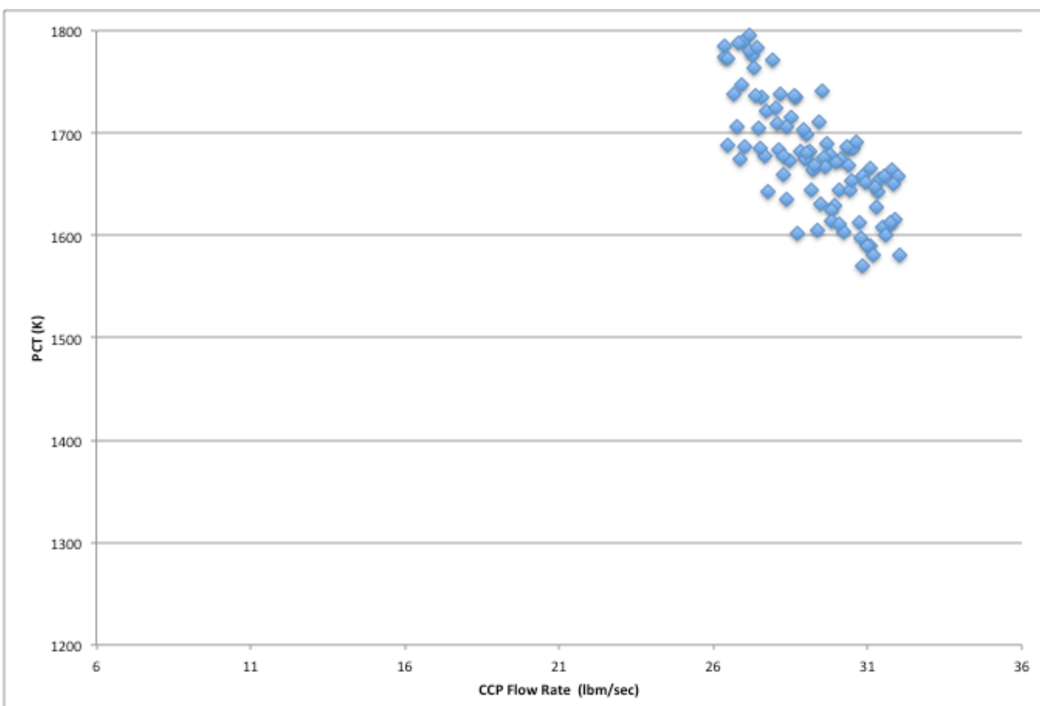


Figure 47. Sensitivity analysis of 1 CCP 2 SI with respect to CCP flow rate.

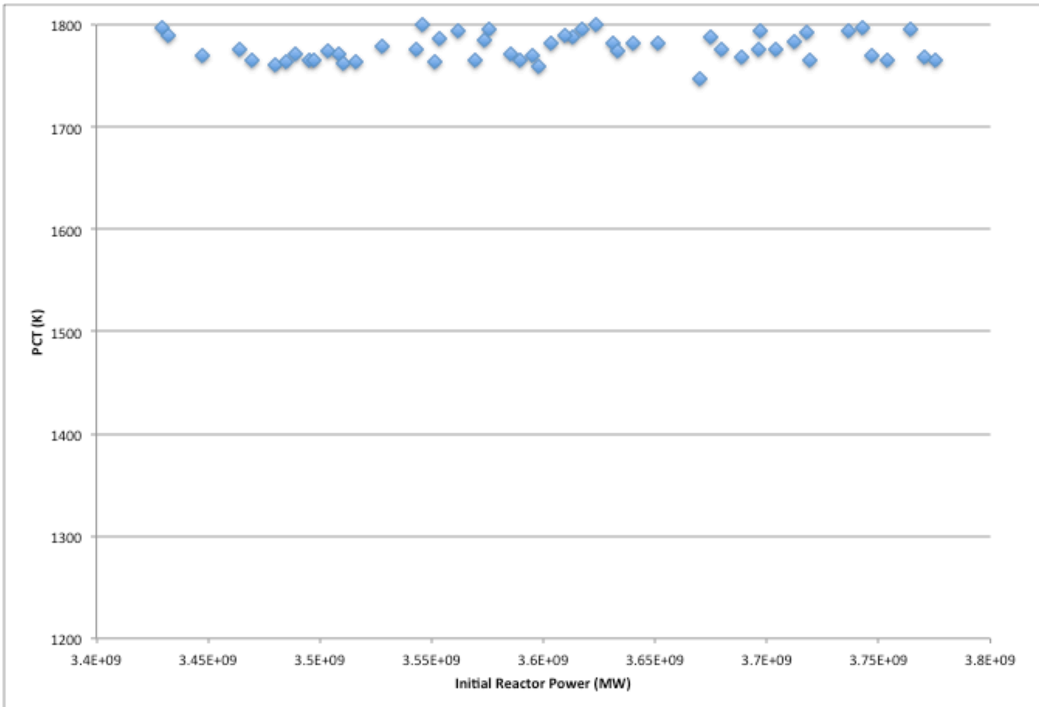


Figure 48. Sensitivity analysis of 0 CCP 2 SI with respect to initial reactor power.

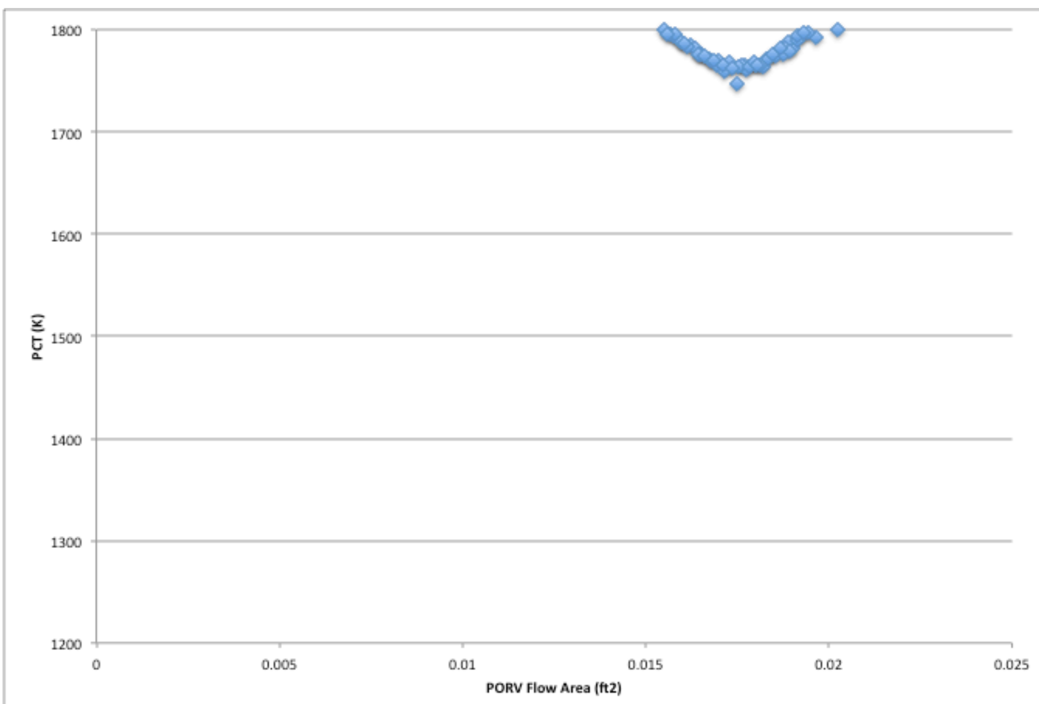


Figure 49. Sensitivity analysis of 0 CCP 2 SI with respect to PORV capacity.

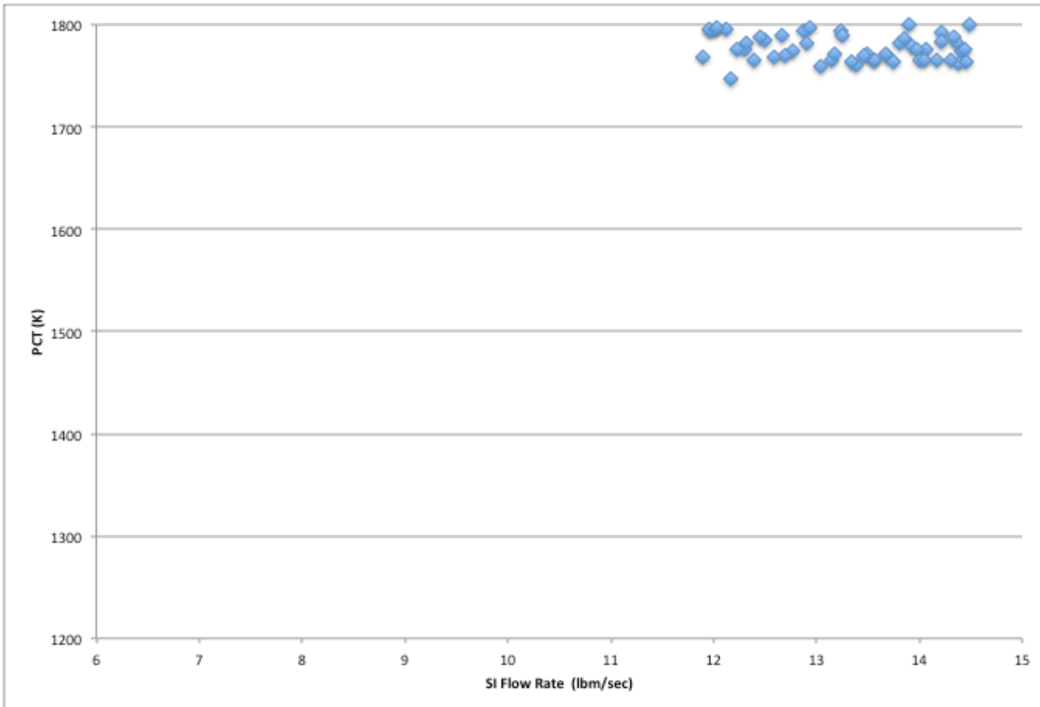


Figure 50. Sensitivity analysis of 1 CCP 2 SI with respect to SI flow rate.

Chapter 7: Boiling Water Reactor Station Blackout

In order to demonstrate the capabilities of the Branch-and-Bound algorithm for addressing highly complex DET simulations, a BWR SBO model is developed and analyzed. The BWR SBO was modeled using the RELAP5-3D code and is representative of the General Electric Mark I BWR [33], similar to the Fukushima Nuclear Power Plant. A diagram of the BWR Mark I reactor is shown in Figure 51. The BWR model consists of 3440 MWt 1152 MWe BWR reactor. The containment of the reactor consists of a Mark I pressure suppression pool design with drywells light bulb shaped. The torus and drywell are constructed of stainless steel. A diagram of the RELAP5-3D BWR model is shown in Figure 52.

The GE BWR has several primary features related to the SBO. This include the drywell, which contains the reactor pressure vessel and the circulation pumps. The Pressure Suppression Pool (torus) also known as the wetwell or PSP. The PSP contains approximately 1 million gallons of fresh water and is used in specific situations as an ultimate heat sink. The reactor circulation pumps provide cooling capabilities to the reactor.

The RPV level control system provides manual and automatic water level control. The reactor core isolation cooling system (RCIC) provides high-pressure injection of cooling water from the condensate storage tank (CST) to the RPV. A turbine driven pump takes steam from the main steam line and discharges the steam to the suppression pool. Water can also be taken from the PSP rather than the CST. The RCIC has a 600 gpm (37.9 l/s) capacity [33] .

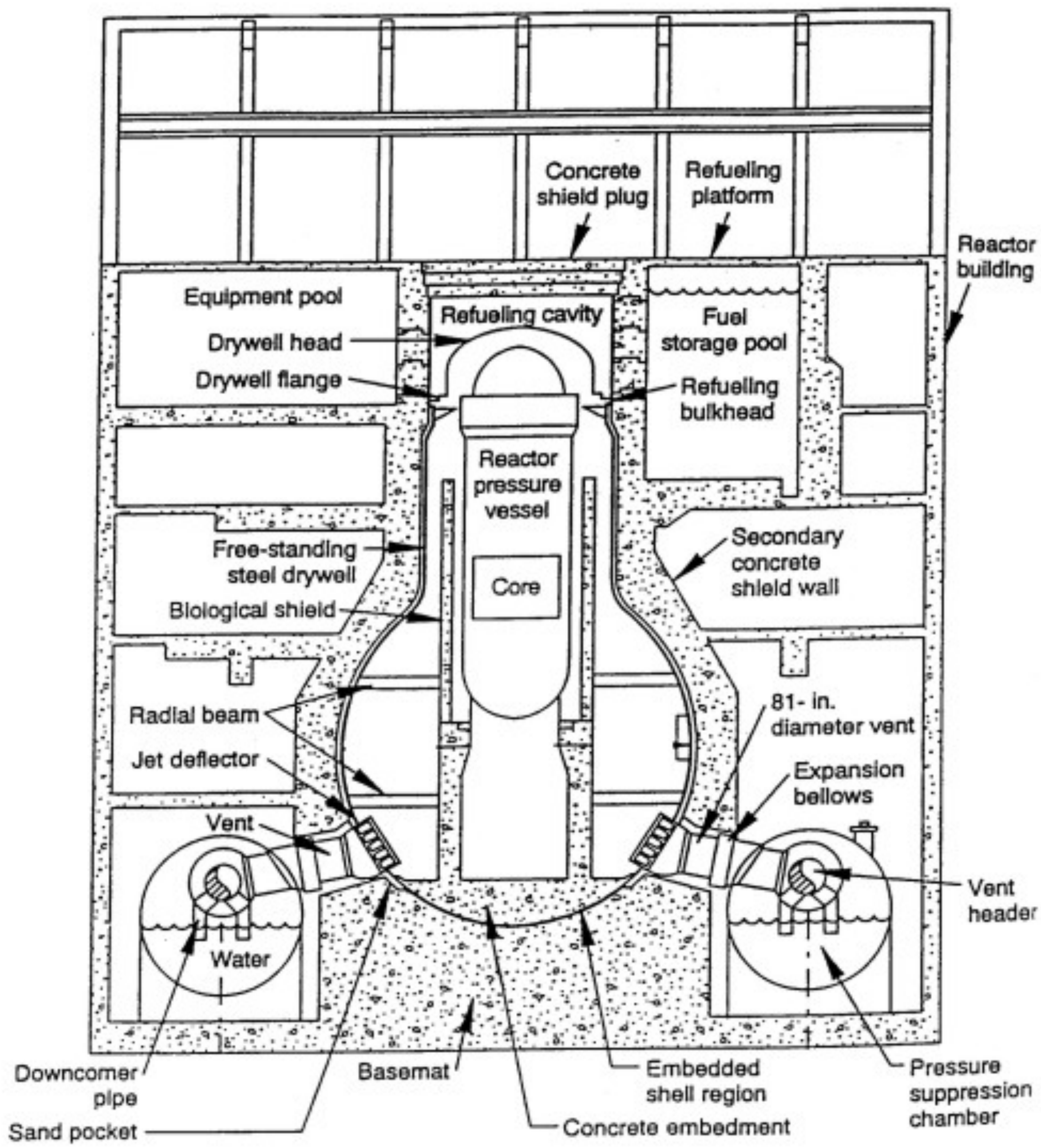
The High Pressure Core Injection (HPCI) is similar to RCIC with a much greater capacity. The RCIC has a capacity of approximately 5000 gpm (315 l/s) of flow, however, requires much lower pressures in the RPV for injection [34][45][46] .

The pressure within the RPV is controlled by the safety relief valves (SRVs). The SRVs can be controlled either manually or automatically. The valves maintain pressure between 1100 psig (7.58 MPa) and 900 psig (6.21 MPa). The actuation of the SRVs require the availability of battery power. In addition to the SRVs, the Automatic Depressurization System (ADS) provides a means to depressurize or blow down the RPV [34][45][46].

Cooling water is typically provided by the CST. The CST consists of a 375K gallon (1419 kl) tank containing fresh water. In addition to the CST, there are two additional 500K (1890 kl) gallon tanks available [34] [45] [46]. Re-alignment of the RCIC/HPCI requires manual operator action and cannot be done automatically. The PSP can provide an additional 1 million gallons of fresh water provides a heat sink if AC power is lost in the case of a SBO [45][46]. The HPCI and RCIC can draw water from the PSP as well. Due to the large amount of fresh water and limited simulation time for this analysis, the depletion of the CST or PSP is not considered.

The BWR electrical power systems, even though not explicitly modeled in the risk analysis consists of 2 separate power grids to supply off-site power. The loss of both power grids results in loss of operability of all safety systems with the exception of ADS, SRV, RCIC, and HPCI, which require DC battery power for operation. The diesel generators are available to provide up to 24 hours of AC power to emergency systems. In the event of a LOSP and loss of diesel generators (SBO), battery systems can provide at a minimum of 30 minutes of power to system and can be reconfigured to provide up to 4 hours of emergency power.

In the event battery power is lost and the reactor is depressurized through the ADS, emergency injection into the RPV can be provided by the firewater injection system. The firewater injection system can inject water at a flow rate of 2500 gpm (158 l/s) at a discharge pressure of 120 psi (0.83 MPa). This action would be performed as a matter of last resort as it would be injecting raw water into the RPV, which would result in the loss of the reactor, however, it may be necessary to maintain cooling.



Mark I General Electric,GE BWR Containment.

Figure 51. BWR Mark I Reactor [33] .

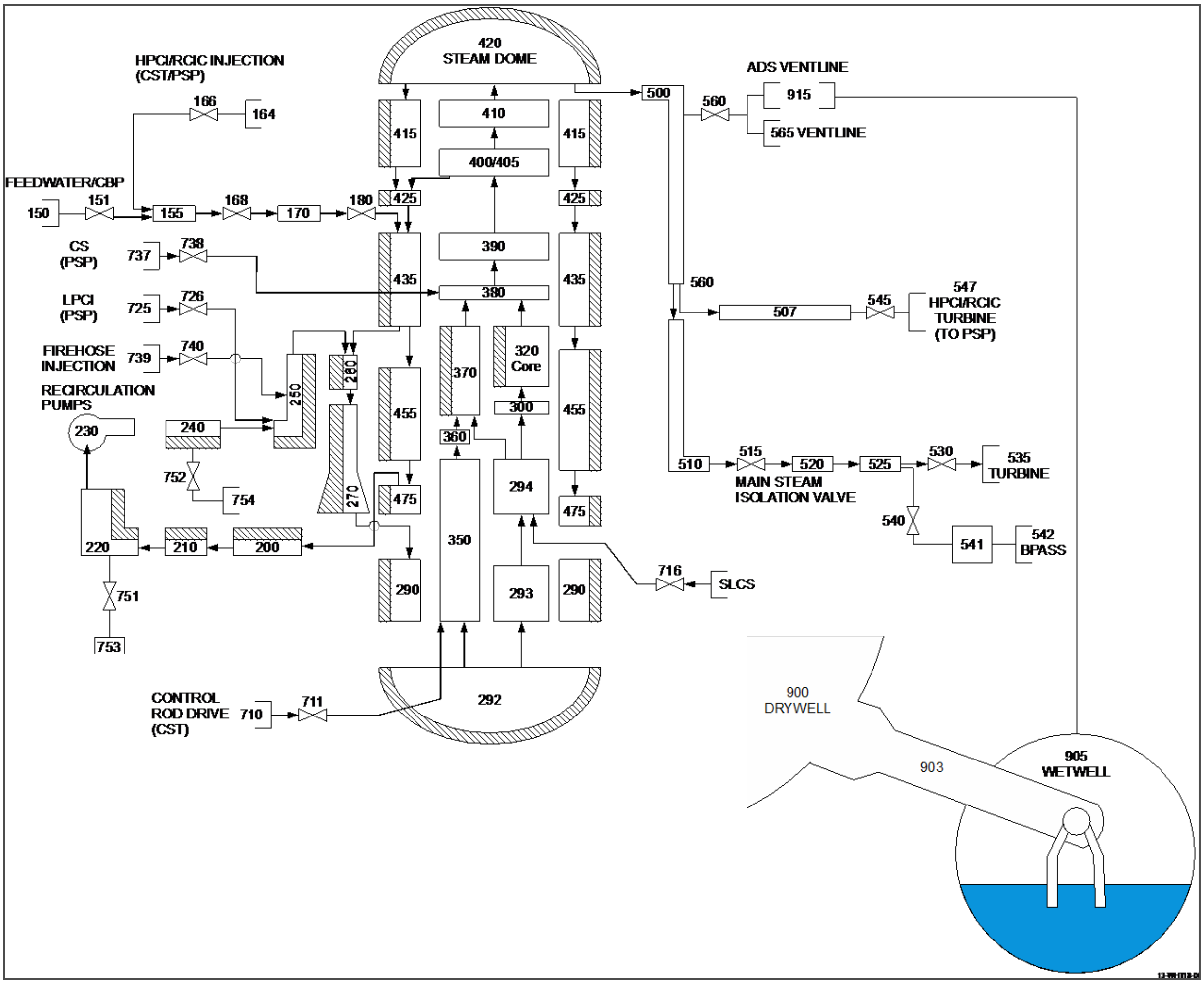


Figure 52. RELAP5-3D nodalization diagram of the GE Mark I BWR [45].

7.1 Classical BWR Event Tree Analysis

Similar to the PWR SBO case described previously, the BWR SBO involves the following sequence of events [45][46] :

- LOSP occurs as the result of loss of both switch yard supplies here at t=0 seconds
- LOSP results in the following actions in time:
  - Operators successfully scram the reactor (Resource and Response sets)
  - Main steam isolation valves automatically closes and provide primary containment isolation (System, Resource, Response sets)
  - Emergency diesel generators start to provide emergency AC power (System, Resource, Response sets)
  - Decay heat from the reactor is provided by the Residual Heat Removal system (System, Resource, Response sets)
  - Batteries are assumed to be initially functional (Resource, Response sets)
  - Pressure is maintained by a regulating SRV (State, System, Response sets)
- DG fail causing a SBO (System set)
- Component Cooling Water and Service Water systems are lost challenging the Reactor Coolant Pump (RCP) seals. A loss of the seals may occur resulting in a small LOCA (System).

The classical event trees for the SBO are presented in Figure 53 through Figure 56. Within a classical event tree, the sequence of events has been historically developed and is considered fixed. As an example, the transient begins with LOSP, followed by reactor scram, emergency power provided by the DG and whether the SRVs close. If the emergency power fails, the plant enters a SBO and if SRVs close , the seal integrity is questioned, as well as actions to extend battery power. The HPCI and RCIC is not questioned if the seals remain in tact.

Additionally, the SRVs open and close multiple times during the transient, however, the SRVs are challenged at each occurrence the reactor pressure decreases to the set point pressure. In addition, the classical event tree assumes that the DG fail immediately, which may not be the case. As was demonstrated in the Fukishima accident, the DG failed at 60 minutes following initial scram [44]. The time the DG failed, allowed for a significant amount of energy to be removed from the core. In addition, once the DG begin operation, the HPCI and RCIC system may be required to provide cooling water to the core. These systems do have the potential to fail prior to loss of DGs in the conventional approach. These types of sequences demonstrate the ability for DETs to evaluate the transients.

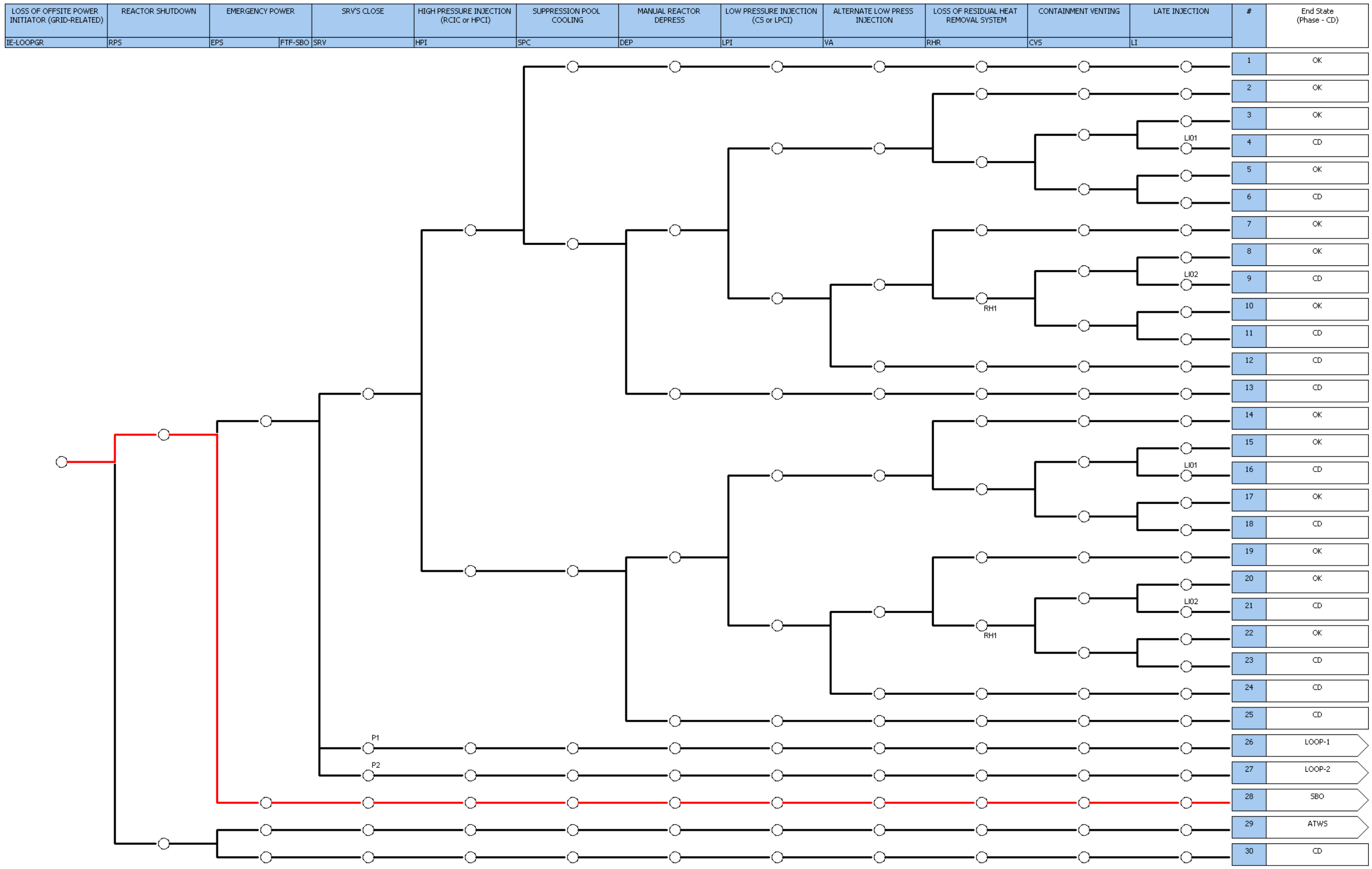


Figure 53. Classical event tree for Loss of Off-Site Power (LOSP).

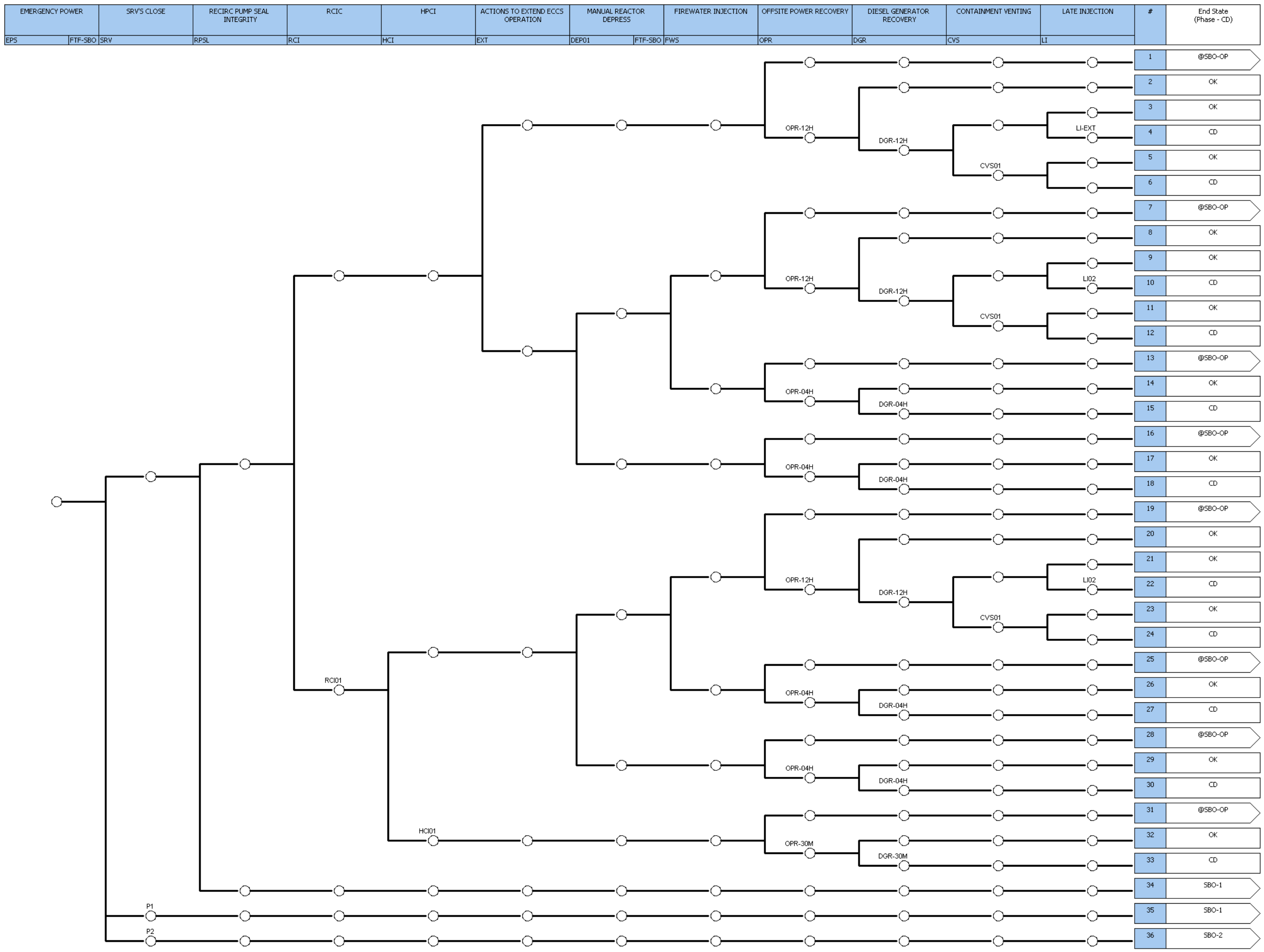


Figure 54. Classical event tree for SBO.

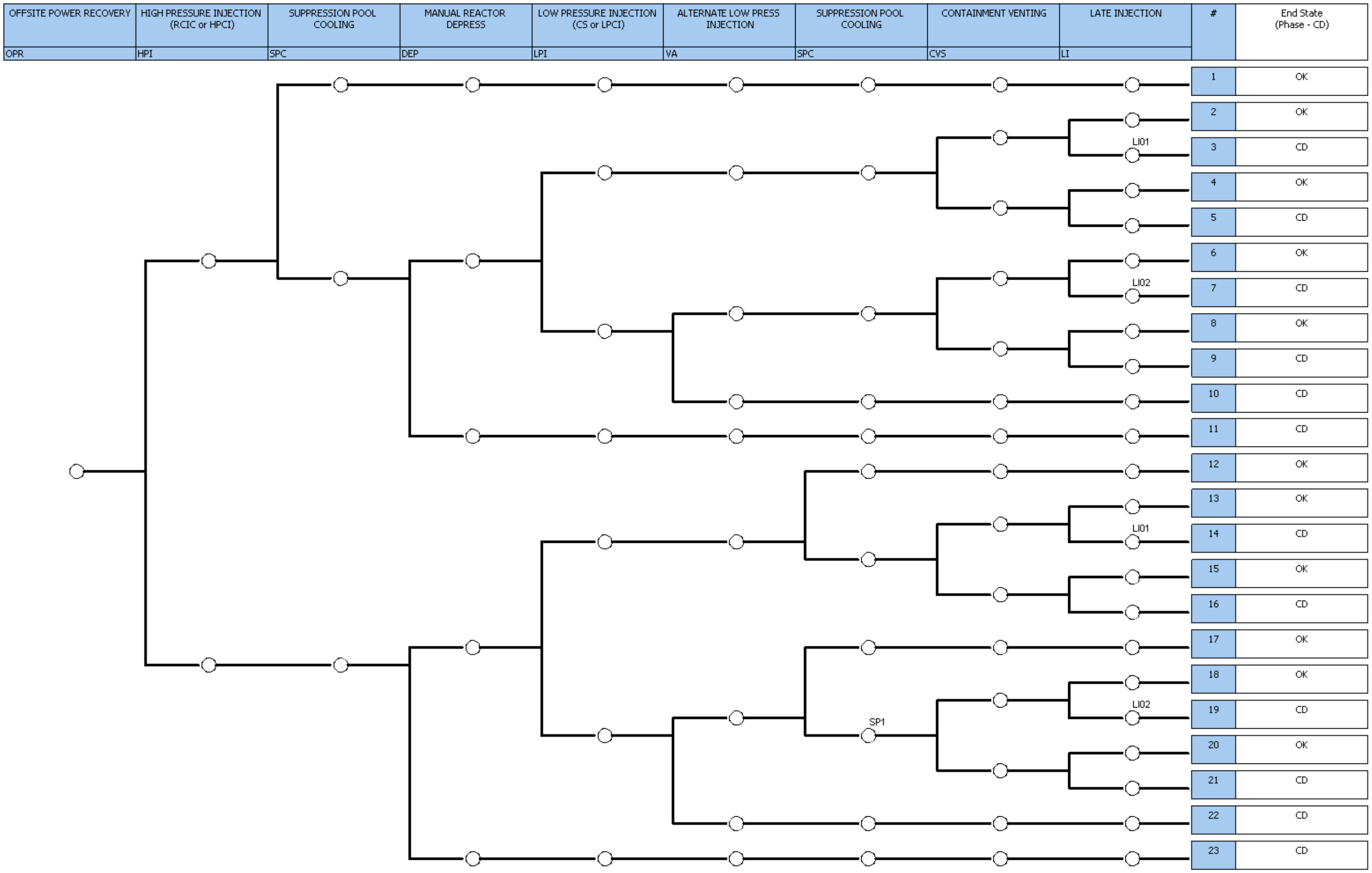


Figure 55. Classical event tree for SBO (cont.).

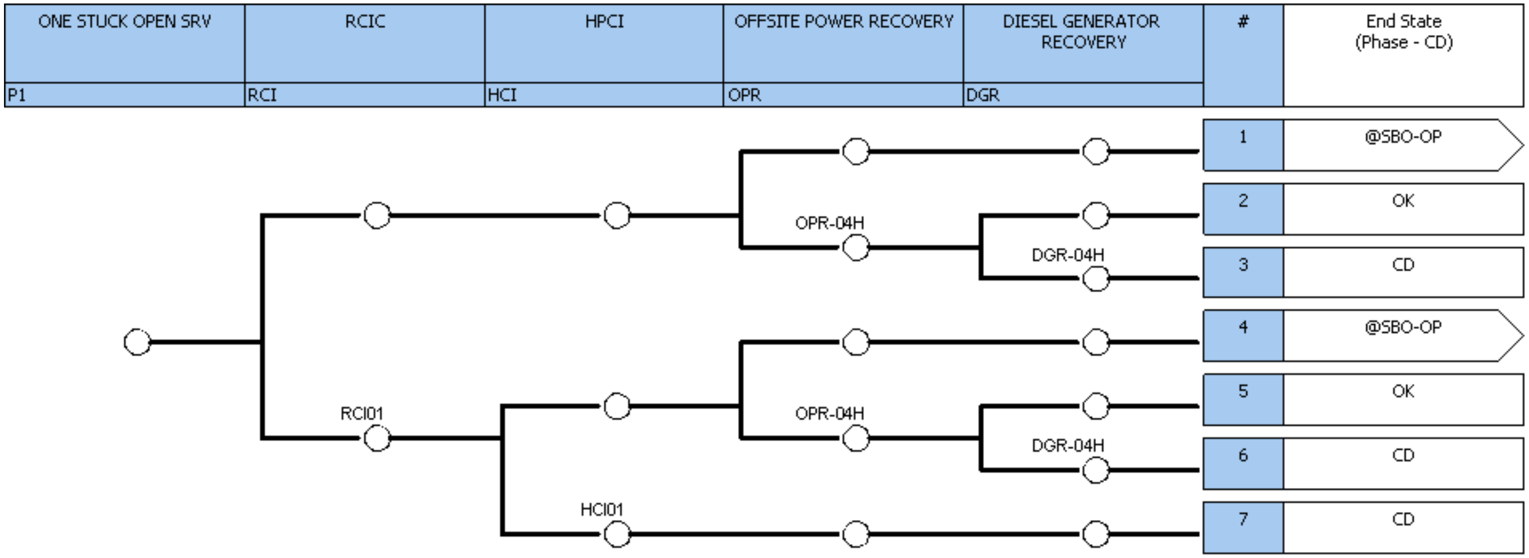


Figure 56. Classical event tree for SBO with stuck safety relief valves (1 and 2 vales are identical).

7.2 LENDIT METRICS, S2R2 and Dynamic Event Tree Development

In order to develop and optimize the DETs, the LENDIT metrics and S2R2 set theory were combined to develop the initial control logic and eventually the constraining functions for the Branch-and-Bound algorithm. The initial LENDIT metrics as described above begins with establishing a sequence of possible scenarios and transitions. Figure 57 provides a diagram of the LENDIT metrics for the BWR SBO. The metrics are established from operating procedures as well as the classical event trees used to quantify risk [46]. The series of events begins with the question of whether or not SBO has occurred. After SBO has occurred, the SRVs may cycle several time reducing pressure in the reactor and maintaining the pressure between 900 psig (6205 kPa) and 1100 psig (7584 kPa). The residual heat removal (RHR) system provides cooling and pressure relief prior to SBO. During this process, one or two SRVs may fail to close resulting in what would be equivalent to a small break loss of coolant accident (LOCA). Additionally, the cooling of the RCP seals may be challenged anytime during a SBO. This could result in seal failure resulting in a small break LOCA.

In addition to SRV failure both the HPCI and RCIC pumps can fail. This condition could result in a loss of cooling capability to the core. If HPCI and RCIC are lost, the reactor needs to be depressurized and coolant inventory can be made up using the low pressure injection system (LPIS) or the less desirable firewater system. Activation of the firewater injection system requires the human intervention and action. The probability of loosing HPCI and RCIC are relatively low, but are still possible.

During the SBO, efforts will be made to extend the battery life while response crews attempt to recover either the EDGs or off-site power. Extension of the battery life, for example, can be realized by reducing the number of components requiring battery power for operation that are not needed for transient response. In fact this is why we have used pressure, temperature, level, and decay heat as our LENDIT metrics. Typically, the battery life can be extended to 4 to 6 hours if operational staff handles the transient response properly.

Once the battery power has been drained, the HPCI, RCIC, and SRVs are no longer operable as power is no longer available to these systems. It may be possible, but not guaranteed that the RCIC system can be operated by the use of the turbine driven pump and manual operation by controlling steam flow through the pump. Operators at this point will be required to make decisions with regards to the probability of recovery AC power. If AC power is not recoverable, firewater may be the last available means to cool the core. The use of firewater (essentially non-reactor grade water) may have severe impact on the economic viability of the reactor resulting in an economical loss. However, the alternative of melting the core would be more catastrophic than a post-accident reactor with chemical impurity contamination of the coolant.

The CDFs, for which the DET is based, for the timing of SBO, manual ADS, and failure of battery power, firewater activation, and AC power recovery are presented in Figure 58 through Figure 62 and summarized in Table 7. The DET simulation assumed a plant mission time of 24 hours. It is assumed in this study that if cladding failure has not occurred in 24 hours, then the additional actions would provide AC power to the plant such as via transport of off-site DG (to the plant). The DET model simulations were run using the RAVEN framework coupled with RELAP5-3D. Initially, a simulation was undertaken using more of "brute-force" method with no optimization to create a baseline model to determine the effects of the optimization. The second model was tested using the Branch-and-Bound optimization technique to demonstrate the capabilities of reducing the number of branches created and thus reduction in overall simulation time.

Similarly to the PWR SBO, optimization of the trees involves developing bounding functions as the simulation progresses. The bounding functions are developed using the "surface" plot approach. The parameters for this study were determined with respect to those important for calculating peak clad temperature.

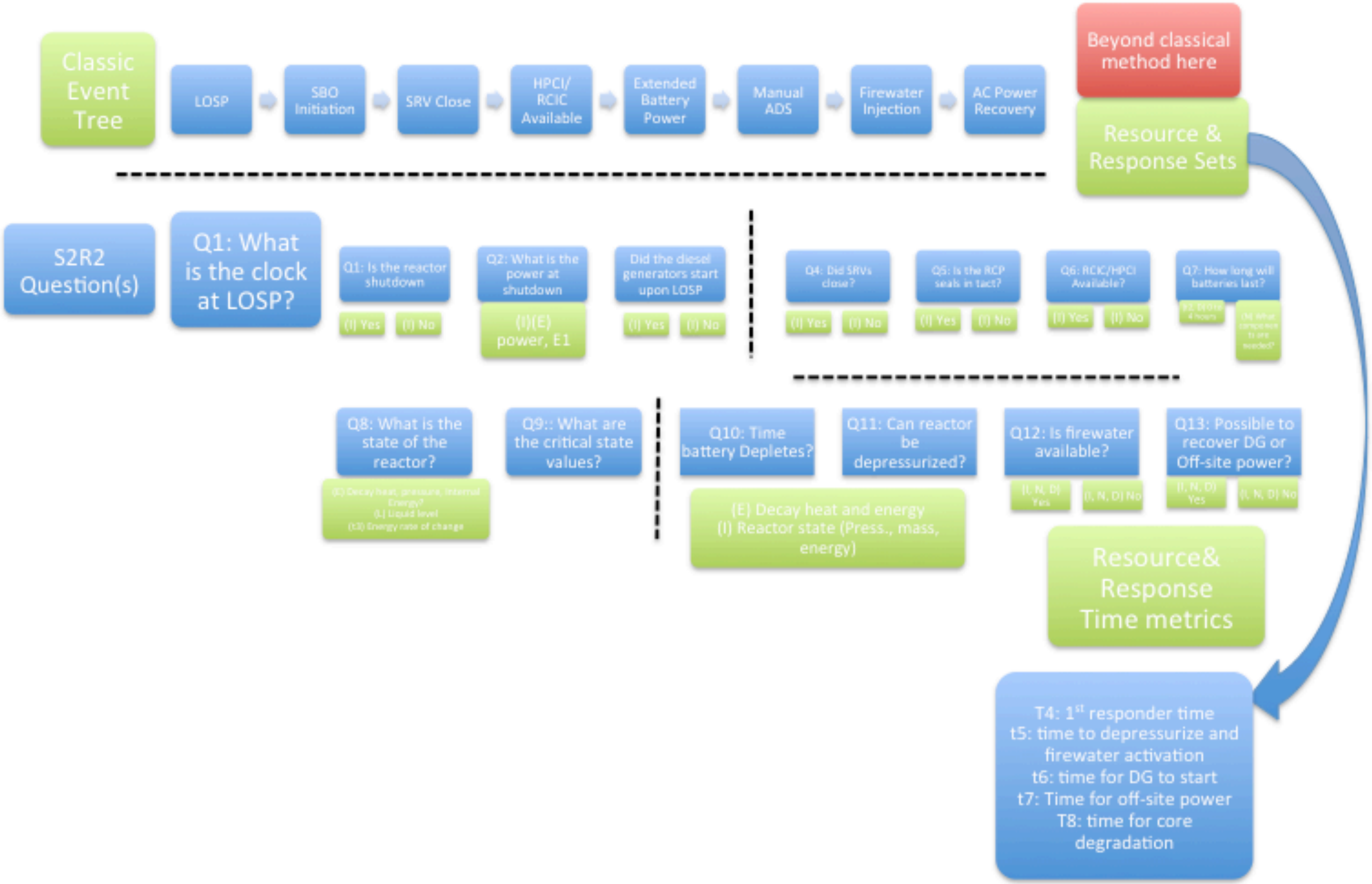


Figure 57. LENDIT Metrics for the BWR SBO Transient.

Table 7. Probability distributions used in BWR SBO DET analysis.

Event	Distribution Type	Distribution Parameters	Distribution Mean	Standard Deviation
Failure of DG*	Exponential	λ=0.0033/second	303 seconds	0.0033 seconds
Failure of Batteries	Uniform	Hi=6 hours Low=30 minutes	195 minutes	95.26 minutes
Failure of HPCI/RCIC	Exponential	λ=1.22503E-6/second	226 hours	0.00441 hours
Pump Seal LOCA	Uniform	Hi=12 hours Low=0 hours	6 hours	3.5 hours
Recovery DG	Weibull	λ=368.4 minutes k=0.745		
Activation of Firewater	LogNormal	--	42 minutes	15 minutes
Manual ADS	LogNormal	--	8.4 minutes	15 minutes
*Failure rate of DG is artificially high to account for failure on demand of DG.				

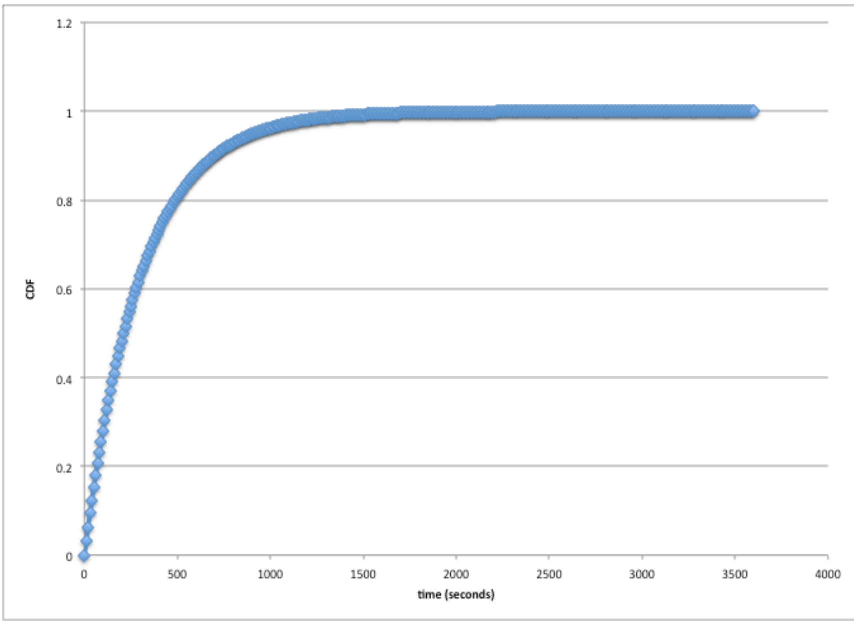


Figure 58. CDF for DG Failure used in SBO Analysis

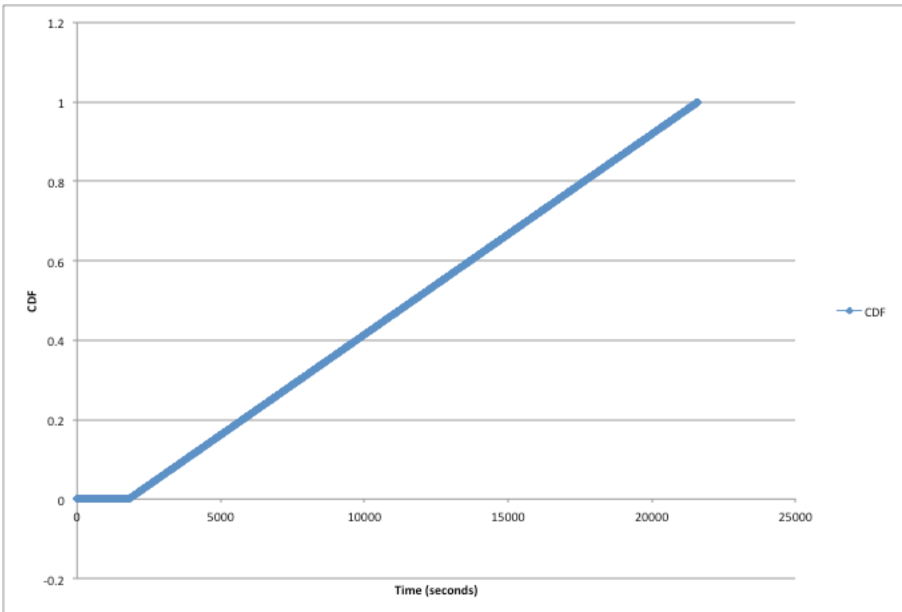


Figure 59. CDF for Battery Failure used in SBO Analysis.

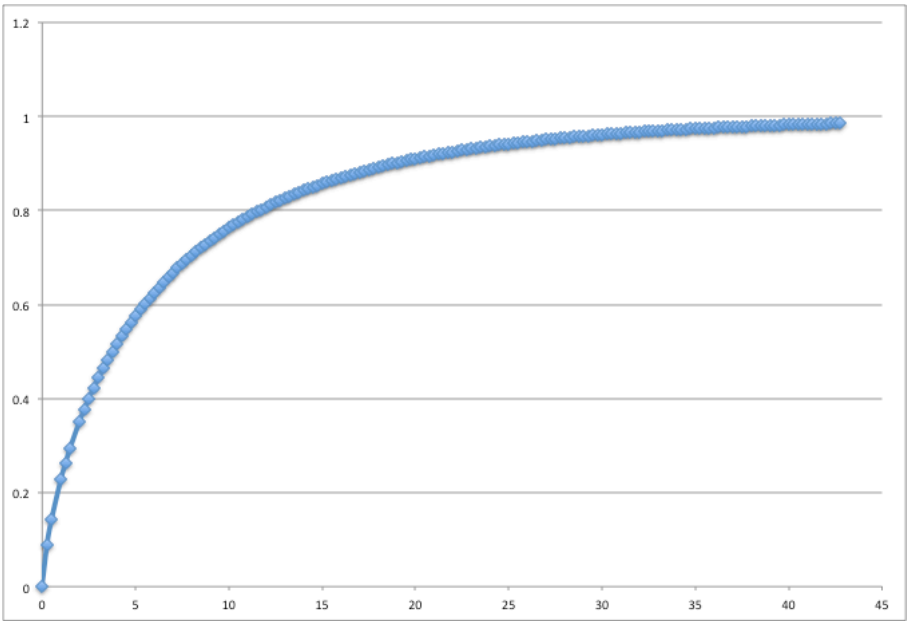


Figure 60. CDF for DG Recovery used in SBO Analysis.

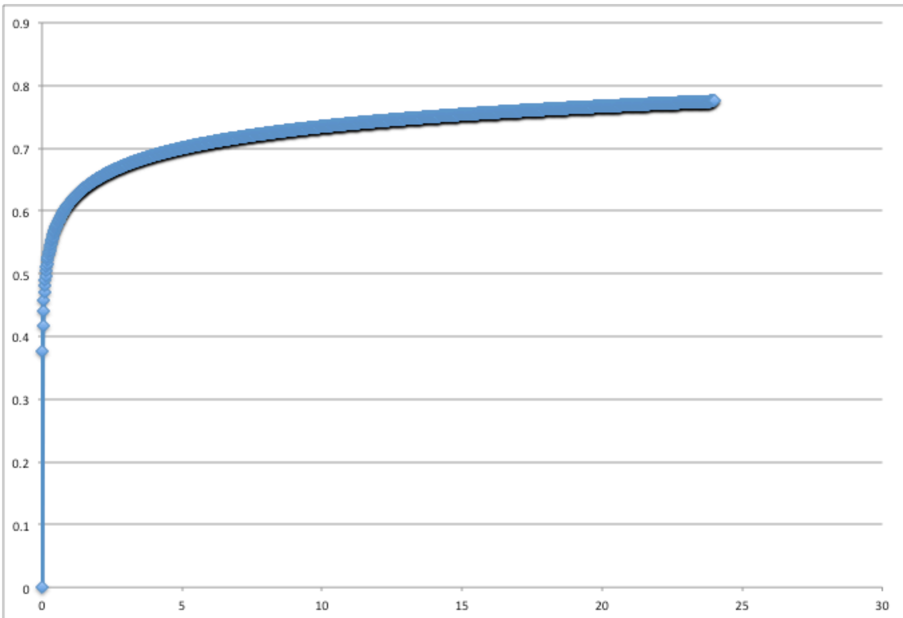


Figure 61. CDF for Manual Activation of ADS used in SBO Analysis.

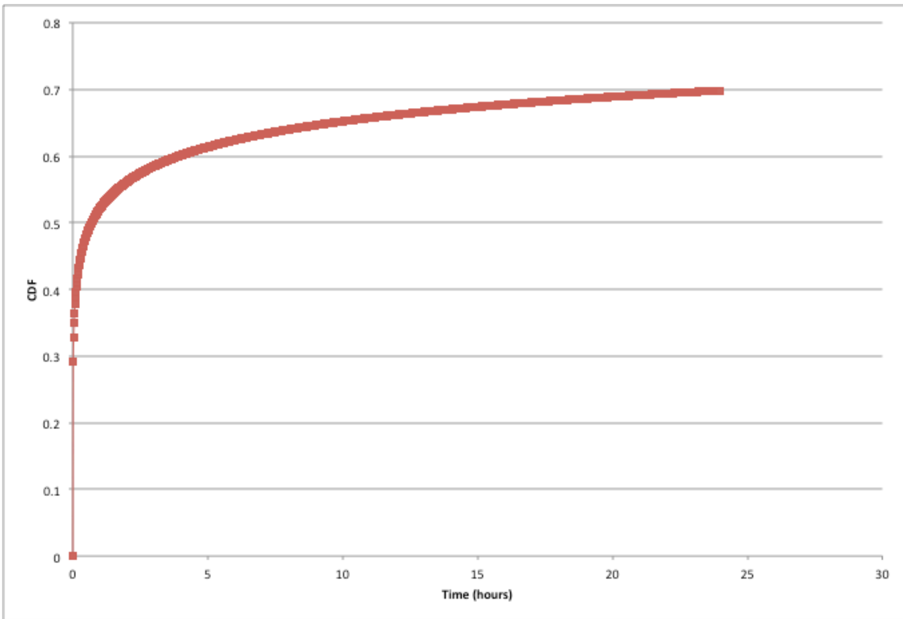


Figure 62. CDF for Firewater Injection used in SBO Analysis.

The simulations for the BWR SBO resulted in nearly 20752 nodes with 8457 final end states. Of the end states 1857 ended in failure and 6600ended in success. Within a risk analysis framework the intent is to find the highest probability of failure. In this simulation, approximately 22% of the simulations ended in failure. These simulations provide the most useful information. Of most importance are the simulations with the highest probability of failure. Examination of a listing of the results from the simulation identified approximately 45 nodes that have a failure rate within 3 orders of magnitude of the highest. The highest failure probability in this simulation was 6.22×10^{-3}. This value is large relative to the core damage frequency of a BWR SBO, however, the simulation assumed an unrealistic failure rate on DGs for the purposes of demonstration and the lack of the ability of RAVEN to handle a combination of on-demand failures and fail to run conditions. If we were to consider the failure leaves within 3 orders of magnitude from the maximum, we could discount 97% of the failure nodes. However, there are some plant failure states that may or may not fall into the top list.

The progression of the transient for a select set of high probability of failure cases and recovery cases is presented in Figure 63 through Figure 74. Table 8 provides a description of the cases and the timing of events that occurred. Case 1 and 2 provides an example of the progression of the highest probability of failure cases. The reactor scrams immediately and DG are lost at approximately 3.5 minutes and 11.4 minutes for cases 1 and 2, respectively. Battery power is lost at 63 minutes and 195 minutes, for cases 1 and 2 respectively. Following battery lost, critical heat flux (CHF) is reached in approximately 2 hours (Figure 66). The time to reach CHF is not greatly effected by the time battery power is lost. The reactor decay heat at this point in time has reached a semi-steady state condition and the difference in energy deposited into the cooling is not significantly different at 195 minutes vs. 63 minutes. Therefore, the time-scale for operators to achieve a safe shutdown condition is on the order of 2 hours.

Figure 63 presents the pressure in the reactor during the transient. The pressure oscillates during the SBO event as SRV are cycled. A high-pressure SRV maintain pressure below 1100 psig (7.6 MPa) even if battery failure has occurred. The HPCI/RCIC pumps provide makeup cooling to the reactor if level drops below 40 ft (12.2 m). The makeup from the HPCI/RCIC is shown in Figure 65. Once battery power has failed, the liquid level begins to drop resulting in core uncovery. Internal energy density presents the same oscillations as the reactor pressure as energy is released through the SRV.

Cases 3 through 6 provide an example of a failure of the SRV to close during the transient as well as the ability for the firewater injection system to prevent core damage. This transient begins with SBO at 3.5 minutes and battery failure occurring at 195 and 327 minutes for cases 3/4 and 5/6, respectively. Firewater injection is successful for cases 3 and 5. Case 4 is similar to Case 3 except firewater injection is not successful. Case 6 is similar to Case 5 with the same condition as firewater injection is not successful. Firewater injection occurs at 215 minutes in Case 3 and 380 minutes in Case 5. The reactor pressure for these cases is presented in Figure 68 and the failure of the SRV to close can be seen. For cases 3/4 and cases 5/6, the SRV fail to close at 47 minutes and 119 minutes respectively or approximately 72 minutes apart. The time of battery failure is irrelevant in the case as the transient has reached a small break LOCA condition. CHF starts in case 4 and case 6 at 343 minutes and 381 minutes, respectively. The time difference in this case is 39 minutes. Therefore, the time-scale for reaching CHF, which is a precursor to cladding degradation is not necessarily linear.

The final case (Case 7) provides a demonstration of operator action involving the manual activation of the ADS. The presented case does not include activation of the firewater injection system, which results in failure. In this case, SBO occurs at 11.4 minutes and follows the normal operating path with the activation of the ADS occurring at 250 minutes. Battery failure occurs at 338 minutes. The case demonstrates the time scale for failure if depressurization occurs without the ability to provide cooling either through firewater injection or the low-pressure injection system. Low-pressure injection in the BWR is not available without AC power. Once the ADS has been activated, the pressure (Figure 71) drops in the reactor quickly, below the operating pressures for the HPCI/RCIC pumps and cooling capability is lost without operators overriding the system. In addition, the liquid level (Figure 73) drops causing uncover of the core.

Table 8. Summary of DET cases resulted in failure.

Case	File Name (Each Sequence Represents a Branching Condition in RAVEN)	Description of Events
Case 1	BWR_1-1-1-2-1-1-1-2-2-2-2-1-1-1-1	DG Failure at 210 sec Battery failure at 3780 sec Cladding failure occurs 14108
Case 2	BWR_1-1-1-1-1-2-1-1-1-2-1-1-2-1-2-2-1-2-2-1-1	DG Failure at 697 sec Battery failure at 11700 sec Cladding failure occurs at 21556
Case 3	BWR_1-1-1-2-1-1-1-3-1-1-1-1-2-2-1-2	DG Failure at 210 sec Battery failure at 11700 sec SRV FTC at 2811 sec Firewater injection at 14430.2 sec
Case 4	BWR_1-1-1-2-1-1-1-3-1-1-1-1-2-2-1-1	DG Failure at 210 sec Battery failure at 11700 sec SRV FTC at 2811 sec Cladding failure at 25073 sec
Case 5	BWR_1-1-1-2-1-1-1-2-2-2-1-2-1-2-2-1-2-2-3-1-1-2-1-1-2-2	DG Failure at 210 sec Battery failure at 19830 sec SRV FTC at 7165 sec Firewater injection at 22350 sec
Case 6	BWR_1-1-1-2-1-1-1-2-2-2-1-2-1-2-2-1-2-2-3-1-1-2-1-1-2-1	DG Failure at 210 sec Battery failure at 19830 sec SRV FTC at 7165 sec Cladding failure at 27485 sec
Case 7	BWR_1-1-1-1-1-2-1-1-1-2-1-1-2-1-2-2-1-2-1-2-1-1-2-1-2	DG Failure at 210 sec Battery failure at 20317 sec Manual ADS at 15002 sec Cladding failure occurs 20772 sec

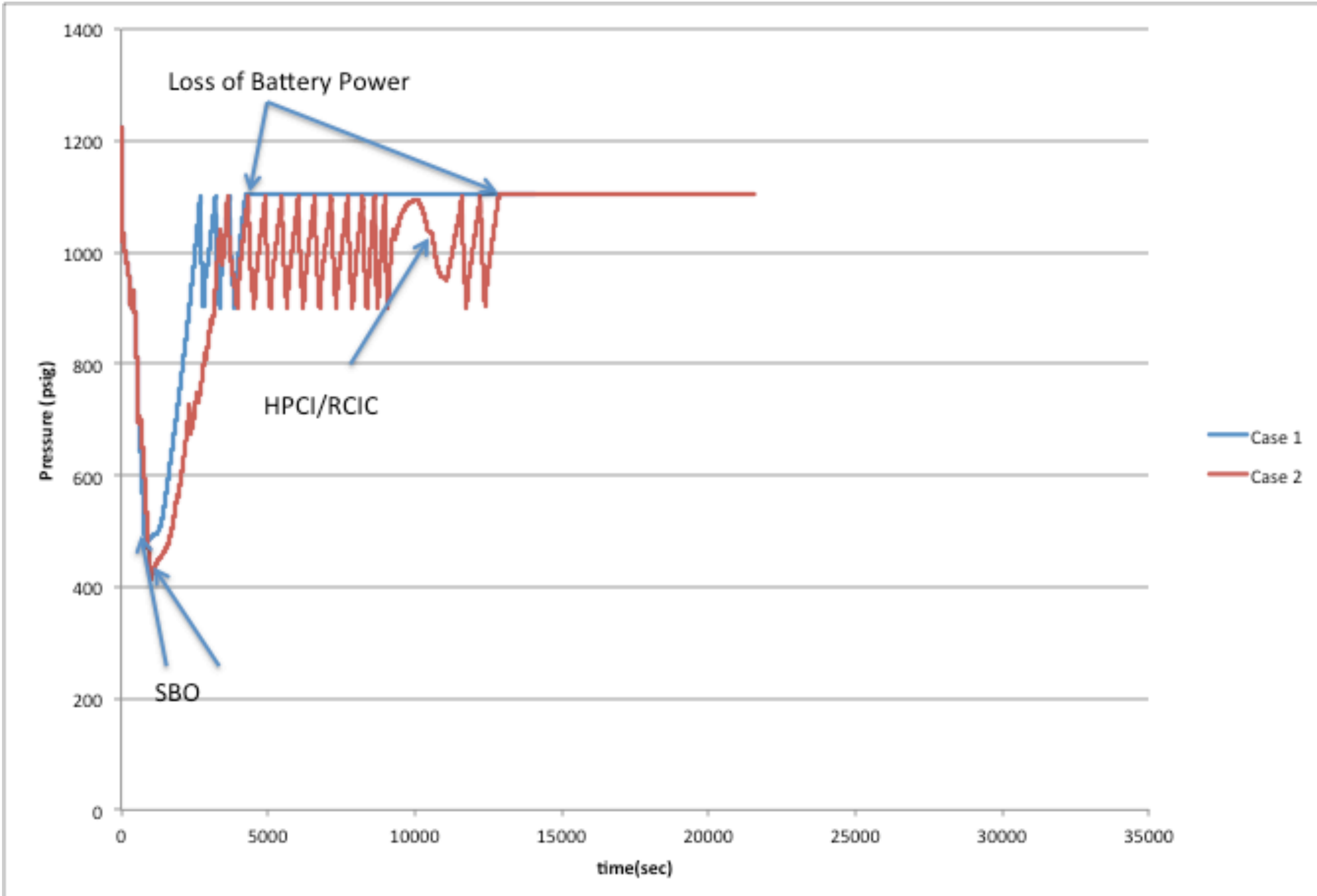


Figure 63. RPV pressure for SBO for case 1 and 2.

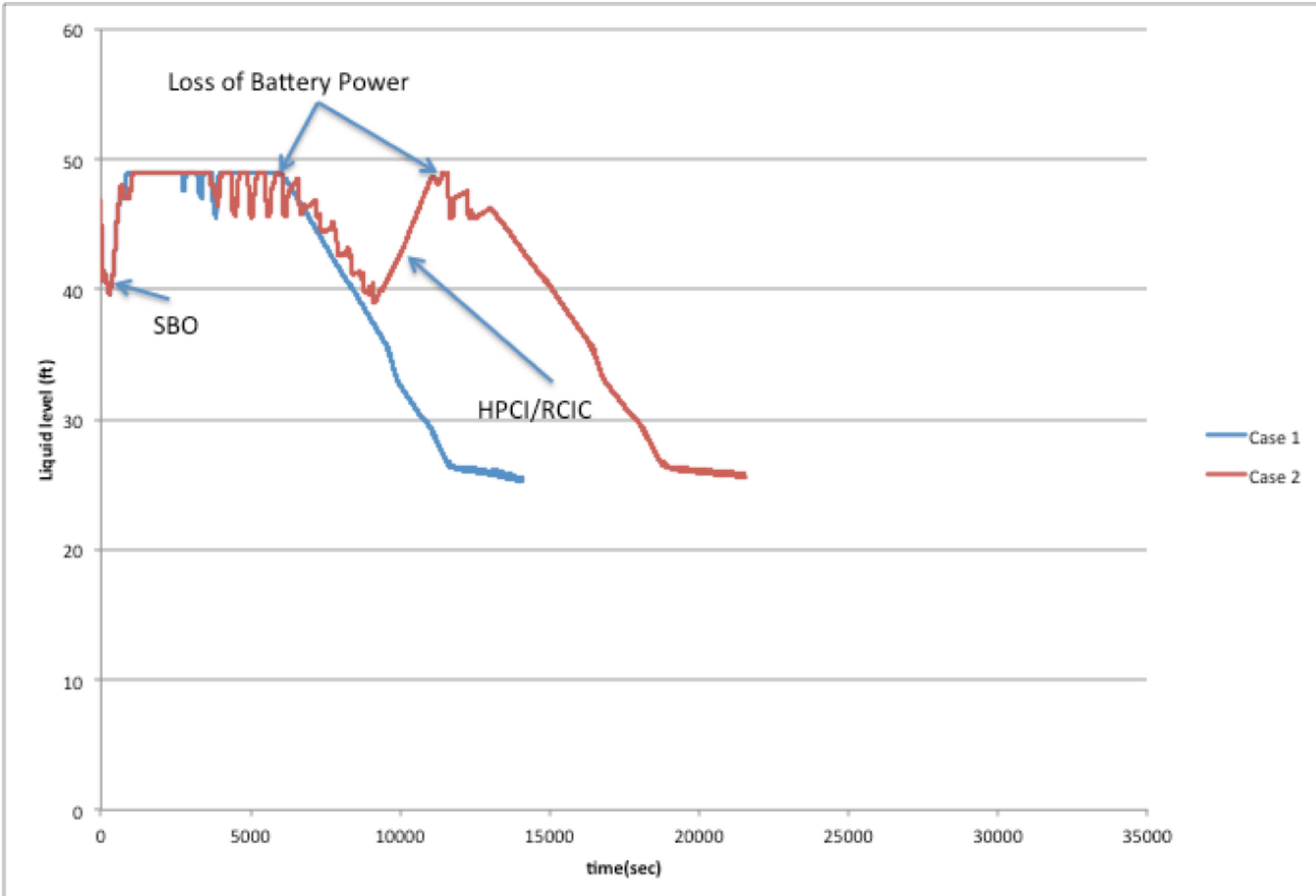


Figure 64 Internal energy density for SBO cases 1 and 2.

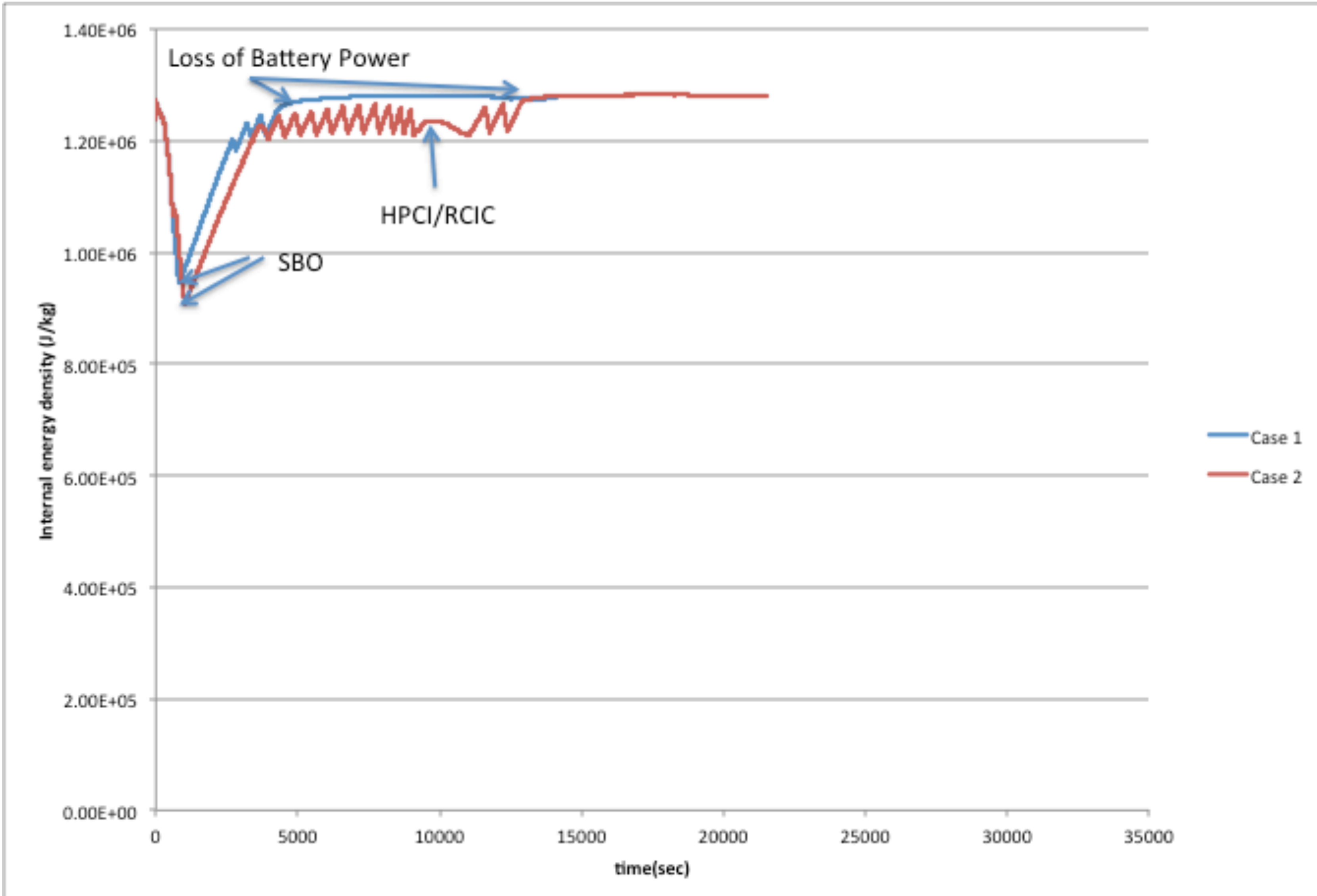


Figure 65. Liquid level for SBO cases 1 and 2.

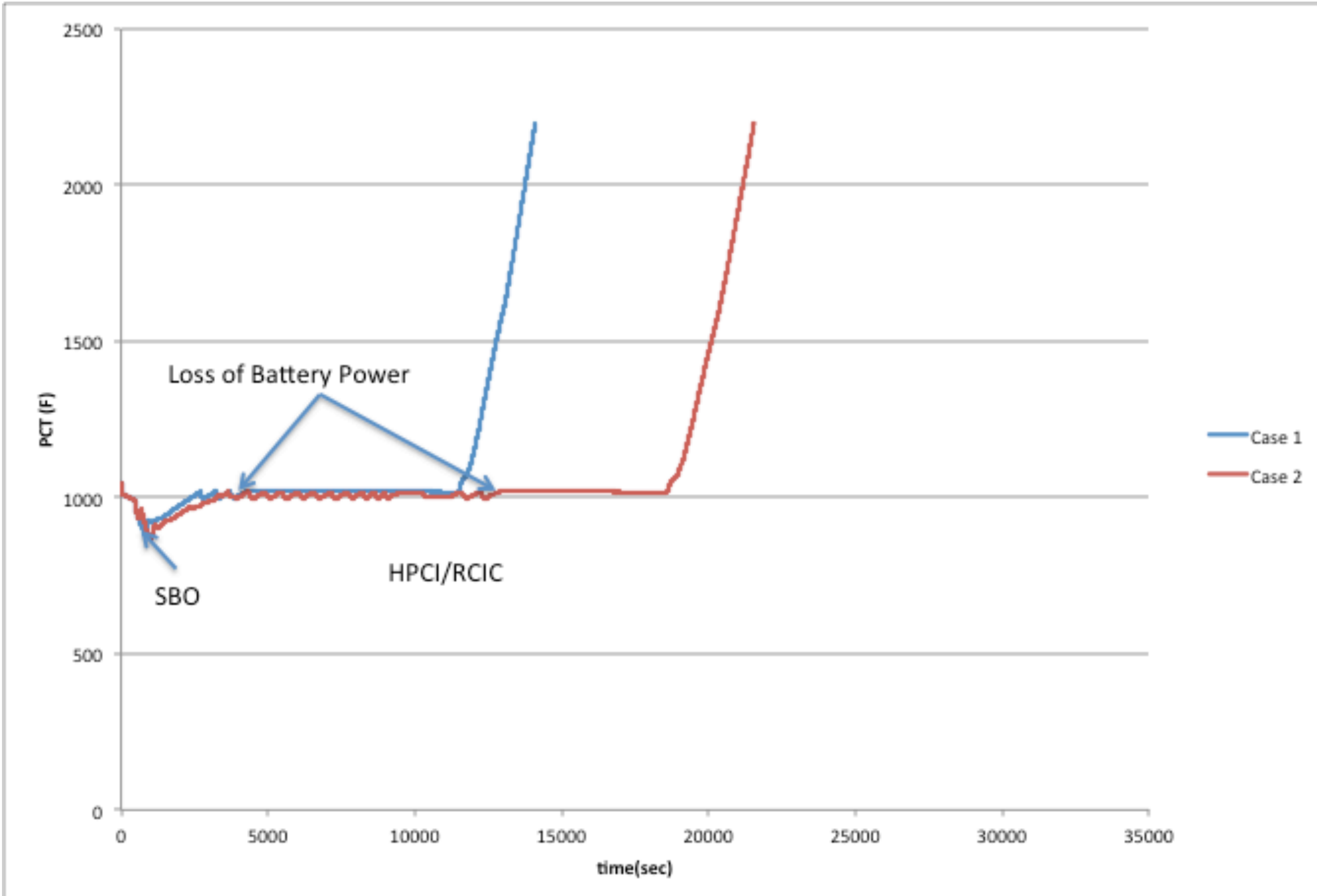


Figure 66. Peak clad temperature for SBO cases 1 and 2.

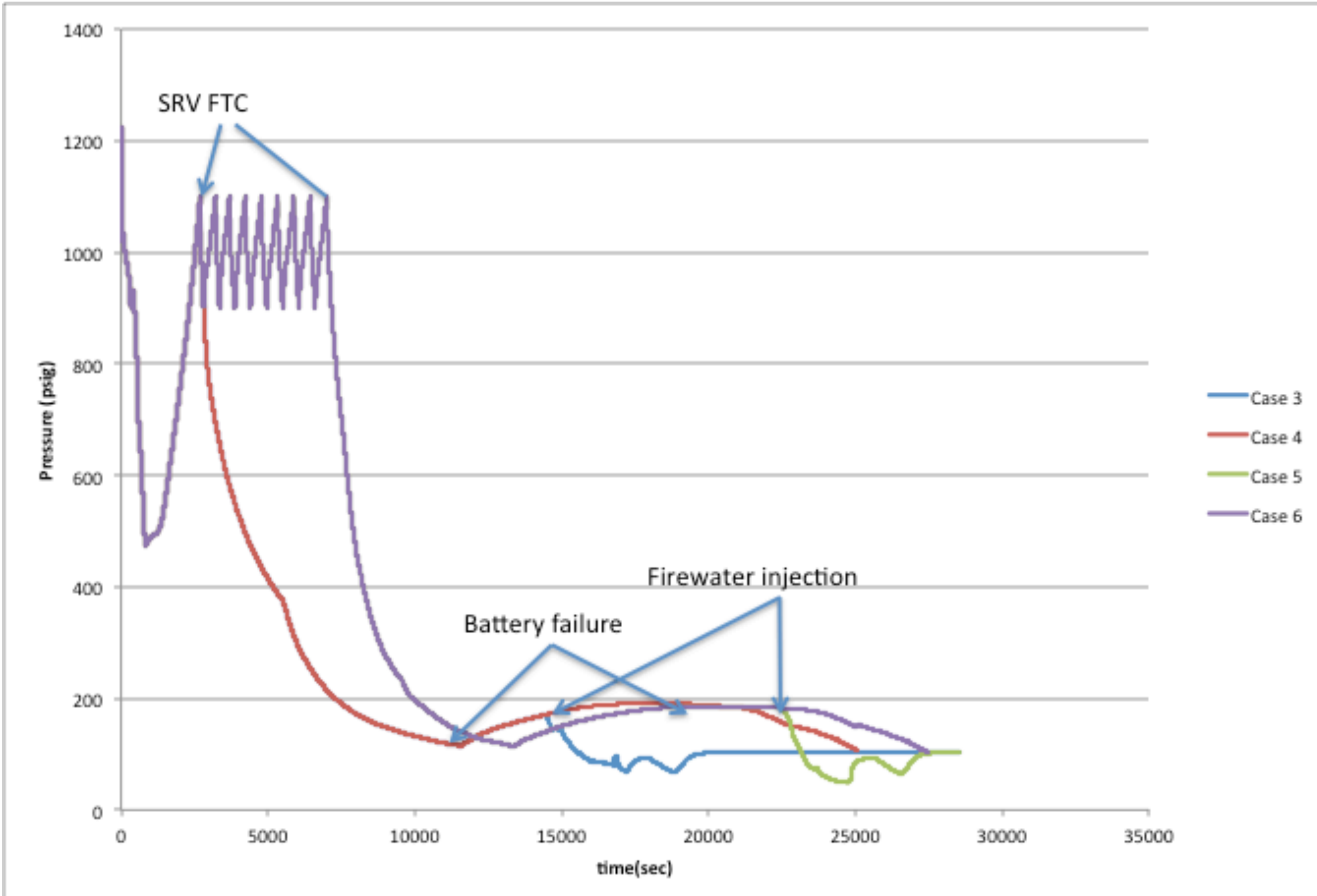


Figure 67. RPV pressure for SBO cases 3-6.

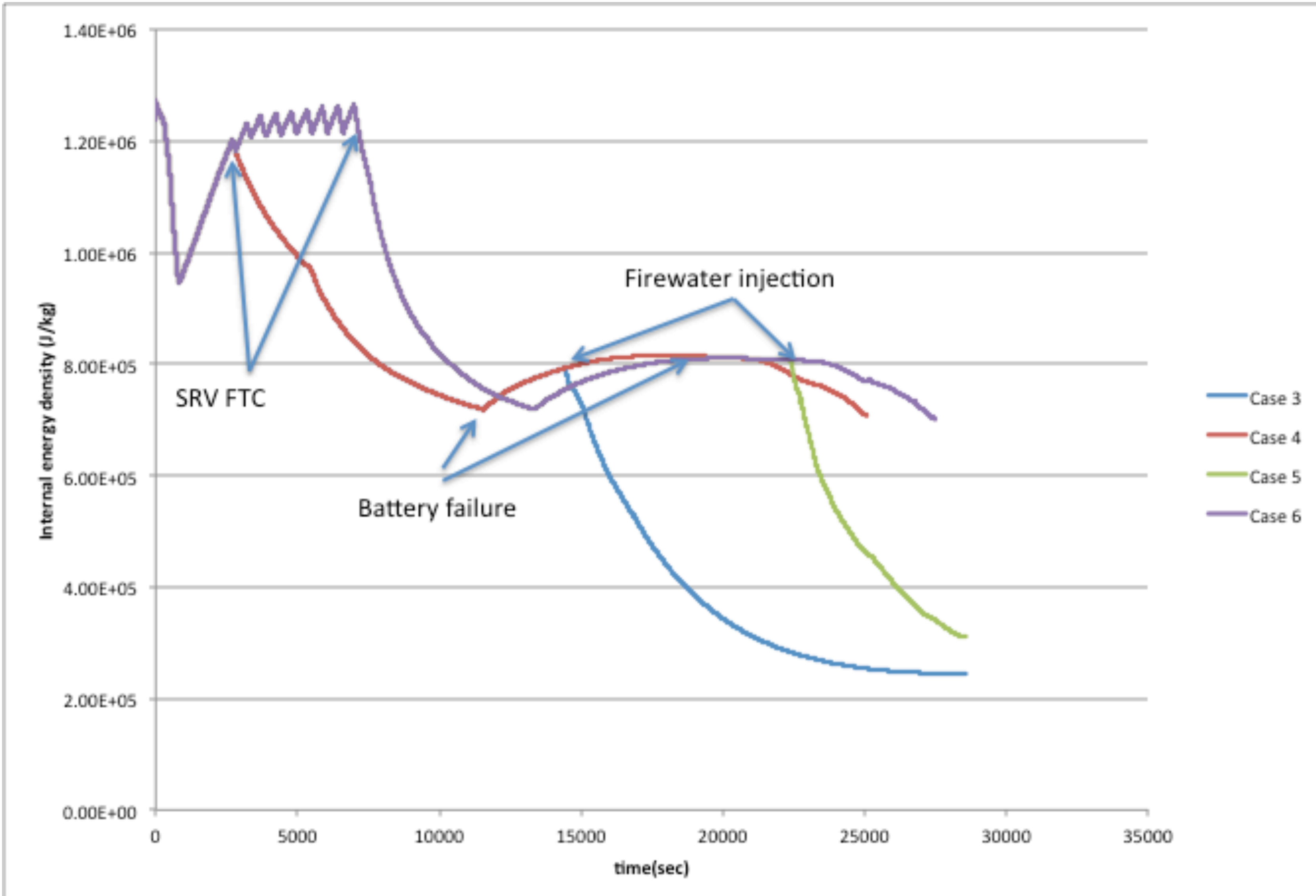


Figure 68. Internal energy density for SBO cases 3-6.

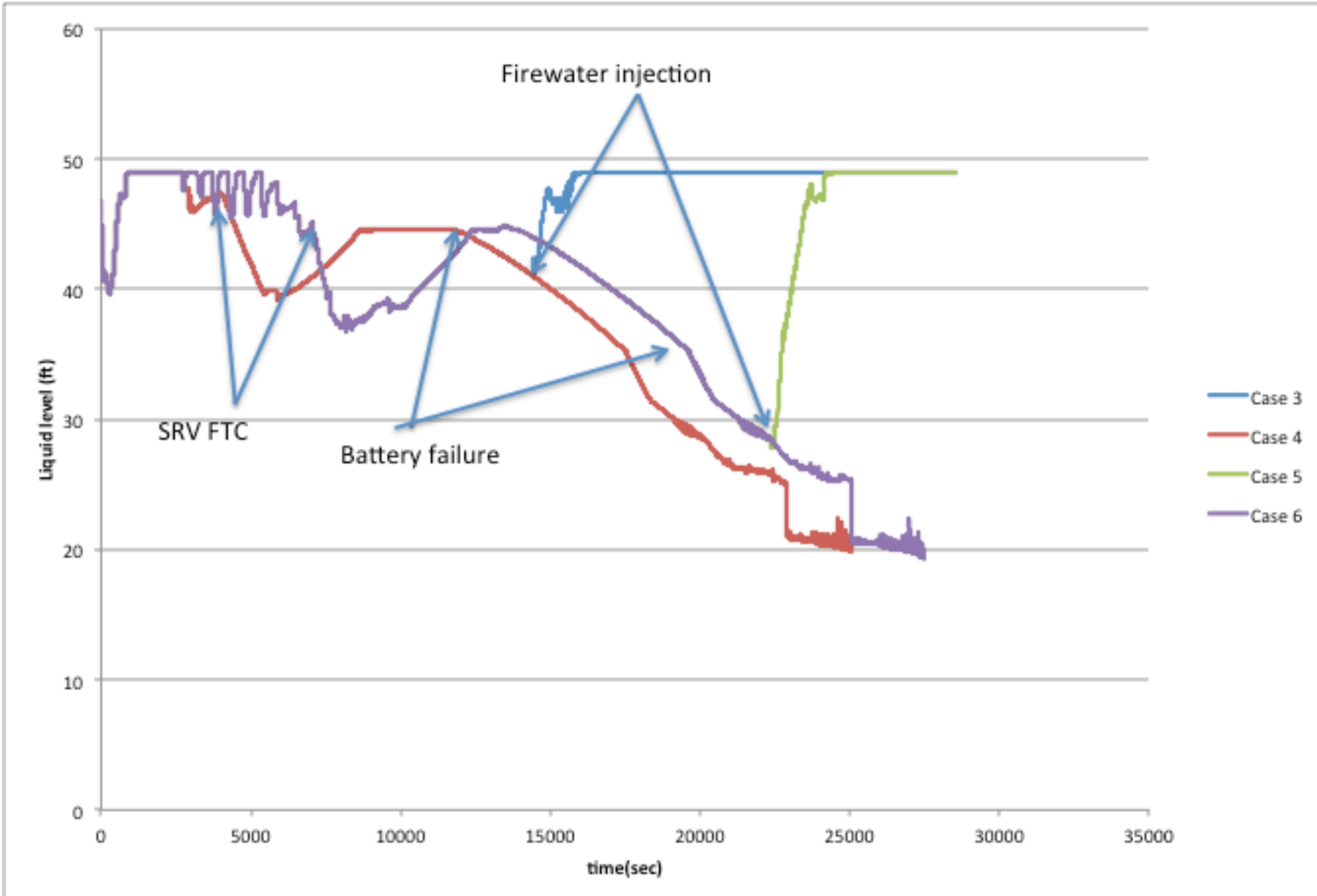


Figure 69. Liquid level for SBO cases 3-6.

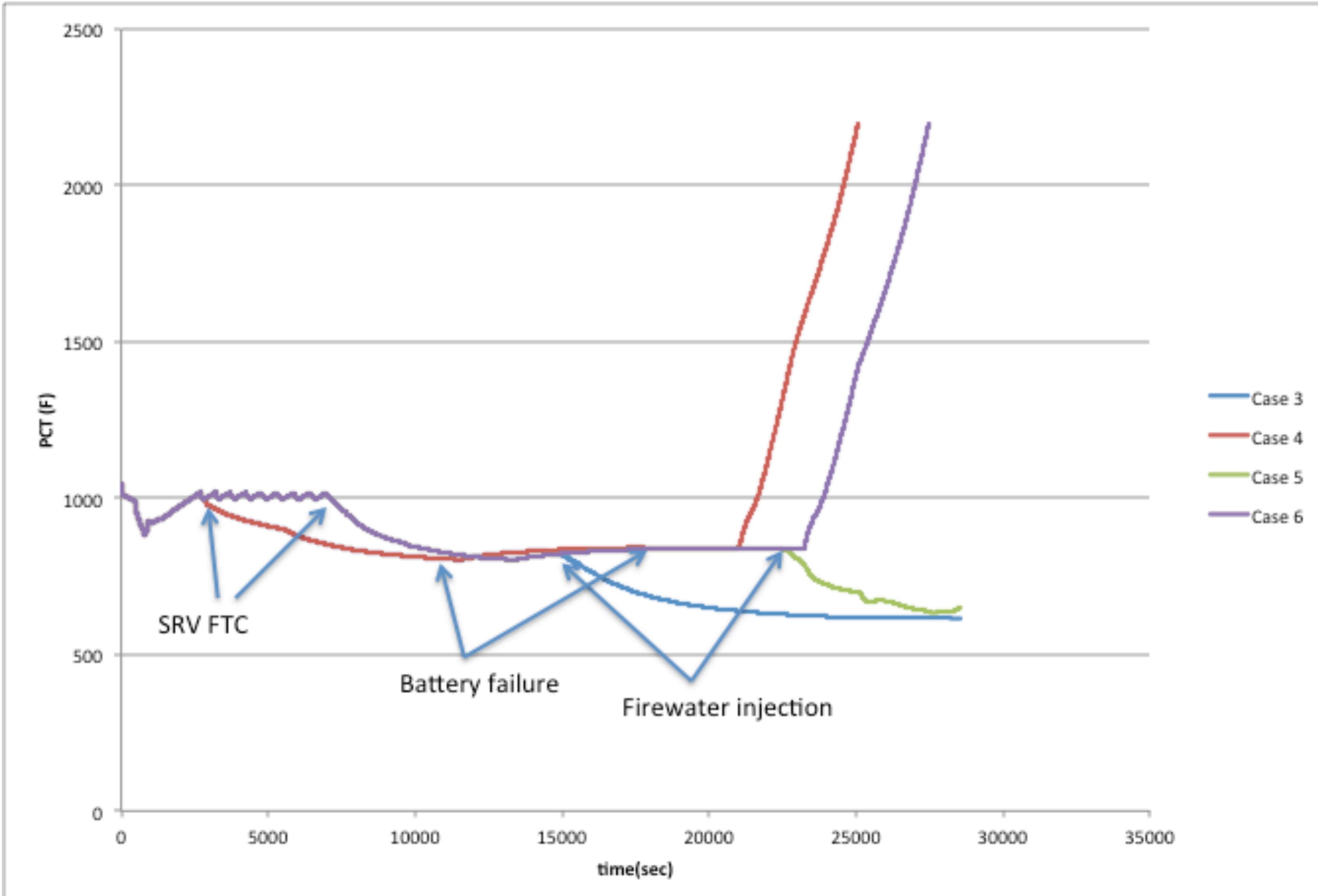


Figure 70. Peak clad temperature for SBO cases 3-6.

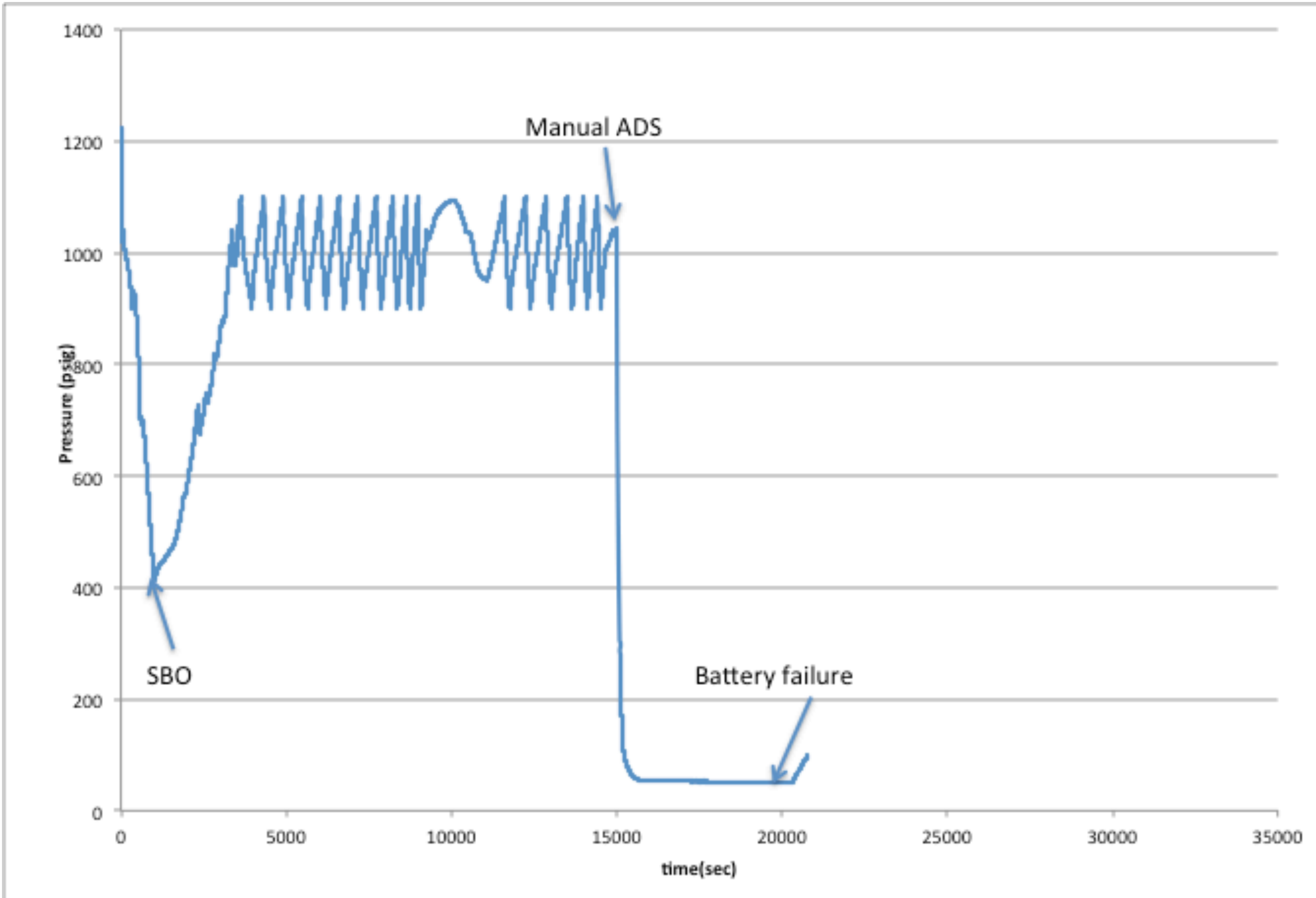


Figure 71. RPV pressure for SBO case 7.

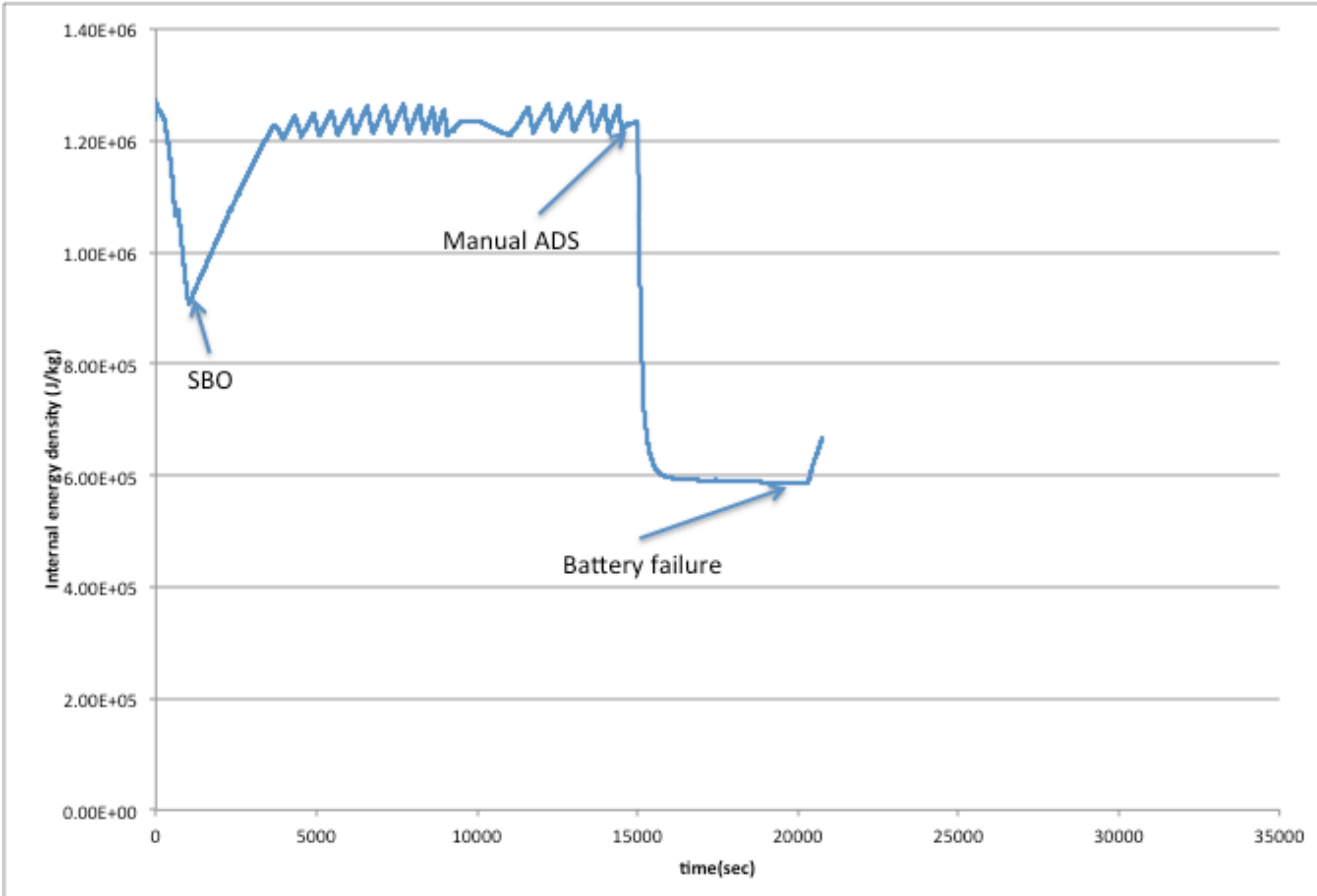


Figure 72. Internal energy cases for SBO case 7.

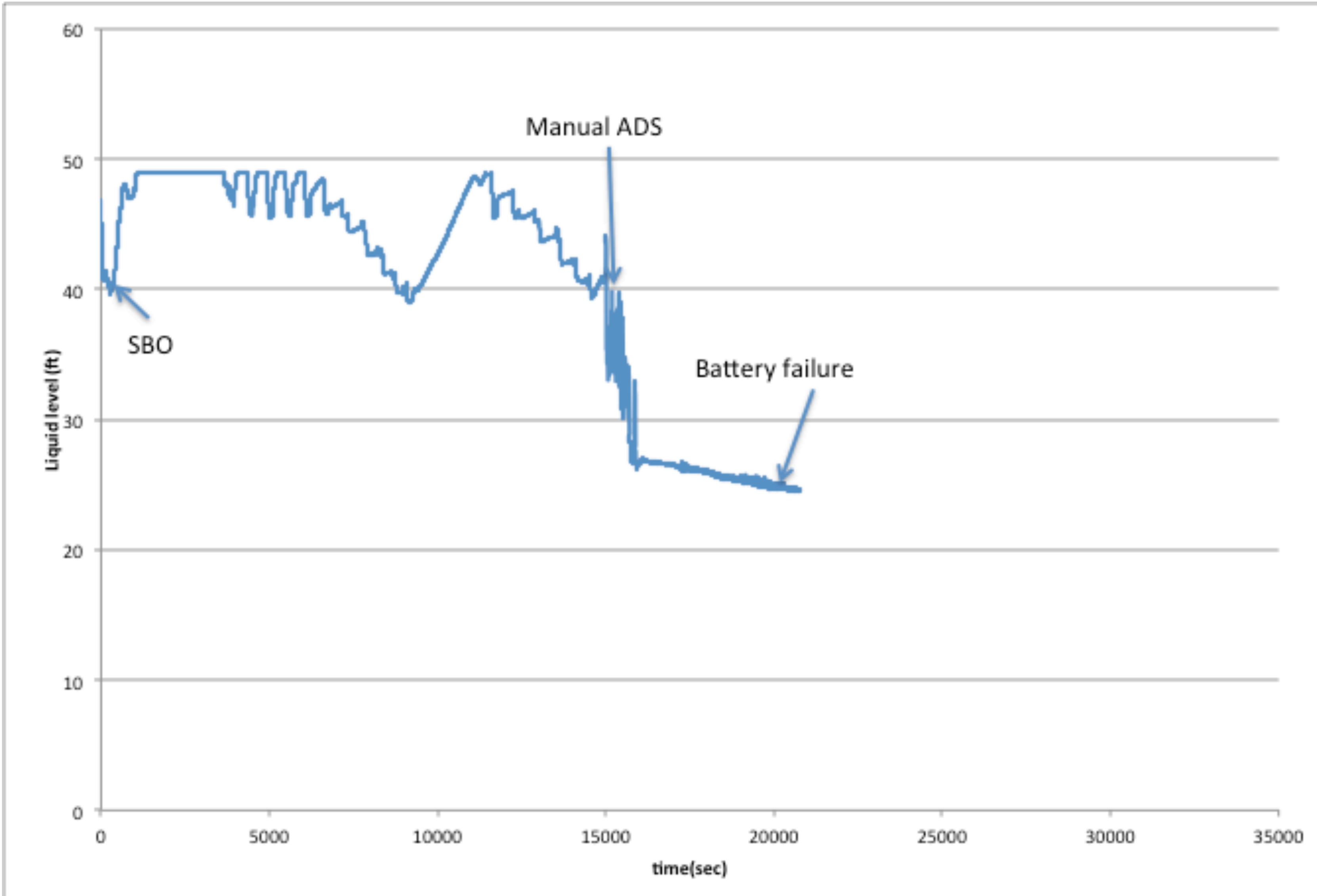


Figure 73. Liquid level for SBO case 7.

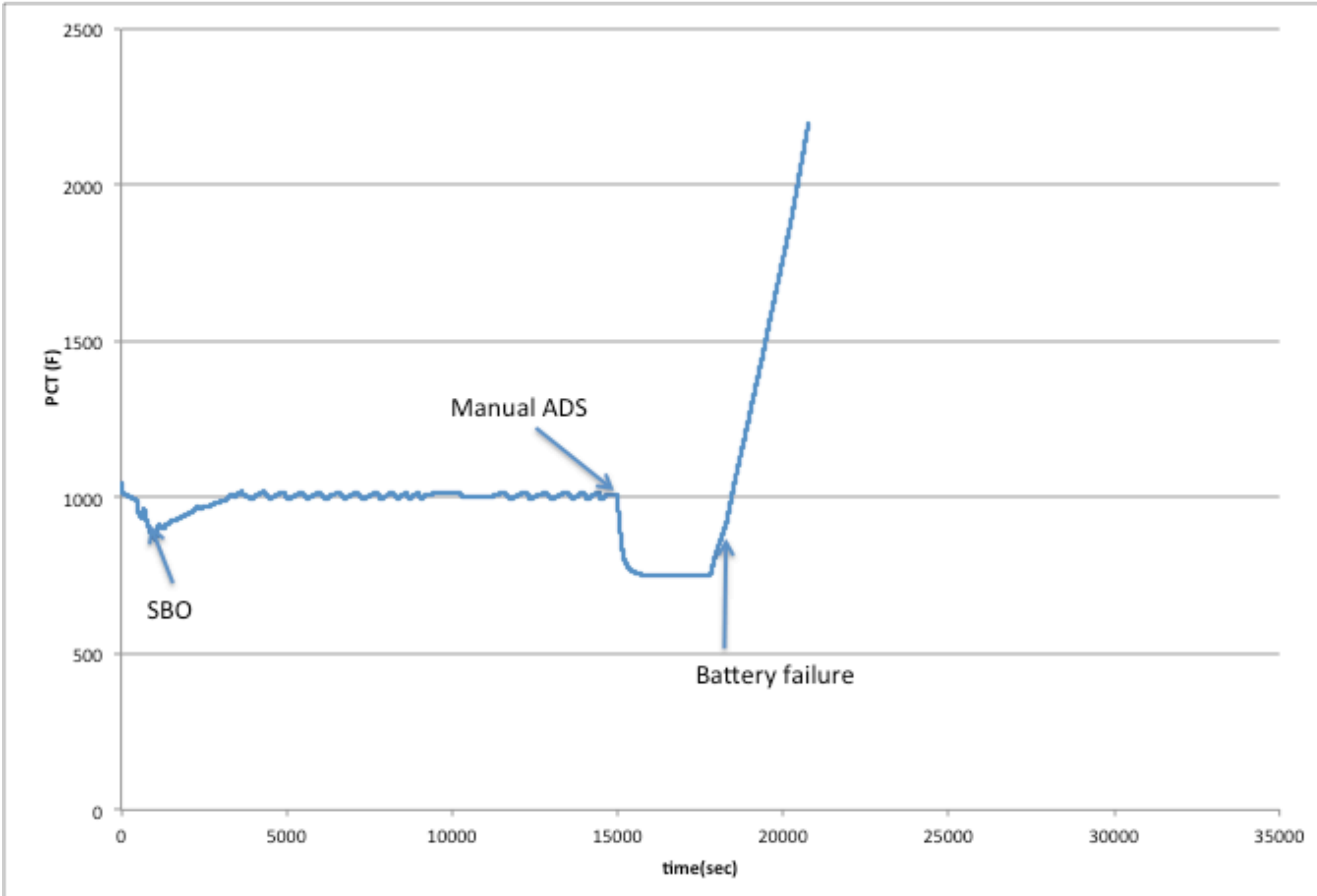


Figure 74. Peak clad temperature for SBO case 7.

7.3 Optimization of BWR SBO

The Branch-and-Bound algorithm was applied to the BWR SBO DET. The BWR SBO is a significantly more complicated DET compared to the PWR SBO due to the greater number of components and states considered. The intent of the PWR SBO was a proof of concept with the BWR case demonstrating that even for significantly complex system with complex dynamics, the Branch-and-Bound algorithm still is successful in finding the leaves that contain the highest probability of failure. The BWR SBO was optimized as described above via pruning of the success branches based on four parameter as opposed to the five used in the PWR SBO. The one parameter not included in the BWR SBO is liquid mass. Due to the design of the BWR, the liquid mass is directly correlated to liquid level, where liquid mass in the pressurizers may or may not be correlated to liquid level in the PWR core.

The BWR simulation consisted of 20752 nodes with 8457 end states prior to optimization. Of the 8457 end states, 1857 end states ended in failure and 6600 end states ended in success. Using the Branch-and-Bound algorithm, the DET was pruned to approximately 5868 nodes and yielded 373 of the highest probability of failure conditions. Approximately 3141 nodes ended in success. A representative diagram of several of the “surface” plots used to define the bounding functions for the BWR SBO is shown in Figure 75 through Figure 77.

Figure 75 shows the surface plots for BWR SBO conditions, which include RCP LOCA, HPCI failure, and the failure of 1 SRV to close with battery failure. If a SBO transient is reached within these conditions, the ability to recover in the allotted mission time of 24 hours can be met. As can bee seen comparing to the other figures, the reactor decay heat is lower, as would be expected since HPCI is not available. All branching conditions following will result in success. Therefore, these surfaces provide a reasonable bounding function for the BWR SBO cases.

Figure 76 provides the bounding functions for a condition of SBO with battery failure and RCP LOCA with HPCI failure. The function provides a much broader range of failure parameter than those presented in Figure 75. The number of bounding surface is fewer than those in Figure 75, however, the difference between the previous plot and those in Figure 76, is due to the cooling capability. The state sets for those represented by Figure 75, demonstrate that the amount of stored energy in the reactor must be lower to allow for a success or the ability to reach cold safe-shutdown. The cases for Figure 76 allows for lower liquid level, higher decay heat and internal energy.

Figure 77 provides the bounding functions for cases where battery failure has not occurred. In this event, the bounding function shows a higher energy, pressure, and decay heat. However, success is highly dependent upon the liquid level in the reactor vessel. The higher level allows for a much larger heat capacity for the reactor coolant as a whole, and can withstand a significant amount of heat prior to core melt. In these conditions, if recovery occurs within 24 hours of the beginning of the simulation, core damage can be averted.

The total computation savings directly involved in the Branch-and-Bound algorithm as implemented here resulted in a computational cost savings of approximately 60%. The actual computing costs can vary depending upon the number of parallel CPUs available to compute the simulation. The BWR simulation was performed using 512 processors, with a simulation time of approximately 5.5 days. The simulation was estimated to have been performed in approximately 2 days[2].

[2] Issues associated with INL HPC prevented a 1 to 1 comparison from being performed. The output files from the brute-force method were used without rerunning the simulation to identify the number of pruned branches.

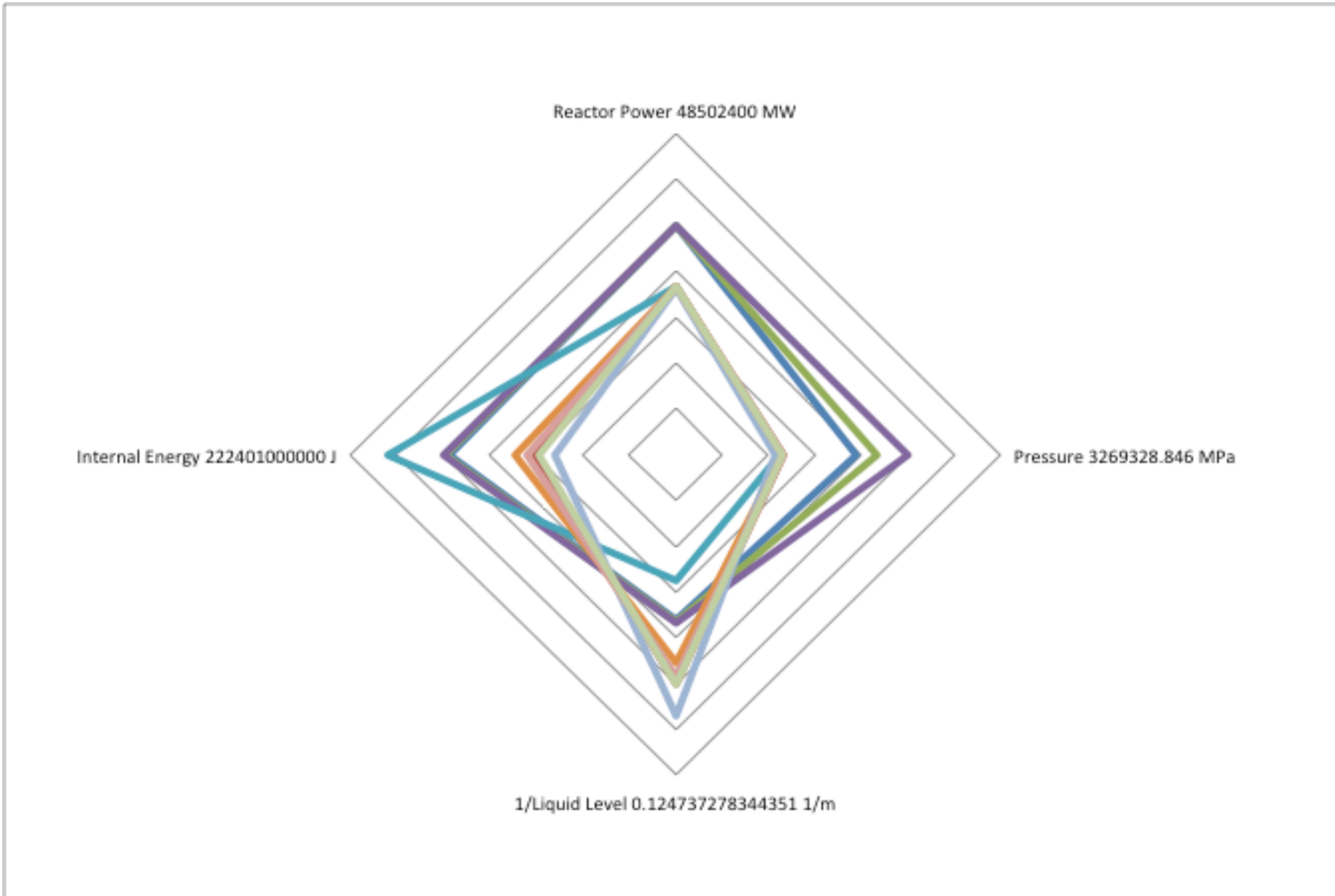


Figure 75. Surface plots for BWR SBO with battery failure 1 SRV fails to close, failure of HPCI, and RCP LOCA.

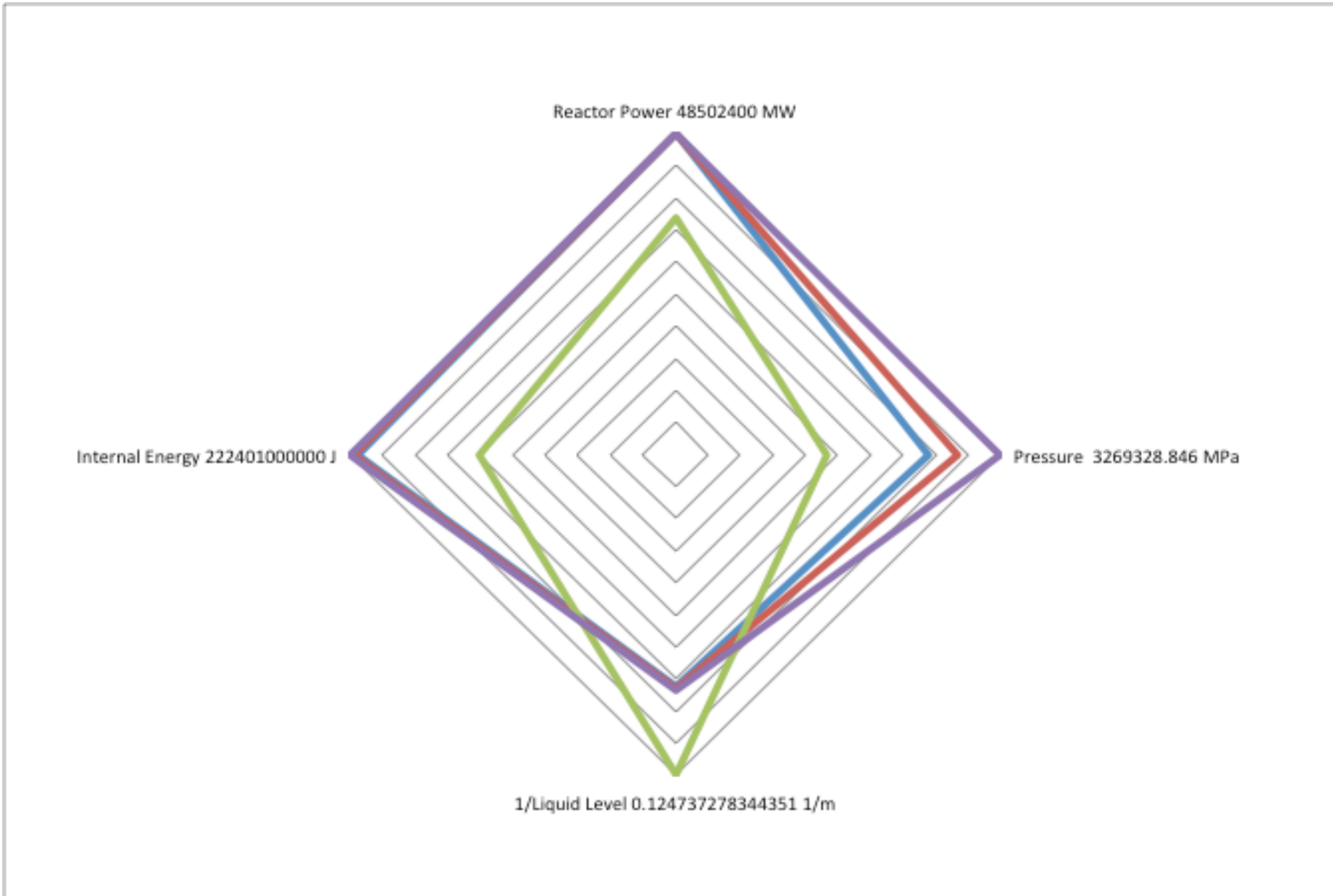


Figure 76. Surface plot for BWR SBO with RCP LOCA, battery failure and stuck SRV.

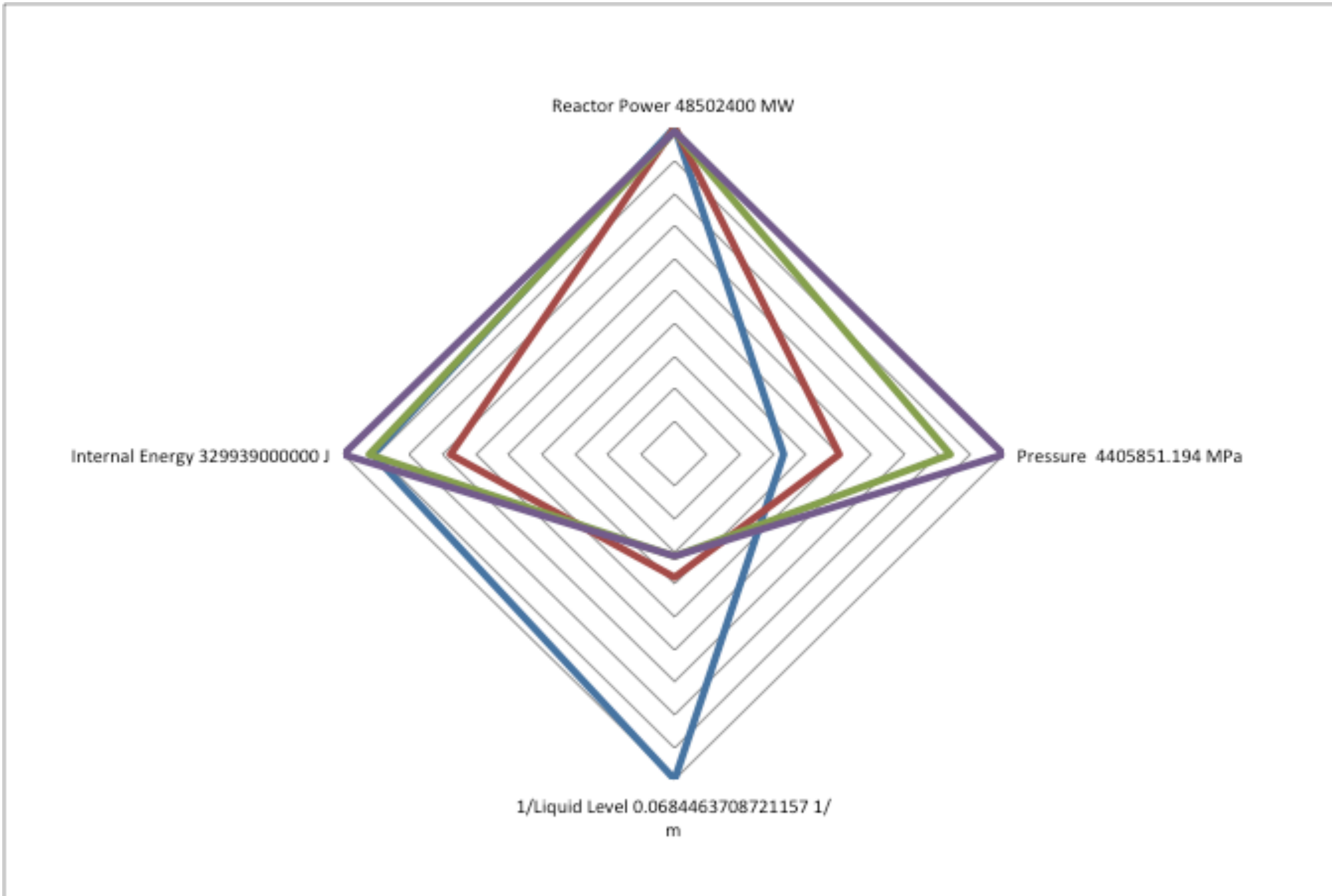


Figure 77. Surface plots for BWR SBO with no battery failure, RCP LOCA and stuck open SRV.

7.4 BWR SBO Sensitivity Analysis

A sensitivity and uncertainty analysis was performed evaluating cases 1 and 3 described above. The SA/UQ was performed for demonstration on parameters that can be modeled or adjusted in a RELAP5-3D input file, in which a PIRT analysis can be conducted. In reviewing Reference [42] , which is a PIRT analysis for the Fukushima-Daiichi plant, a small subset of parameters were chosen based on the capability to either add energy or remove energy from the core. In the PIRT analysis, there were 1047 different phenomenological effects identified. Most of those parameters were a direct response function that may or may not be calculated in RELAP5-3D. The intent of this study was to identify the parameters that have a direct input into RELAP5-3D and to evaluate the effects of those parameters directly on core damage. Using the DAKOTA simulation tool described above, a correlation matrix can be obtained to determine various phenomenological effects associated with the actual model relative to the results of interest (i.e., peak clad temperature). The parameter chosen in this research included initial reactor power, SRV capacity, HPCI capacity, RCIC capacity, and firewater capacity. For each of the leaves, the effects of the parameters discussed above on the peak clad temperature was examined. The intent was to determine which of the components as modeled had the largest impact on core damage.

Table 9 provides a listing of the subset of parameters used in this analysis. In order to evaluate the uncertainty of the parameters, a Latin Hypercube Sampling is performed on each parameter for each branch condition. Each parameter was assumed to have a uniform distribution with an uncertainty of +/-10% for this demonstration case. The branch resulting in the highest probability of failure is used in this discussion to demonstrate the method. As discussed previously, approximately 373 leaves ended in failure and 3141 leaves ended in success in an optimized DET. Without the use of the optimization, the number of simulations would have increased by a factor of 3 or an increase of 66%, resulting in much greater simulation time and time needed for data reduction. The parameters were sampled using 100 samples varying the parameters. The importance of each parameter is determined from the correlation matrix, that provides an indication of that particular parameter and the results on the objective function.

Table 9. Sensitivity parameters evaluated in SBO study.

Parameter	**Nominal Value**
SRV flow area	0.085 ft^2 (0.0079 m^2)
HPCI capacity	5600 gpm (424.3 l/s)
RCIC capacity	5600 gpm (424.3 l/s)
Firewater capacity	2500 gpm (189.4 l/s)
Power	3293 MW
Zr thermal conductivity	0.00209 BTU/s/ft/F (13.02 W/m^2K)
Zr heat capacity	35.18 BTU/ft^3/F (2.35×10^6 J/m^3K)
U heat Conduction	3.906×10^{-4} BTU/ft^3F (2.43 W/m K)
U heat capacity	56.55 BTU/ft^3/F (3.82×10^6 J/m^3 K)

The above results were used to evaluate their potential effects on liquid level and peak clad temperature. The results are presented in Table 10 and Table 11 with a summary of the ranking for each parameter. Evaluation of the parameters with regards to the peak clad temperature, the initial reactor power has the greatest impact on the PIRT ranking followed by firewater injection in Case 3. Case 1 did not include firewater injection activation in the model and thus is not applicable. The next important component for modeling in Case 1 is the thermal conductivity of Zr cladding, however, it is still ranked low. During SBO with loss of battery power, there is no capability to remove heat from the core and peak clad temperature would be related to the rate at which water is boiling off in the reactor. As this simulation has ended in failure, the mean peak clad temperature for the simulation using a LHS was 2165 K with an standard deviation of 119 K. The cladding would have failed before these temperatures were met, however, the methods for this type of analysis are still valid for performing a sensitivity analysis. A plot associated with the sampling of reactor power, SRV capacity and HPCI capacity, and Zr thermal conductivity are shown in Figure 78 and Figure 81. The data demonstrates that the initial reactor power has the largest impact on PCT, and a reduction in the initial reactor power directly results in a decrease in PCT during the transient.

Case 3 was modeled to evaluate the effects on the ability of operators to inject firewater into the reactor. The plots of initial reactor power, SRV capacity, and firewater injection are shown in Figure 82 through Figure 84. The initial reactor power and firewater injection capacity for this case, demonstrates that the modeling or initial conditions are important to the simulation. As the initial reactor power is decreased, the PCT in this simulation decreases as would be expected. Firewater injection capacity is also demonstrated as being important (PIRT=High). The capacity of the SRV to remove energy from the system are negligible in this case as the SRV became stuck during the transient at 46 minutes. Battery failure occurred at 185 minutes leaving a significant time for the reactor to blow down and thus the impacts on the conditions for important to recovery (i.e., reactor pressure) are not significant. Firewater injection began after 230 minutes leaving approximately 3 hours for the reactor to blow down and still recover.

Table 10. PIRT ranking for failure condition in SBO for Case1.

Parameter	Correlation Coefficient (PCT)	PIRT Ranking
SRV flow area	0.083	Low
HPCI capacity	0.068	Low
RCIC capacity	0.189	Low
Firewater capacity	N/A	N/A
Power	0.785	High
Zr thermal conductivity	0.225	Low
Zr heat capacity	0.133	Low

Table 11. PIRT ranking for failure condition in SBO for Case3.

Parameter	Correlation Coefficient (PCT)	PIRT Ranking
SRV flow area	-0.194	Low
HPCI capacity	0.051	Low
RCIC capacity	0.203	Low
Firewater capacity	-0.930	High
Power	0.817	High
Zr thermal conductivity	0.063	Low
Zr heat capacity	-0.026	Low

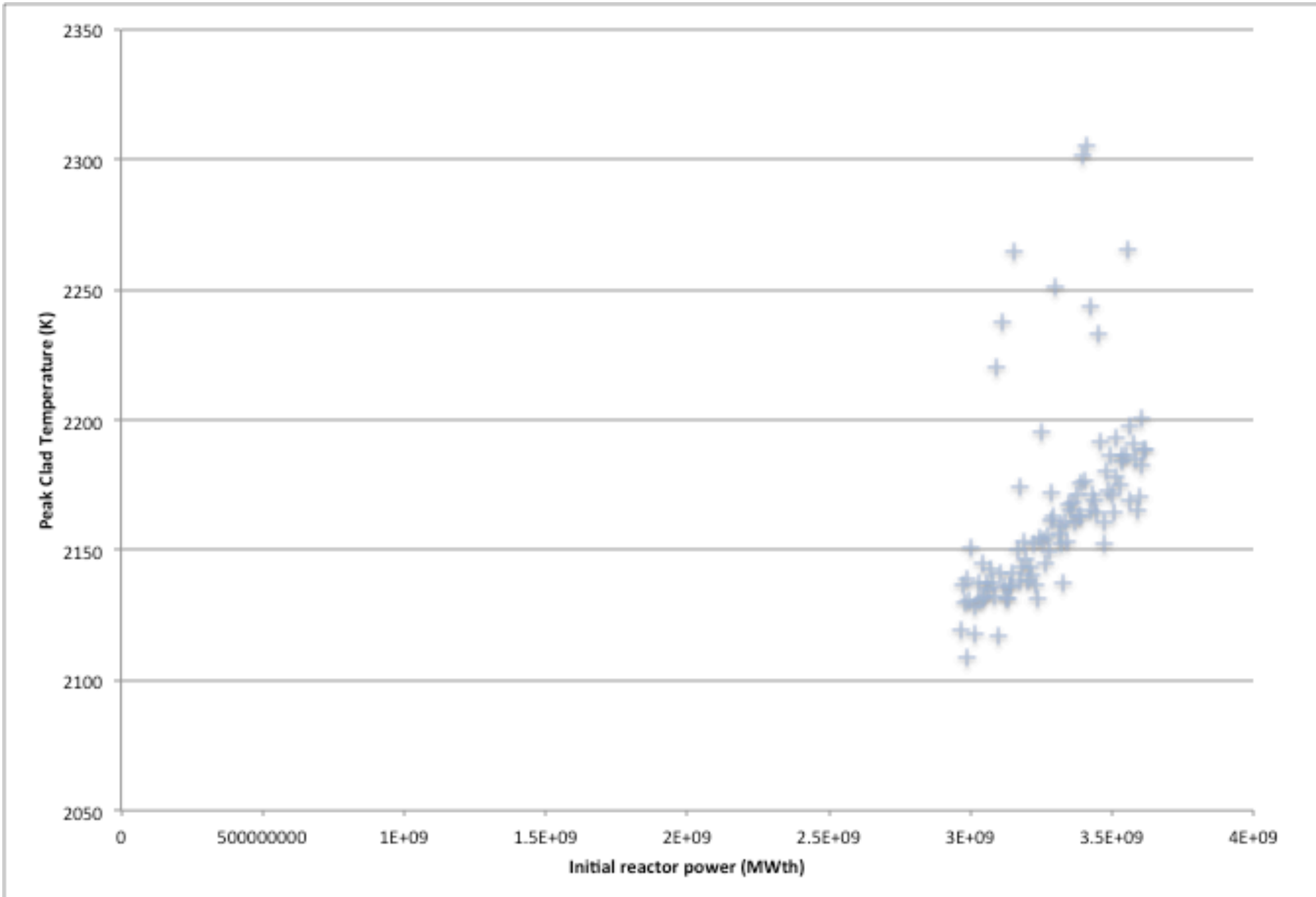


Figure 78. Sensitivity analysis associated with initial reactor power for Case 1.

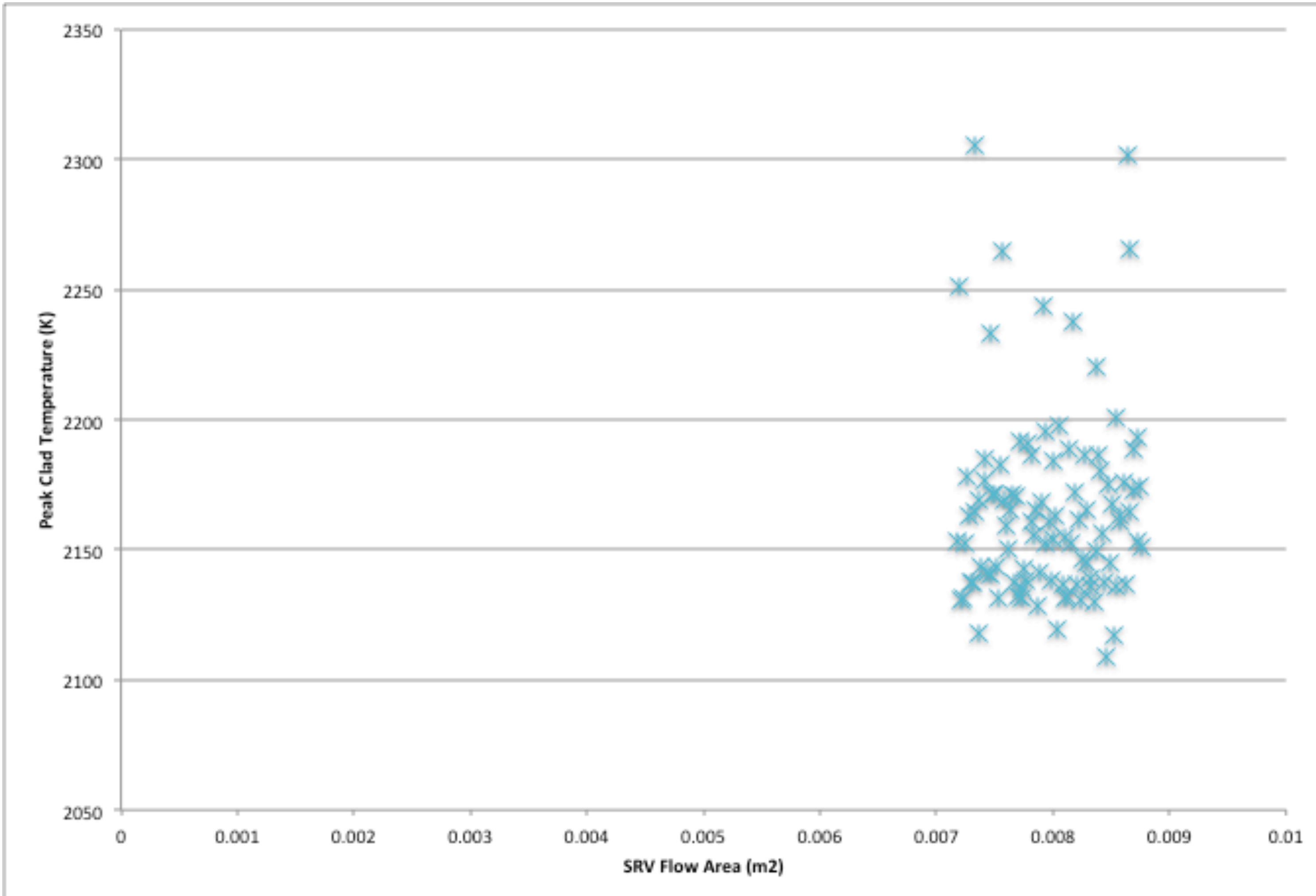


Figure 79. Sensitivity analysis associated with SRV capacity for Case 1.

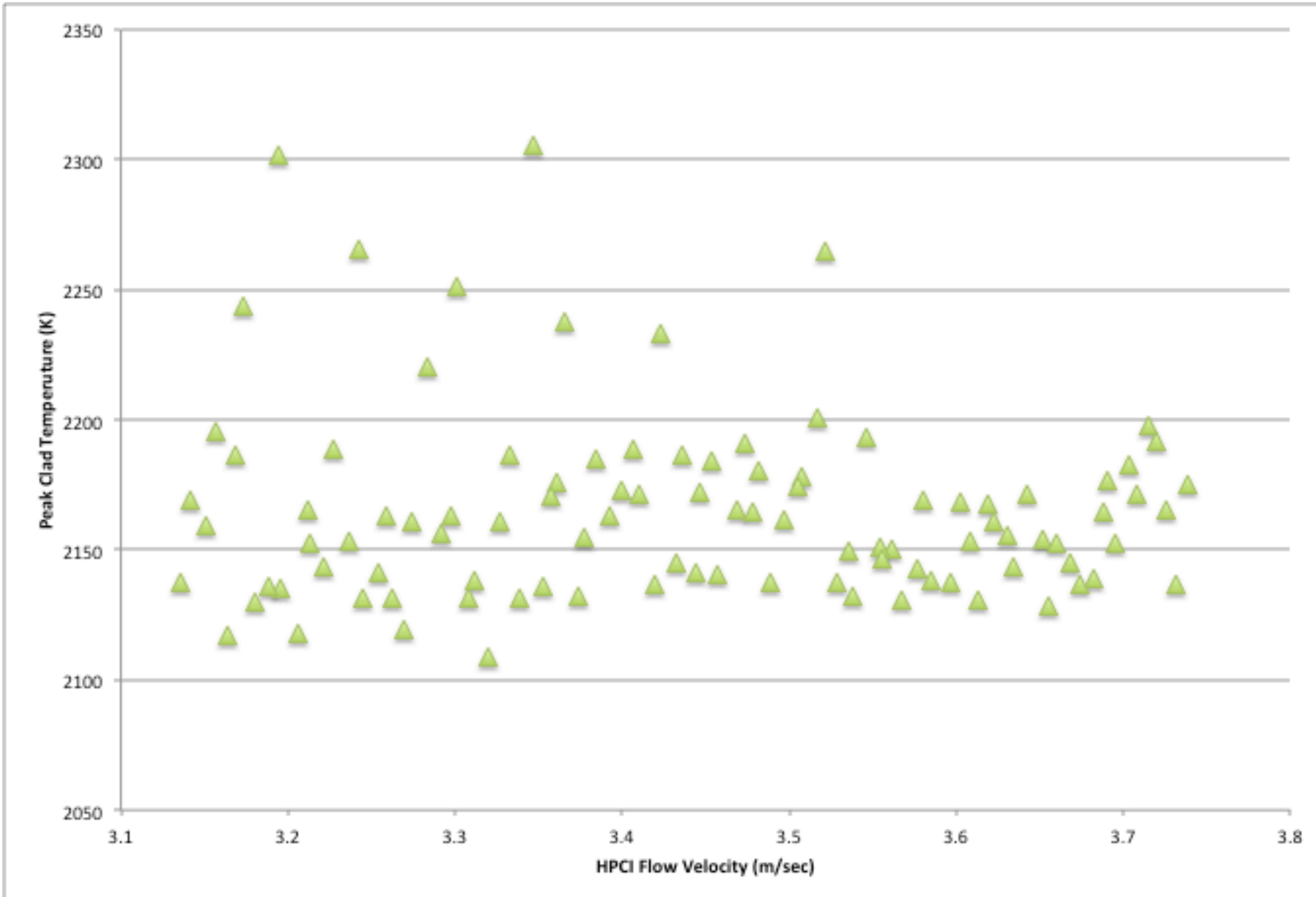


Figure 80. Sensitivity analysis associated with HPCI capacity for Case 1.

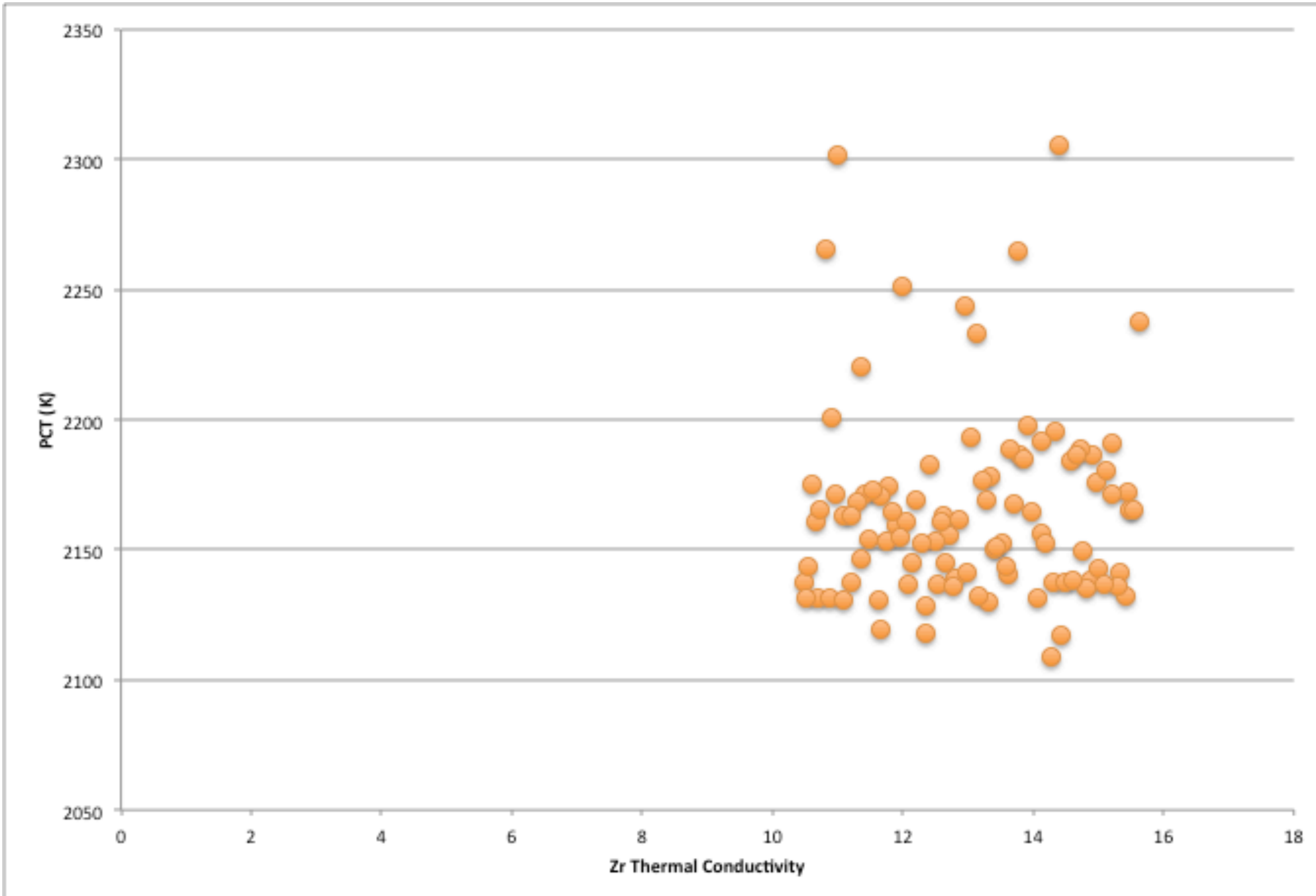


Figure 81. Sensitivity analysis associated with Zr thermal conductivity for Case 1.

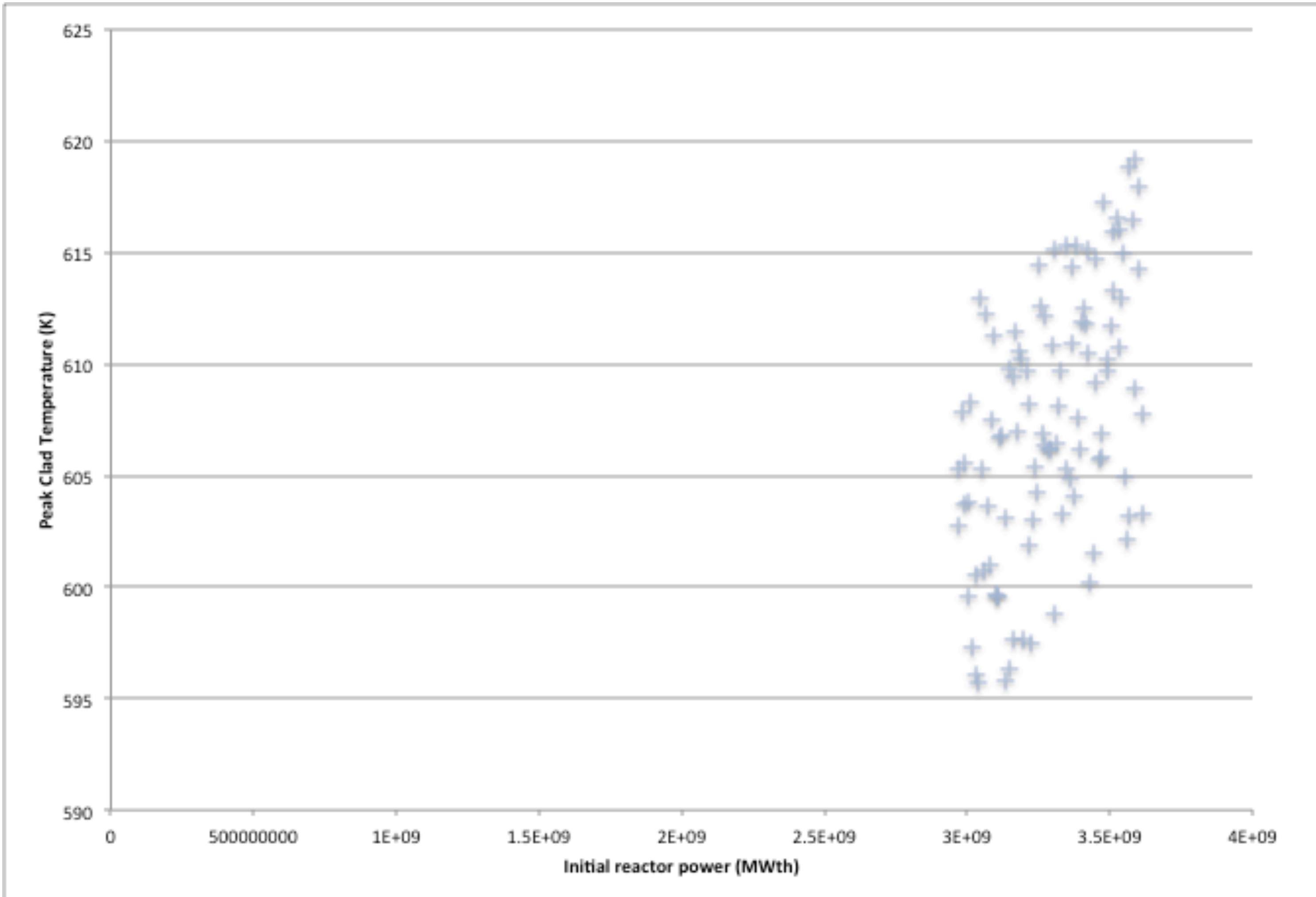


Figure 82. Sensitivity analysis associated with initial reactor power for Case 3.

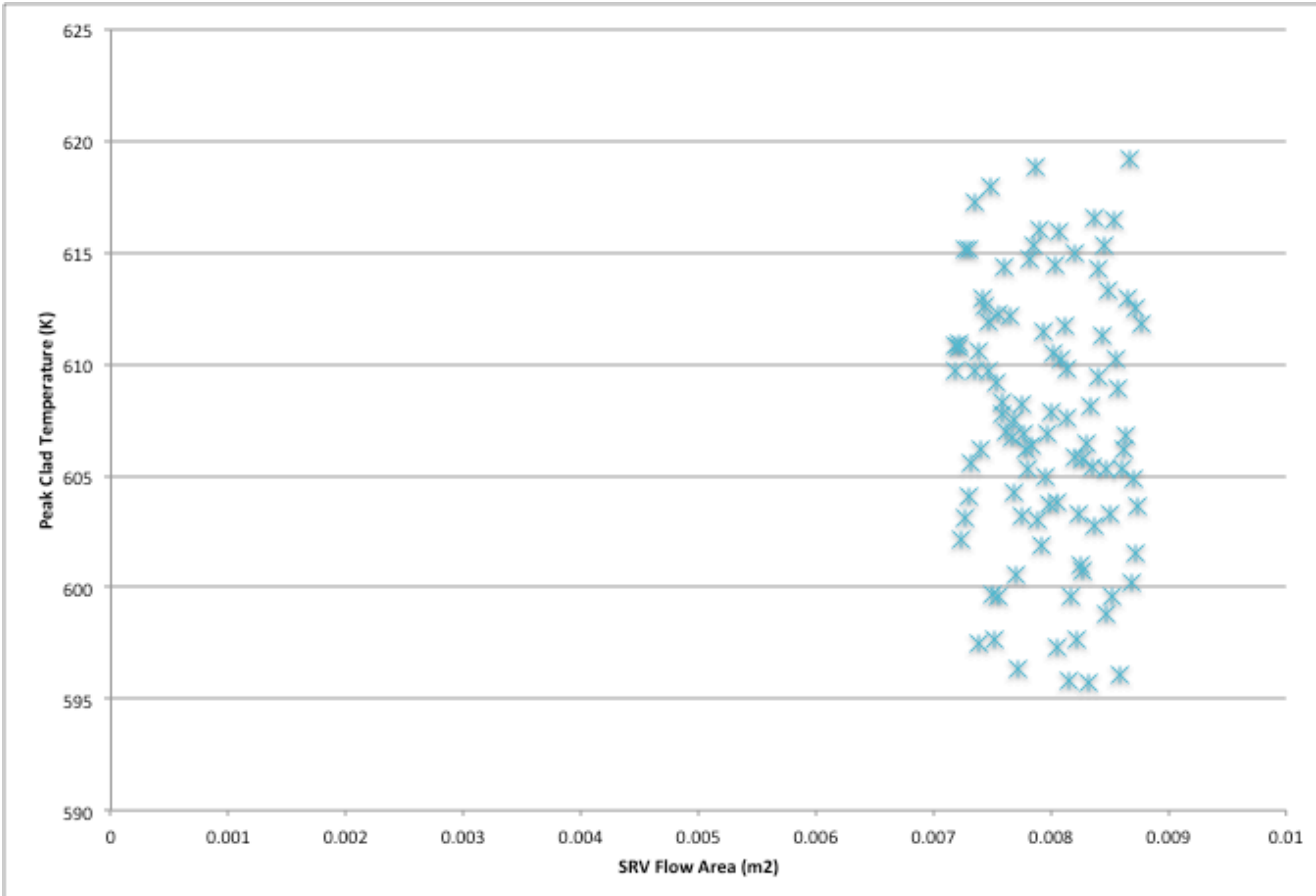


Figure 83. Sensitivity analysis associated with SRV capacity for Case 3.

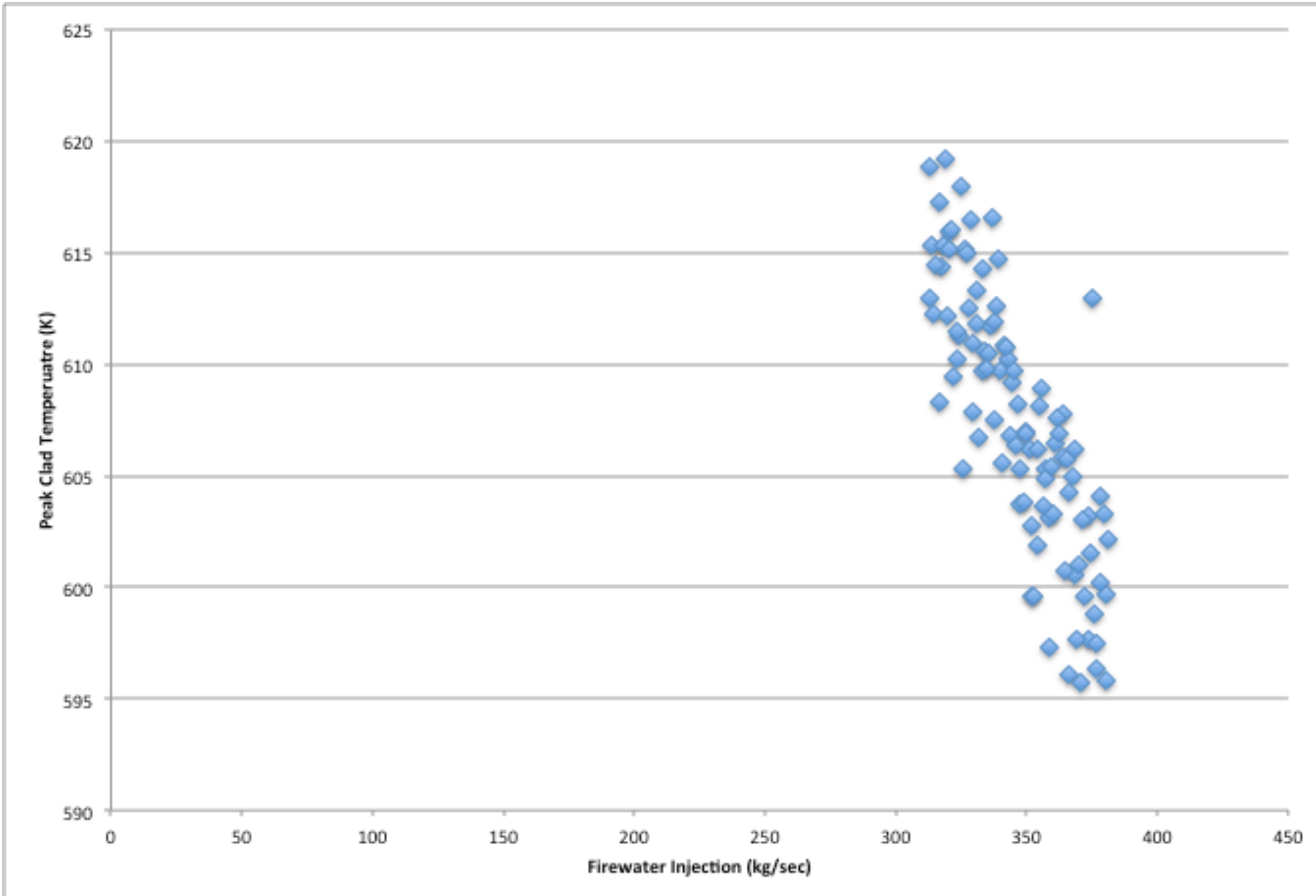


Figure 84. Sensitivity analysis associated with firewater injection for Case 3.

Chapter 8: Conclusions

Dynamic Event Trees provide a more rigorous approach to evaluating time-relevant risk in complex dynamic systems. The ability to couple the simulation software to the risk analysis software allows for an accurate risk analysis framework. Traditional PRA methodologies rely heavily on expert based knowledge to the timing of events that lead to catastrophic outcomes. Expert-based analysis is often called upon to evaluate complex systems. This is especially true of 'legacy' engineered systems like nuclear reactors where, the knowledgeable individuals are few and far between. Of particular relevance in the post-Fukushima era are again, reactor transients that require human interaction, and thus are difficult to characterize.

The research presented in this thesis has concluded the following items:

1. DPRA methods can utilize traditional PRA methods and expert knowledge to address issues associated with state explosion.

2. LENDIT metrics combined with S2R2 set theory allow for a formal approach for developing DET simulations and establishing appropriate constraints and parameters for bounding functions for use in the Branch-and-Bound algorithm.

3. The Branch-and-Bound algorithm is effective in reducing the number of simulations associated with DETs and can be used to prune branches that are of little interest with respect to risk.

4. The utilization of the Branch-and-Bound algorithm provides a framework for performing SA/UQ on system models to address safety margin associated with modeling uncertainty.

5. A PIRT process can be performed using a risk-informed methodology that considers high probability of failure transients that rely on system modeling and expert-based knowledge.

Usage of dynamic PRA in conjunction with expert-based approaches can allows for a more complete quantification of risk. DPRA methods provide a comprehensive analysis of risk, but suffer from state or combinatorial explosion. As the systems become more complex but rigorously evaluated, the computational time and data generated to evaluate such system grows exponentially. Dynamic event trees provide a rigorous method that has advantages over Monte Carlo simulations. Monte Carlo simulations have relatively few samples in regions of low probability such as component failure conditions. Additionally, Monte Carlo simulations repeat many time-dependent transient simulations. Codes such as RELAP5-3D, that contain a restart capability can generate branching conditions for sampled parameters and avoid repeating simulations from the beginning of the transient. Additionally, DET simulations do not rely on variance reduction techniques or adaptive sampling methods to efficiently quantify low probability of failure conditions. Computational costs are still a significant issue associated with DET methods. However, gains in DET capabilities are continuing. DET simulations are preferred as the DET approach is more complete, where Monte Carlo simulations require tens of thousands of simulations to properly characterize an accident condition.

In this research we proposed and demonstrated that the Branch-and-Bound algorithm can efficiently identify high probability of failure conditions. These conditions still have a relative low probability of failure and are difficult to quantify using Monte Carlo methods. The Branch-and-Bound algorithm utilizes a series of constraints and bounding functions to optimize the search space of trees. In this research, DETs are treated as a set of data that is produced dynamically from simulation codes such as RELAP5-3D. Constraints are placed on the search algorithm with the objective function to identify the highest probability of the peak clad temperature exceeding 2200 F (1455 K). In a typical Branch-and-Bound algorithm, bounding functions are well-defined and are able to prune branches of the tree that will not yield the optimal solution. In the case of the DETs, bounding functions are not well-defined at the beginning of the simulation. Bounding functions may exist from previous simulations that can be used to optimize more quickly.

In this research, bounding functions are developed from the simulation as the result of success branches or branches resulting in no core damage. The physical parameters that were identified at the beginning of the node are used to create a list of bounding functions that represent reactor conditions that will yield successful results and are used to prune branches later reached in the simulation. Additionally, the ordering of the search routine of the tree by probability, ensures that the highest probability cases will be found first and the leaves that have a significantly lower probability of failure will be pruned as these leaves do not produce results with regards to risk.

The development of the DET is supported by an experienced-based methodology using a series of metrics referred to as LENDIT. The LENDIT metrics in conjunction with S2R2 sets help define the simulation with regards to branching conditions and the progression of the

DET. Branching conditions that will not yield the optimal solution (i.e., clad failure conditions) are immediately discarded and prevented from being created in the simulation. In addition, using the knowledge of experienced analysts as expressed via LENDIT metrics and S2R2 sets, the timing of events that are important to the simulation can be identified. That is to say, the sampling frequency with regards to the cumulative distribution functions can be created that will result in optimal search of probabilities of failure.

Using the Branch-and-Bound algorithm in conjunction with DET developed from S2R2 set theory and LENDIT metrics, the optimization has been achieved for reactor transients. Two case studies were performed to demonstrate the feasibility of the method as well as more complicated system. The work has shown that this method is successful in identifying the branches for each particular state condition with the highest probability of failure. A computational reduction of 75% has been demonstrated with a PWR SBO case with Feed-and-bleed recovery. The same transient for a BWR SBO with more complexity has resulted in a reduction of 60% of the simulations being pruned and resulted in significant cost savings. The cost savings is realized in computer simulation time and human resource time analyzing data from the simulations.

Optimizing the search space for highly complex dynamic PRA for nuclear reactors creates the ability to more efficiently identify conditions associated with risk. Additionally, by evaluating the high-risk scenarios leading to failure, a more rigorous uncertainty quantification method can be performed on modeling assumptions to identify improvements in models, validation experiments and operating conditions that could lead to higher power uprates for utilities. The PWR and BWR cases studies were used to demonstrate the ability to perform these analyses. As shown above, the highest impacts on the PWR SBO are reactor power along with CCP capacity. If both CCP are available as well as the PORVs, the redundancy in the system leads to less importance on the modeling of those parameters. Model develop and validation would not yield significantly different results unless 1 CCP or 1 PORV is unavailable. In this case, additional model analysis and validation would be required to support safety margin improvements to allow power uprates.

In evaluating the BWR SBO, the model developed for the PSP and the thermal-hydraulic conditions leading to manual ADS activation creates the difference between core damage and success. If ADS is actuated, the pressure is significantly reduced and recovery can be achieved by firewater injection. If manual ADS is not activated, the pressure in the reactor remains high and low pressure injection either through the LPIS or firewater injection is not possible. Improvements in modeling the manual ADS activation would provide a greater understanding of margin of safety associated with the BWR plant.

8.1 Future Work

The Branch-and-Bound algorithm has been demonstrated to be effective in optimizing DETs. The creation of bounding constraints was based on conservative assumptions with regards to the non-linearity and correlation between the variables used to create the bounding function. Additional research can be performed in removing the conservative assumptions imposed to handle the non-linearity of the bounding functions. This could result in greater computation efficiency as approximately 25% of the nodes pruned were deleted through the bounding functions. The remainder of the pruned nodes was the result of ordering the queuing system to evaluate higher probability nodes first.

Additional work can be performed to extend the DET approach to include economic considerations. Rather than looking at particular aspects of risk, optimization of maintenance can be identified to allow utilities the optimized time to perform certain maintenance activities to extend the life of the current fleet of nuclear power plants.

The work presented in this report can be expanded beyond the scope of risk analysis associated with core damage. Additional analysis, such as economic analysis associated with plant upgrades and plant uprates can be performed. Research associated with the optimization of maintenance and component replacements while minimizing the economic impact and risk associated with plants would provide additional benefit to the commercial utility industry.

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Appendix A Constraints Class

```python
class constraints:

  def __init__(self):


    self.bound=0.0   #   bounding condition most likely temperature
    self.parameters ={}
    self.states={}
    self.stateSet=[]
    self.failureStates=[]


  def Update(self,dict,prob):
      old_state=dict['states'].split()[0]
      new_states=dict['states'].split()
      new_states.pop(0)
      if len(new_states)==0:
        if float(dict['bounds']['value'])>=float(dict['bounding']): PCT='Fail'
        else:   PCT='Pass'
      else:  PCT='None'
      return PCT
      old_state=dict['states'].split()[0]
      new_states=dict['states'].split()
      new_states.pop(0)
      if len(new_states)==0:
        if float(dict['bounds']['value'])>float(dict['bounding']):
          if old_state in self.states.keys():
            if 'failure' in self.states[old_state].keys():
                self.states[old_state]['failure'].append(dict['parameters'])
                self.states[old_state]['probability'].append(prob)
            else:
              self.states[old_state].update({'failure':[dict['parameters']]})
              self.states[old_state].update({'probability':[prob]})
```

```
     else:
      self.states[old_state]={'failure':[dict['parameters']],'probability':[prob]}

    else:
     if old_state in self.states.keys():
      if 'success' in self.states[old_state].keys():
       self.states[old_state]['success'].append(dict['parameters'])
      else:
       self.states[old_state].update({'success':[dict['parameters']]})
     else:
      self.states[old_state]={'success':[dict['parameters']]}
#    for j in self.states[old_state].keys():
   else:
    pass

   return

 def updateFailure(self,state,probability):

  stateSet=set(state.split())
  for i in range(len(self.failureStates)):
   if self.failureStates[i]==stateSet:
    if self.failureStates[i]['probability']>probability: return
    self.failureStates[i]={'state':stateSet,'probability':probability}
    return
  self.failureStates.append({'state':stateSet,'probability':probability})
  return

 def Compare(self,dict,state,branch,prob):
   stateSet=set(state.split())
   for i in range(len(self.failureStates)):
    if stateSet==self.failureStates[i]['state']:
     if float(prob)<=float(self.failureStates[i]['probability']):
```

```
          return None

    for i in self.stateSet:
      if i['state']==stateSet:
          tempFLAG=[]
          tempFLAG1=None
          if not str(branch) in i.keys(): return True
          for j in range(len(i[str(branch)])):
            for k in dict['parameters'].keys():
              if dict['parameters'][k]['direction']=='lt':
                 if float(dict['parameters'][k]['final'])<float(i[str(branch)][j][k]['final']):
                   tempFLAG1=True
                   break
                 else: tempFLAG1=None
              if dict['parameters'][k]['direction']=='gt':
                 if float(dict['parameters'][k]['final'])>float(i[str(branch)][j][k]['final']):
                   tempFLAG1=True
                   break
                 else: tempFLAG1=None
            if tempFLAG1==True:tempFLAG.append(True)
            else: tempFLAG.append(None)
          if None in tempFLAG:
            return None
          else: return True
    return True
```

Appendix B Defense Presentation

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Branch-and-Bound Algorithm Applied to Dynamic Event Trees for Risk Analysis in Nuclear Reactors

PhD Candidate – University of Idaho
September 19, 2014

Major Professors:

Akira Tokuhiro
Robert Hiromoto

Idaho National Laboratory

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- Committee Member – Carol Smidts and Diego Mandelli
- Idaho National Laboratory – Work was performed under Laboratory Directed Research and Development
- RAVEN team - Christian Rabiti, Andrea Alfonsi
- Vince Mousseau – Thoughts inspired some of this work

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Objective

- Implement the Branch and Bound algorithm to Dynamic Event Trees to optimize the solution and identify the conditions resulting in the highest probability of cladding damage
  - Research in optimization of dynamic event trees is continually ongoing to reduce state or combinatorial explosion
  - The use of the Branch-and-Bound algorithm as applied in this research demonstrates a new optimization technique that results in an improvement of greater than 60% computation time
- Utilize the optimization of Dynamic Event Trees to perform modeling sensitivity analysis and uncertainty quantification to identify modeling and validation improvements

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Introduction

- Probabilistic Risk Assessment and Risk Informed Safety Margin Characterization (RISMC)
- Dynamic Probabilistic Risk Assessment (DPRA)
- Discrete Dynamic Event Trees (DET)
- Branch-and-Bound Algorithm
- Application of the Branch-and-Bound Method for optimization
  - Development of Bounding Constraints Using LENDIT Metrics and State, System, Response, and Resource Sets (S2R2)
- Implementation of DET and UQ methods in RAVEN Framework to develop a PIRT for reactor transients
- Example case of a Station Blackout for a Pressurized Water Reactor
- Example case of a BWR SBO

Classical PRA

- Risk is quantitatively determined using an Event Tree/Fault Tree Approach (WASH-1400)
- Scenarios are determined using fixed timing and ordering of events based on knowledge of the analyst.
- Probability of branching conditions in event tree (ET) are determined by solutions to fault trees (FT)
- Fault trees are series of Boolean algebraic solutions to determine probability of failure of high level components.

Limitation of Classical PRA

- Traditional PRA methods (i.e., Fault Tree/Event Tree) lacks the ability to account for dynamics than can be encountered in complex systems
- ET/FT probabilities are based on fixed timing of events and ordering of events
- Failures and modes of failure may be sensitive to physical parameters (e.g., probability of pipe failure as a function of pressure)
- Simplification is sometimes performed by lumping transients into one event tree, which does not take into account the different possible state conditions and transients involved

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Risk Informed Safety Margin Characterization

- RISMC Methodology is intended to quantify the load distribution and capacity distribution of complex system
- Load curve refers to the probability distribution of the operating parameters of a complex system (e.g., clad temperature, pressure, etc.)
- Capacity curve is the failure distribution of the parameters of interest (e.g., cladding melting temperature, containment failure pressure)
- Intersection of the two curves is the area of vulnerability
- Ideally, we want to focus modeling fidelity on this region to improve the safety margin
  - Improve validation database that has the largest impact into an increase in the margin of safety (i.e. decrease uncertainty)
  - Improve modeling capabilities in this region to decrease uncertainty

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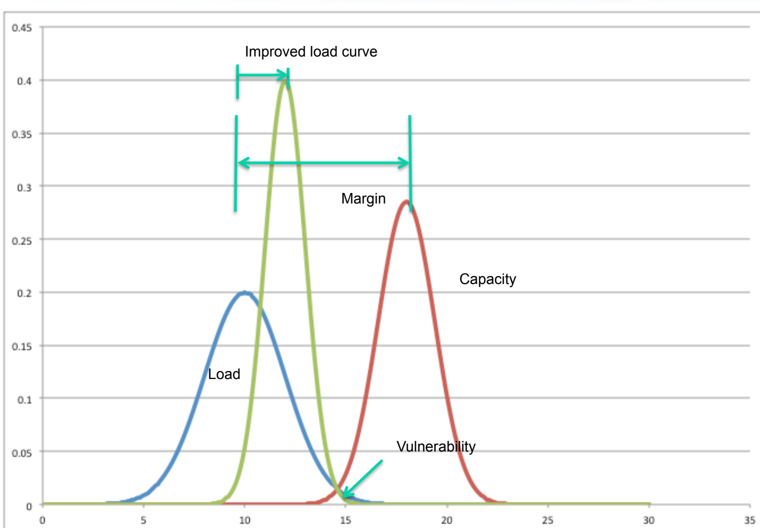
RISMC



Dynamic PRA

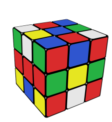
- Dynamic PRA allows for coupling simulation tools such as RELAP and MELCOR to the risk analysis code
- Allows for time dependent coupling and phenomenological modeling of failures based on system parameters
- Allows for more complete modeling of system risk
- Allows for inclusion of time scales associated with reactor transients

Condition	Time scales	Response
Reactivity insertion	<10 seconds	Automatic safety system
Initial shutdown Cooling	Seconds to minutes	Automatic
Intermediate shutdown	Hours to day	Automatic and operator actions
Long term decay	Days to weeks	Operator action
Component Failures	Low Probability/Anytime	Automatic safety systems and operator action

Dynamic PRA

Drawbacks of Dynamic PRA

- Computationally expensive
  - Parallel computing is working to overcome computational limitations
- Ginormous amounts of data created
  - Each simulation generates huge amounts of data that must be post processed
  - Data clustering algorithms are currently being investigated
  - Simple simulation with a 4 hour transient using RELAP5 created approximately 1100 nodes and 200 GB of data
  - Many files are text files that have to be mined either during the simulation or following simulation
  - Even super computing has limitations
- Traditional PRA Input File ≈ 10 MB



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DDET Method

- Similar to classical event trees, except branches in the tree represent time of events occurring.
- Time is discretized and branches occur at discretized time or when equipment reaches “demand” set points such as a PORV reaching opening pressure
- Branching conditions discretized by cumulative distribution functions
  - Pro – More complete than MC methods
  - Pro – Restart capability can reduce simulation time by not repeating nearly identical simulations
  - Con – Combinatorial Explosion leads to numerous branching states that results in little information with regards to the problem
  - Con – Requires analyst knowledge of the system and transients to reduce number of possible branching conditions
    - Analyst knowledge for existing fleet of nuclear plants is substantial

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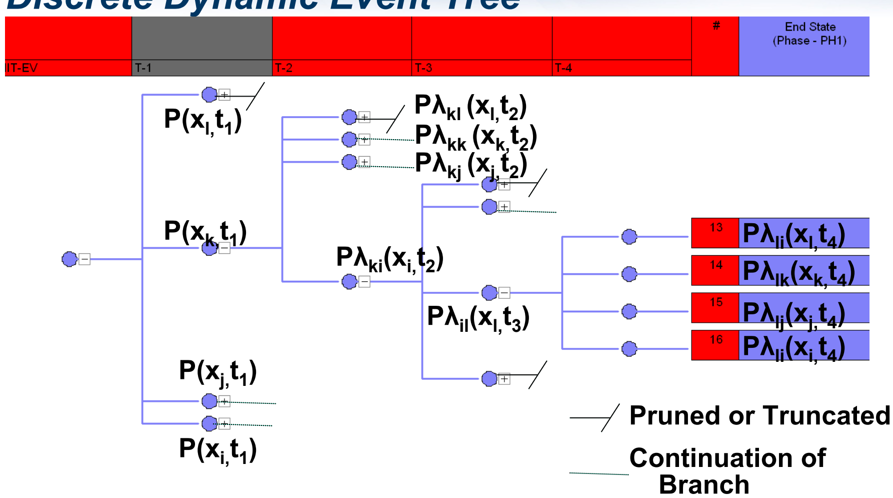
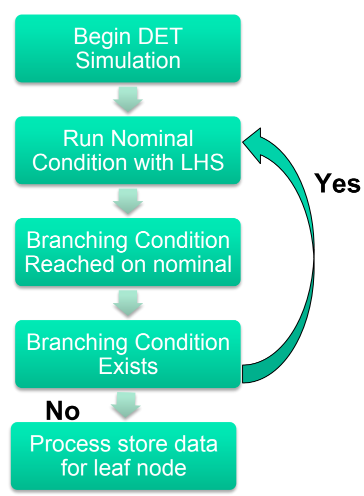
Discrete Dynamic Event Tree



Hybrid Method to Support Uncertainty Quantification and Sensitivity Analysis

- Run LHS method inside inner loop while creating dynamic event trees
- Sample on parameters that are NOT dependent upon time (e.g., time of SBO or Recovery) or result in a change in plant state (e.g., SRV opening/closing) but on modeling properties (e.g., valve flow area for flow capacity, initial reactor power, etc).
- Run the simulation until branching condition is created and create branches, process uncertainty parameters and continue with simulation with new branches
- Combinatorial explosion makes this process difficult outside of the HPC environment
- Even with HPC, still cumbersome and creates several hundred GB for simple simulation
- Proposed Branch-and-Bound optimization algorithm to identify high probability failure branches and prune less interesting branches

Hybrid Method Flow Chart



RAVEN Framework DET and SA/UQ

- RAVEN control modules perform control logic to create branching conditions for DET
- Provides random sampling of parameters of interest for SA/UQ
- Each branching condition, we utilize the LHS for parameters of interest and obtain Spearman's Rank Correlation Coefficient (Gertman and Messina 2012)
  - Parameters are ranked to support a PIRT by the correlation coefficient as follows:

$$|\zeta| \in [0.01,0.29] \Rightarrow \text{Weak relationship (PIRT=Low)}$$

$$|\zeta| \in [0.30,0.69] \Rightarrow \text{Moderate relationship (PIRT=Med)}$$

$$|\zeta| \in [0.69,1.00] \Rightarrow \text{Strong relationship (PIRT=High)}$$

Branch and Bound Algorithm

- f(x) is defined as the probability distribution function of cladding temperature
- The algorithm is designed to minimize (maximize) an objective function f(x) with variables $(x_1, x_2, x_3, \ldots x_n)$ over a region of feasible solutions, S:

$$max_{x \in S} f(x)$$

- The value of x is constrained for the optimization such that x=Temp>2200 F, x=core pressure<containment pressure etc.

Branch and Bound Algorithm

- Approximate an optimal solution x_h of f(x) and store the value in a global variable B (Bounding function)
- Initialize the tree/queue with the bounding function
- Loop through the queue until empty:
  - Given node N from the queue
    - If N is a candidate solution and f(x)>B then x is the best solution and update B
    - Else Branch N to produce new node N_i:
      - If $g(N_i)<B$ prune N_i
      - Else store N_i in queue

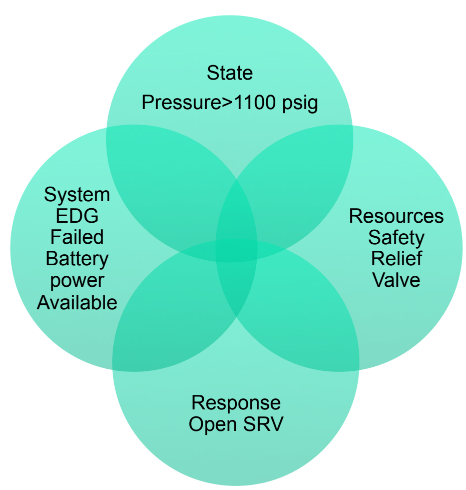
Implementation of Branch and Bound Algorithm

- Using LENDIT, we develop a method for defining bounding functional relationships for the branch-and-bound algorithm
- Utility of LENDIT metrics and S2R2 can be applied consistently throughout DET simulation
- LENDIT scales are physical quantities with nuclear power plant operations depend
  - L-Length (Liquid Level)
  - E-Energy (Internal energy)
  - N-Number (Number of Operators)
  - D-Distribution (Possible component states)
  - I-Information (Information such as pressure, temp, flow)
  - T-Time (time for core damage)

Framework

- LENDIT scales are used in conjunction with set-theory based approach
- Define sets of S2R2 –State, System, Resource, and Response set
  - State – Pressure, temp, flow rate
  - System – component configuration such as reactor scram, RCP operating etc.
  - Resources – resources such as EDG availability, operators
  - Response – potential responses for a transient

S2R2 Sets Example

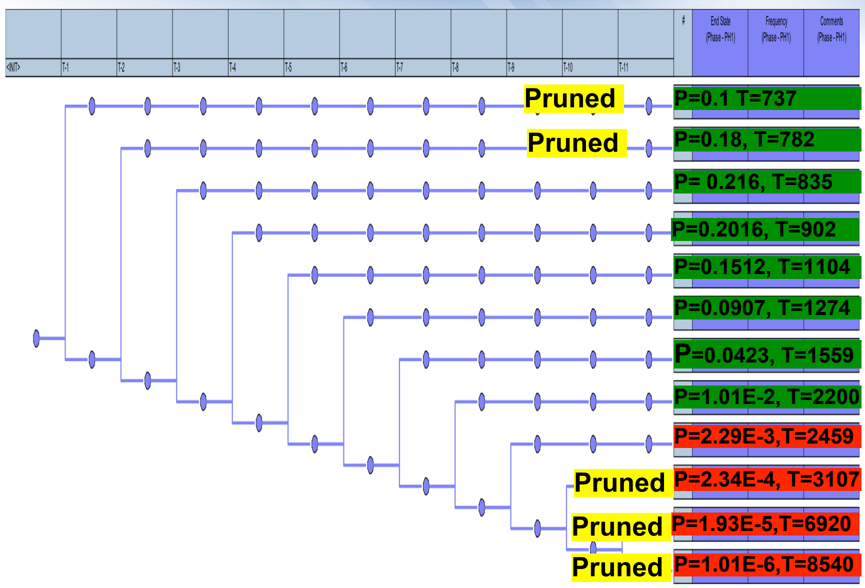


Pruning/Optimizing DET

- Order branches to process based on probability and plant system set
- If the plant system set has resulted in failure and probability of the current branch under evaluation is less (within a user specified tolerance) prune the branch
- If the probability is greater, evaluate the branch against the bounding functional relationships
- Bounding functions are defined by leaves of the tree that resulted in success
  - If a leaf does not exist, evaluate the simulation
  - If leaves do exist, then bounding functions are represented by a surface of parameters defined by LENDIT metrics (i.e., expert knowledge)
  - Advantage and Disadvantage
    - Advantage - Allows for user to apply engineering judgment to define bounding functional relationships
    - Advantage – Does not require supervised learning which can be problematic for complex dynamic non-linear systems
    - Disadvantage - If the bounding functions are not adequately represented than over pruning may occur

Simple Dynamic Event Tree Case

- Simple reactivity insertion defined by an exponential increase in power
- Transient terminated at branches defined by a CDF
- Sort branches in the queue by probability
- If branch results in no damage, any branch prior to it will end in success as defined by our bounding functional relationships
- Objective function is to identify the highest probability of failure



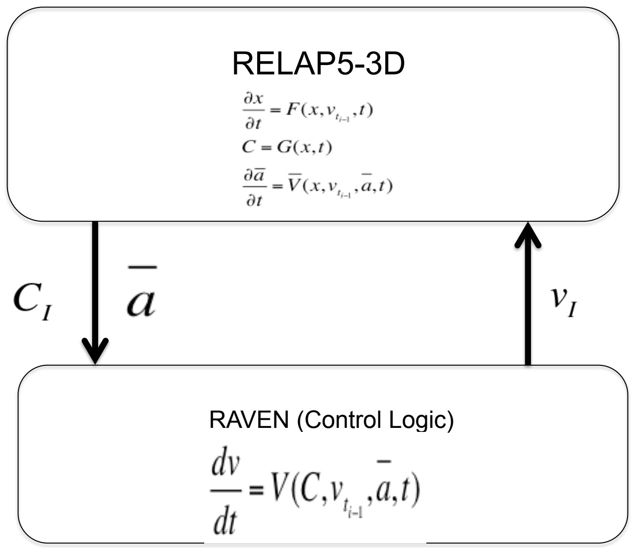
RAVEN Framework

- Utilize the RAVEN (Reactor Analysis and Virtual control ENvironment) to create a DET simulation using RELAP5-3D
- RAVEN framework based on an Operator Splitting Technique
- Use RELAP5-3D to calculate the following parameters and pass to the control module of RAVEN:

$$\frac{\partial \overline{x}}{\partial t} = \overline{F}\left(\overline{x}, \overline{\upsilon}_{t_{i-1}}, t\right)$$

$$\overline{C} = \overline{G}\left(\overline{x}, t\right)$$

$$\frac{\partial \overline{\upsilon}}{\partial t} = \overline{V}\left(\overline{C}, \overline{\upsilon}_{t_{i-1}}, t\right)$$



Example Case

- Consider a PWR SBO transient
- Possible states include normal shutdown, SBO, and recovery through feed and bleed
- Westinghouse PWR 4-loop RELAP5 model is used to evaluate transient
- Utilize RAVEN Framework to run the DET simulation to identify the timing of events resulting in the highest probability of failure.
- Branch-and-Bound Algorithm used to identify the branches with the highest probability of failure.

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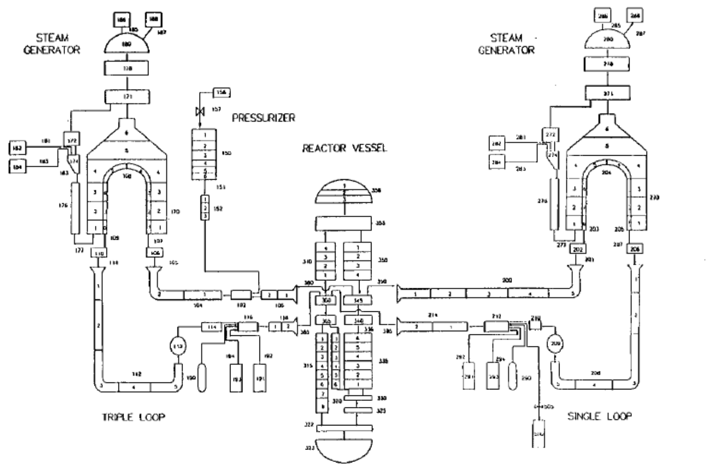
RELAP5 Model of Westinghouse PWR



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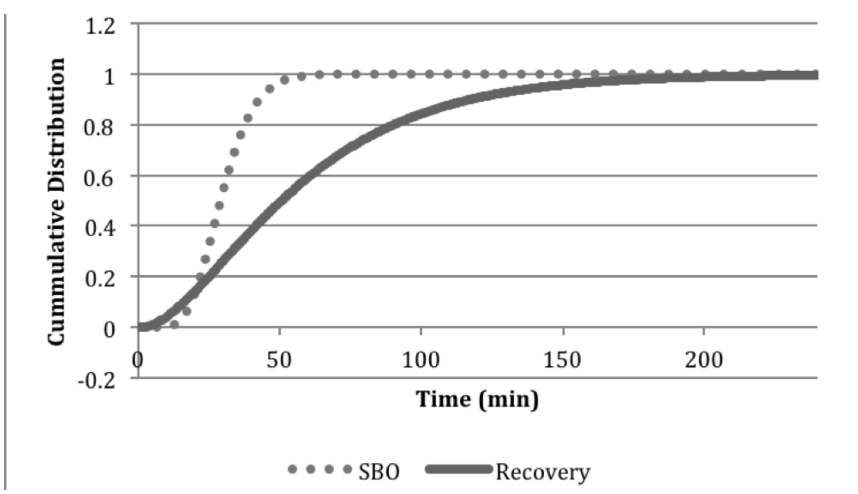
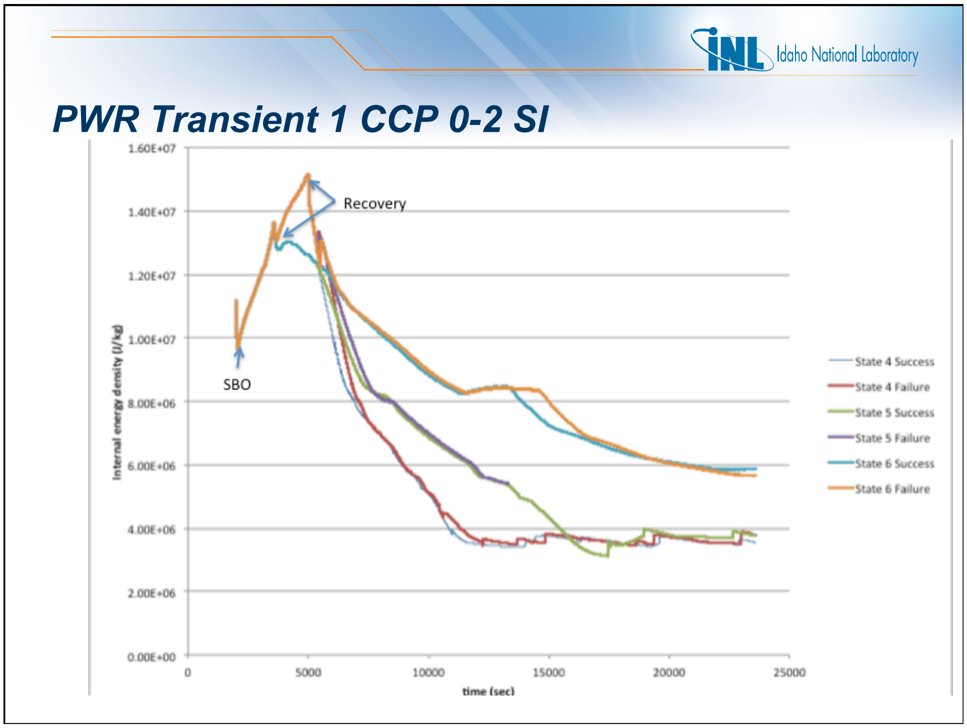
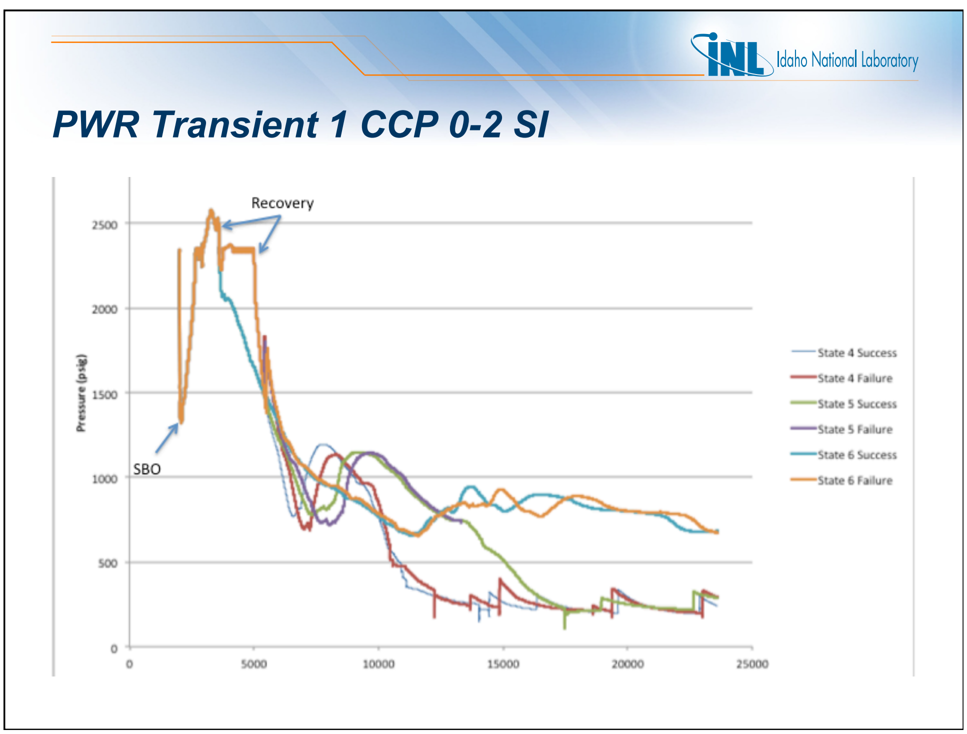
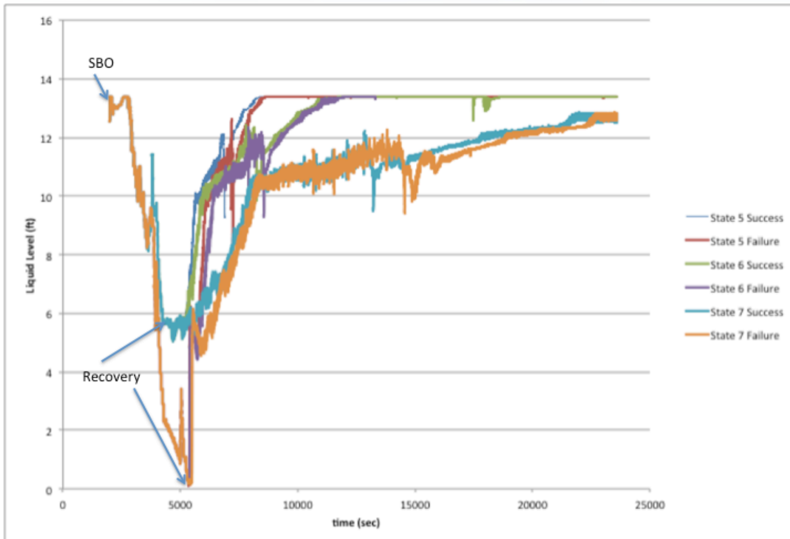
SBO and Recovery Cumulative Distribution Functions



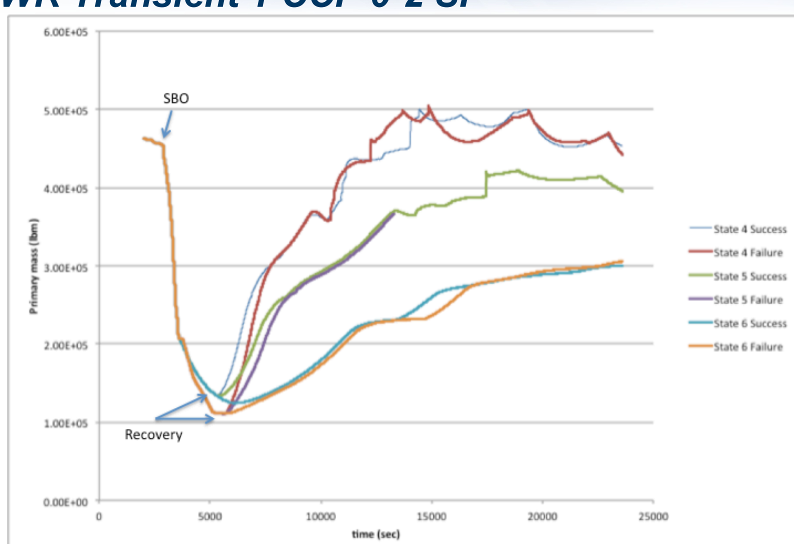

Idaho National Laboratory
PWR Transient 1 CCP 0-2 SI
Recovery
SBO
Internal energy density (J/kg)
time (sec)
State 4 Success
State 4 Failure
State 5 Success
State 5 Failure
State 6 Success
State 6 Failure


Idaho National Laboratory
PWR Transient 1 CCP 0-2 SI
Recovery
SBO
Pressure (psig)
State 4 Success
State 4 Failure
State 5 Success
State 5 Failure
State 6 Success
State 6 Failure

PWR Transient 1 CCP 0-2 SI



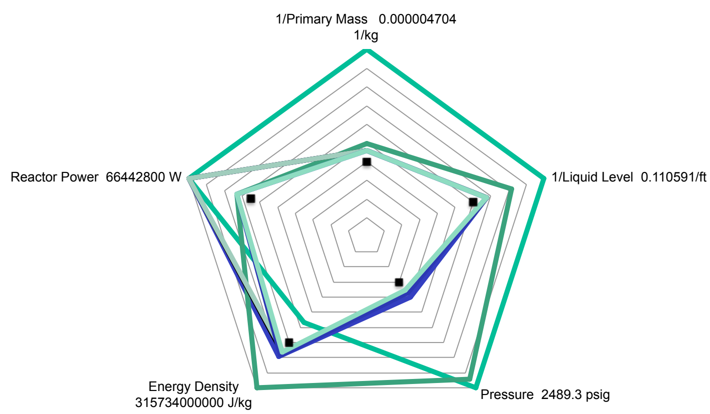
PWR Transient 1 CCP 0-2 SI



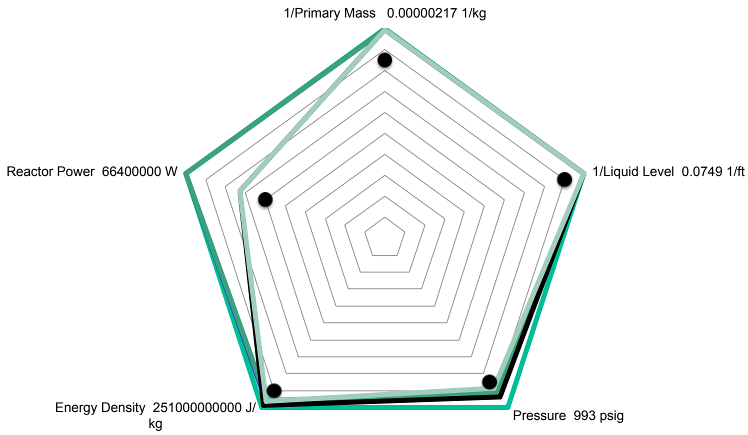
Bounding Functional Relationships

- Create a bounding functional relationships for each successful branch (i.e., leaf with no clad failure)
- Set of bounding functional relationships 1 for each success
- As a node reaches the System set that contains a bounding functional relationship the state set is compared against each individual parameter.
- Consider a spider chart where each axis represents a parameter of interest
- If State set falls within the bounding functional relationships than the branch is pruned
  - That is to say if the all parameters defined in a set, all fall within the parameters on the axis, from a single set of bounding functional relationships, the branch will be pruned

PWR Transient Bounding Functions 1 CCP



PWR Bounding Functions 0 CCP availability



Branch-and-Bound for SBO case

- Using the Branch-and-Bound algorithm we have pruned approximately 75% of the tree resulting in a significant amount of savings and identified the highest probability of failure cases.
- The efficiency of the algorithm varies depending on the number of processors used. Some simulations are started before a bounding simulation is finished.
- More processors can be used for performing SA/UQ for the models rather than running simulations that yield little to no value in the results.
- Advantages of the Branch-and-Bound algorithm
  - Efficiently prune the DET using bounding functional relationships defined on user knowledge
  - Bounding functional relationships do not rely on machine learning algorithms which suffer from dynamic non-linear systems
  - Programming is easily incorporated into the RAVEN framework

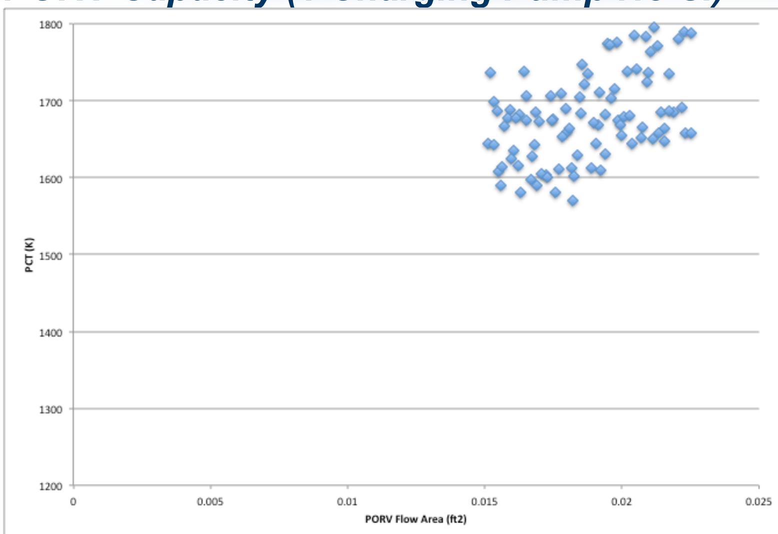
PIRT Demonstration

- To provide a demonstration case, 5 parameters from the input file were chosen to evaluate the effects on final results
  - Initial Reactor Power
  - Safety rod worth
  - PORV capacity
  - SI pump capacity
  - CCP capacity
- Final ranking of correlation coefficients used to create a PIRT.

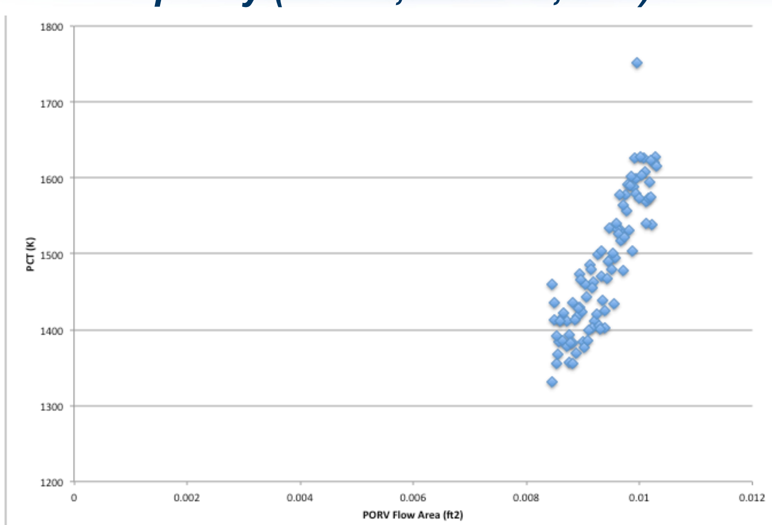
Uncertainty Parameters in Input

- Reactor Power +/- 5%
- Safety Rod Worth 20.65$ +/-10%
- PORV Capacity 64.6 lbm/sec/valve +/- 10%
  - Used a critical flow model where flow area was adjusted
- SI Capacity
  - 160.92 lbm/sec +/- 10% at 15 psig
  - 34.11 lbm/sec +/- 10% at 128 psig
  - 13.21 lbm/sec +/- 10% at 1418 psig
  - 3.30 lbm/sec +/- 10% at 1529 psig
- CCP Capacity
  - 29.15 lbm/sec +/- 10% at 683 psig
  - 7.94 lbm/sec +/- 10% at 2620 psig

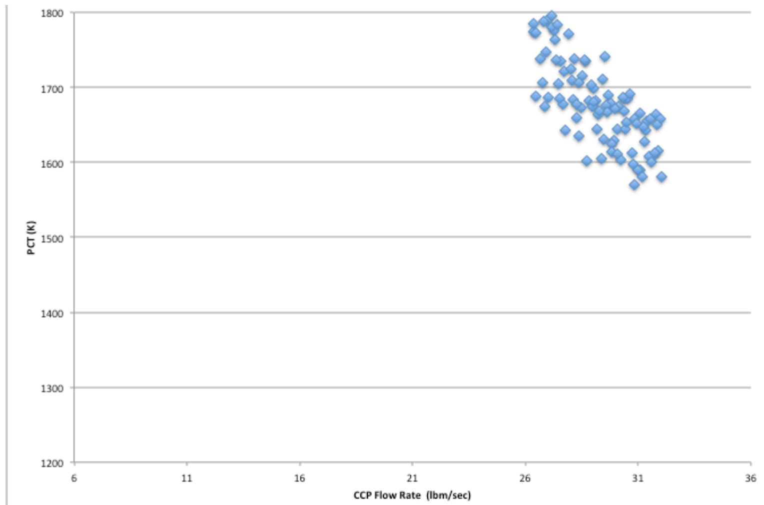
PORV Capacity (1 Charging Pump No SI)



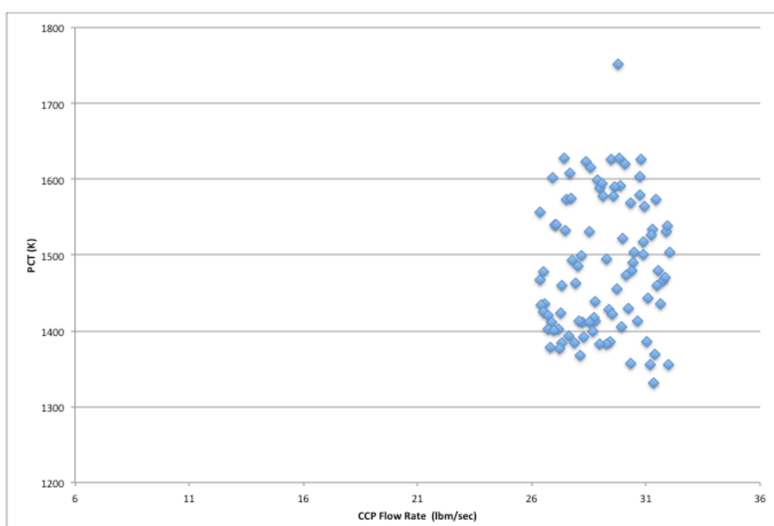
PORV Capacity (1 CCP, 1 PORV, 0 SI)



Charging Pump Capacity (1 CCP, 2 PORVs, 0 SI)



CCP Capacity (1 CCP, 1 PORV, 0 SI)



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Summary of SA/UQ Ranking

Parameter	2 CCP 2 SI	2 CCP 1 SI	2 CCP 0 SI	1 CCP 2 SI	1 CCP 1 SI	1 CCP 0 SI	0 CCP 2 SI	0 CCP 1 SI
Initial Power	0.025	0.079	0.144	0.291	0.041	0.726	0.088	0.149
Safety Rod Worth	0.035	0.108	0.054	0.011	0.159	0.033	0.064	0.038
PORV	0.161	0.212	0.018	0.544	0.203	0.348	0.625	0.805
CCP	0.328	0.313	0.548	0.460	0.498	0.341	N/A	N/A
SI	0.129	0.178	N/A	0.244	0.179	N/A	0.190	0.122

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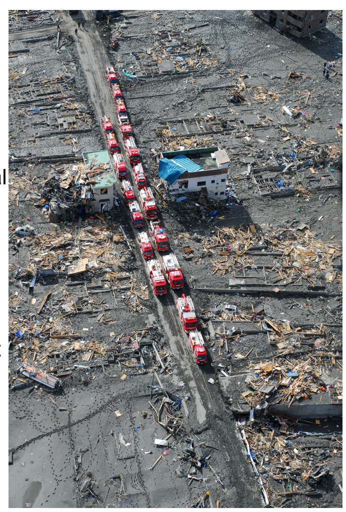
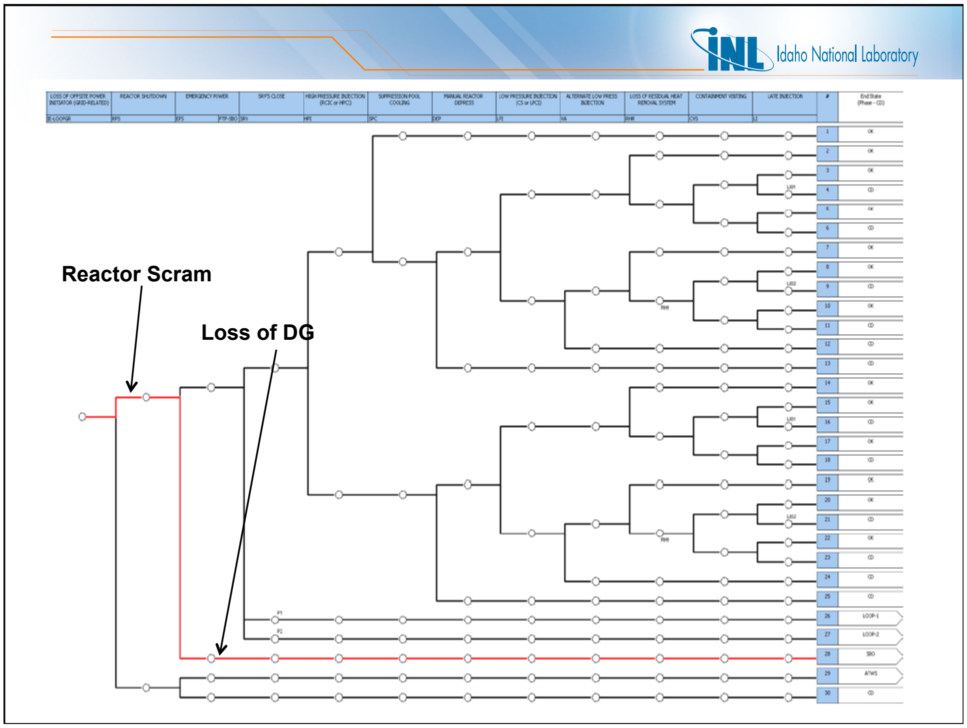
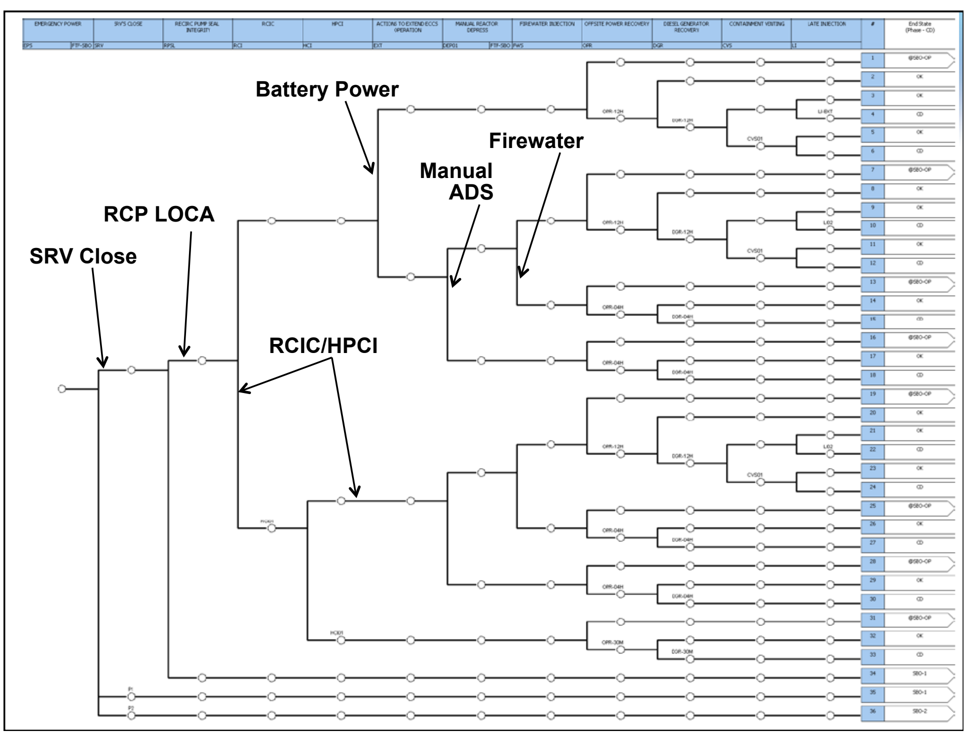
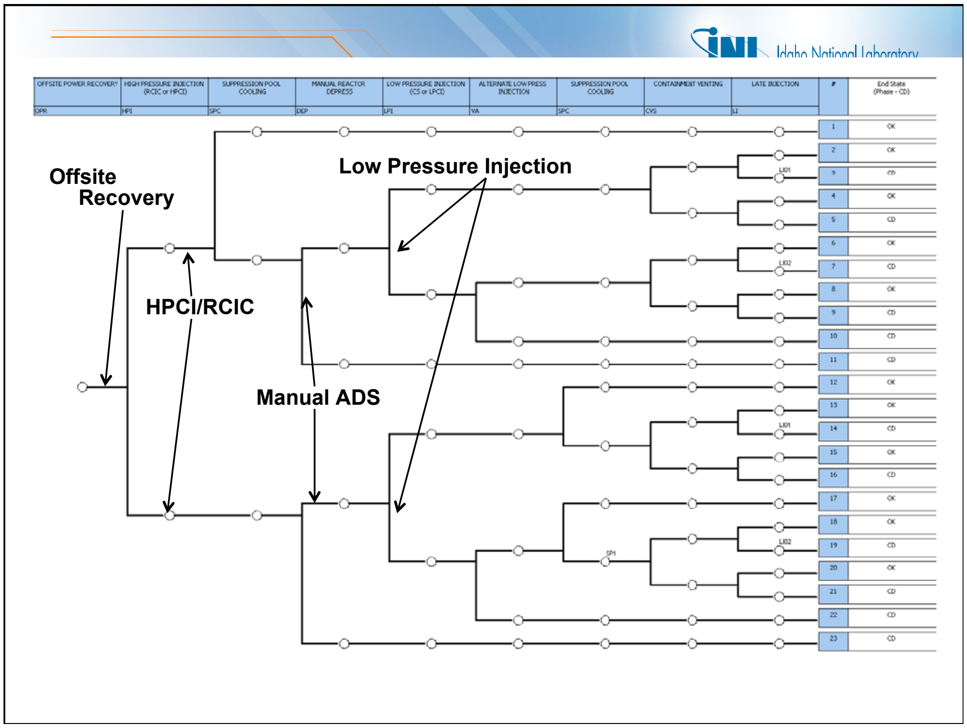
BWR SBO Transient

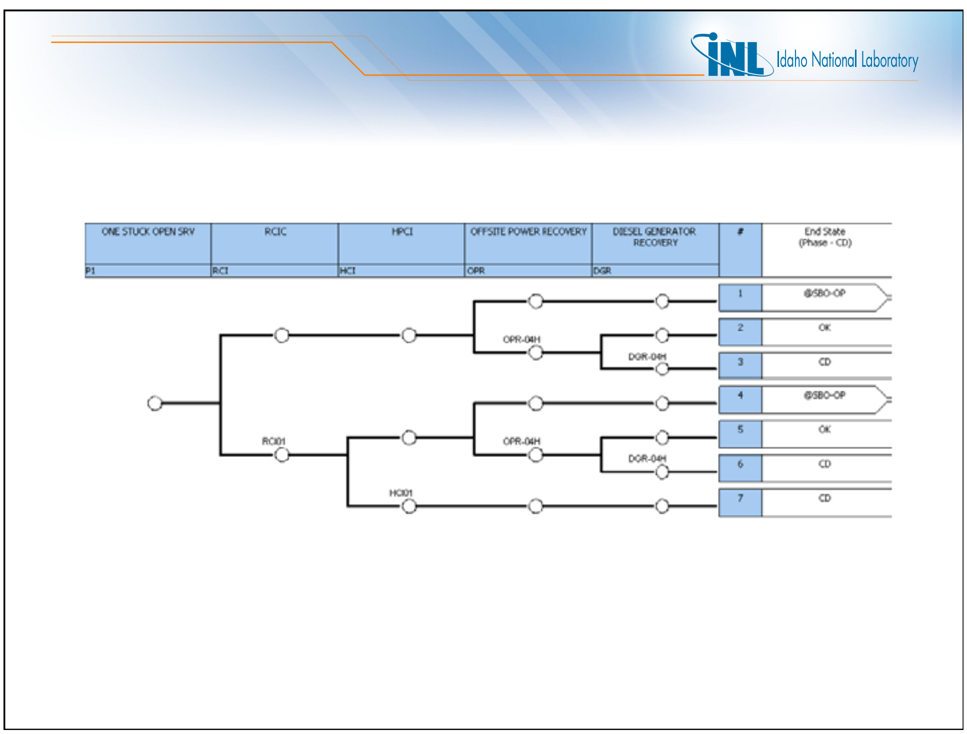
- BWR DET for SBO was evaluated
- The model consisted of a much greater number of plant states
  - After failure of DG energy removed from reactor through SRVs to Wet Well
  - RCIC and HPCI provide cooling capability
  - RCP seals not cooled potential LOCA from seal failure
  - Battery power estimated to last 4 to 8 hours
    - Fukushima RCIC powered by TDP for more than 48 hours
  - SRV can fail to close causing LOCA
  - Operators can actuate ADS to blow down reactor if thermal-hydraulic conditions require it
  - Battery failure causes failure of RCIC or HPCI
  - Recovery by restoration of AC or DG
  - Firewater injection available but requires operator action




Idaho National Laboratory
Reactor Scram
Loss of DG


Battery Power
Firewater
Manual
ADS
RCP LOCA
SRV Close
RCIC/HPCI


Idaho National Laboratory
Offsite Recovery
Low Pressure Injection
HPCI/RCIC
Manual ADS


Idaho National Laboratory
ONE STUCK OPEN SRV
RCIC
HPCI
OFFSITE POWER RECOVERY
DIESEL GENERATOR RECOVERY
#
End State (Phase - CD)
P1
RCI
HCI
OPR
DGR
OPR-04H
DGR-04H
RCI01
HCI01
1 @SBO-OP
2 OK
3 CD
4 @SBO-OP
5 OK
6 CD
7 CD

DET Creation

- Use the classical ET to build the LENDIT/S2R2 response for DET
  - The simulation reads in parameters from RELAP
    - State parameters provided by MINOR EDITS in RELAP (e.g., pressure, temperature, flow rate, power etc)
    - System parameters are read in from "Trip" functions in RELAP (i.e., Trip 586 means DG failure, Trip 588 is Battery Failure)
    - Resources defined in control module for RAVEN
    - Response uses Boolean Algebra to evaluate System parameters and return a two or more lists (one for each branch) to modify RELAP input file
  - Use LENDIT to identify distributions for branching conditions and heuristically eliminate infeasible branches up front based on knowledge of classical ET

BWR S2R2 Sets

State	System	Resource	Response	
Pressure < 6.21 Mpa	SRV Open SBO	SRV Battery Power	Branch 1 Branch 2 Branch 3	SRVs Close 1 SRV Fail to Close 2 SRV Fail to Close
	SBO	Battery	Branch 1 Branch 2	Battery power available Battery power depleted
ADS Trip Conditions	SBO	Battery Power	Branch 1 Branch 2	No ADS ADS
Pressure < 1.03 Mpa	SBO and Battery Power	Firewater Injection	Branch 1 Branch 2	Firewater failure Firewater initiation
	SBO	HPCI	Branch 1 Branch 2	HPCI Operational HPCI Failure
	SBO	RCIC	Branch 1 Branch 2	RCIC Operational RCIC Failure
	SBO	RCP Seals	Branch 1 Branch 2	RCP Seals Intact RCP Seals Failed
	SBO	Diesel Generators	Branch 1 Branch 2	Diesel generator failure Diesel generator recovery

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DET Creation and Branch and Bound

- Many branches will not end in failure so we create bounding surface for important physical parameters(pressure, internal energy, liquid level, and reactor power)
  - Determined from knowledge of analyst (LENDIT)
  - Note Liquid mass is not included as level is directly correlated to mass in BWR
- Branches are sampled on CDF provided by analyst and branching frequency is determined in by analyst using LENDIT

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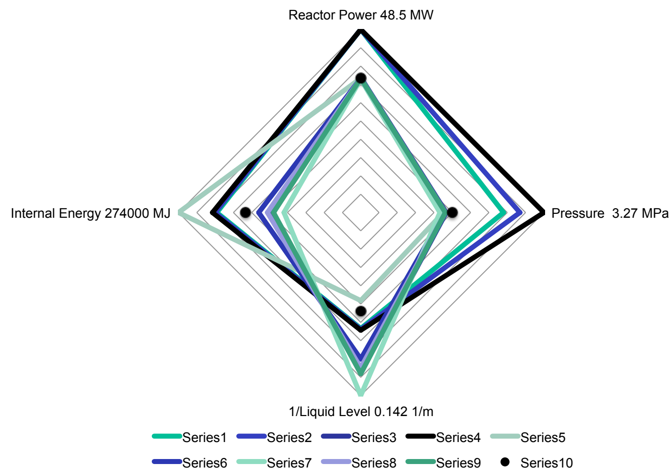
DET Simulation

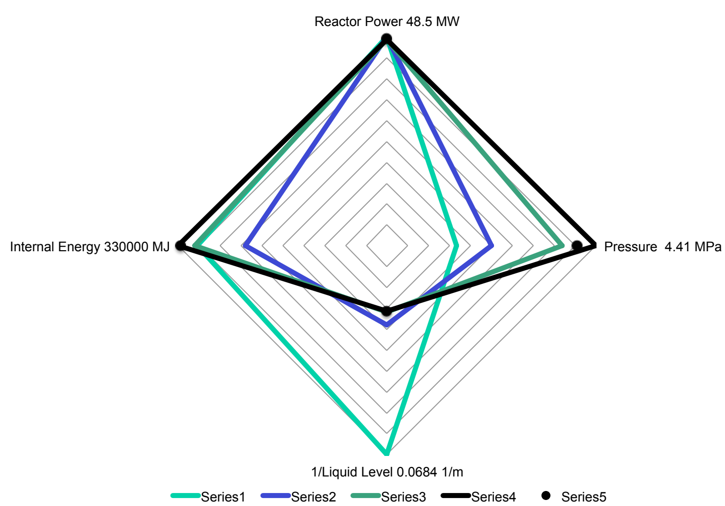
- Surfaces for energy density, reactor power, pressure and liquid level were evaluated. Liquid mass was not included as mass in a BWR is directly correlated to Liquid level.
- DET with a Brute Force Method Compared to Branch and Bound
- No SA/UQ in comparison

Brute Force Method	**Branch and Bound**
512 Processors	512 Processors
5.5 days	2 Days
20752 Nodes	5868 Nodes
1857 Failure Nodes	373 Failure Nodes
6600 Success Nodes	3141 Success Nodes
270 GB Data (Not counting restart files)	143 GB (Not including Restart

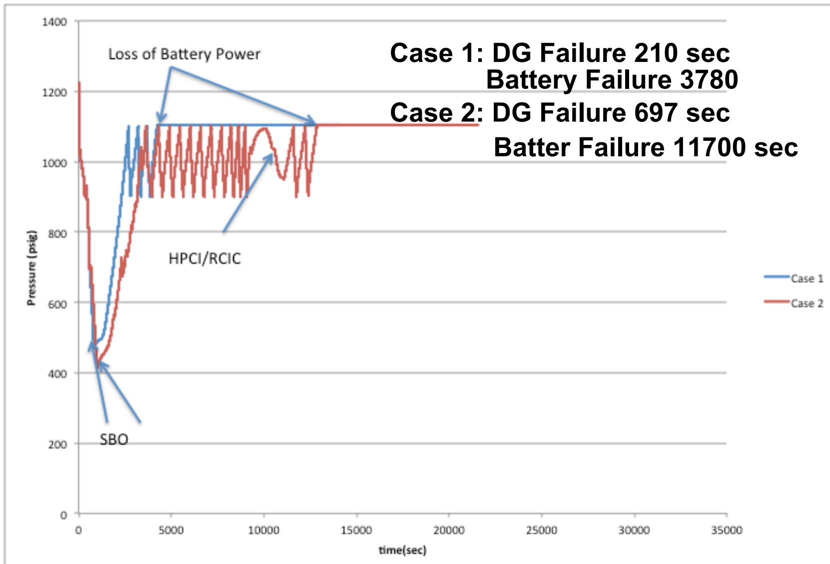
Sample Bounding Functional Relationships (Battery failure RCP LOCA and stuck SRV)



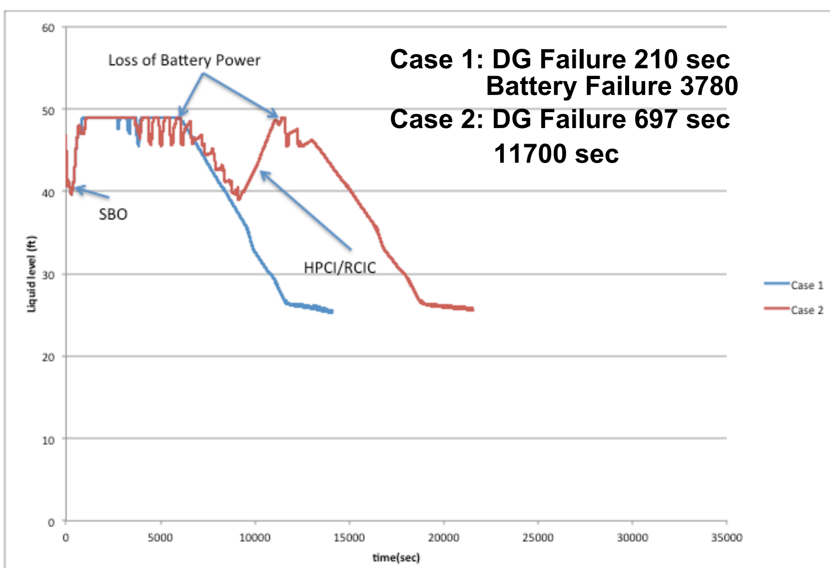
RCP LOCA and 1 Stuck SRV No Battery Failure



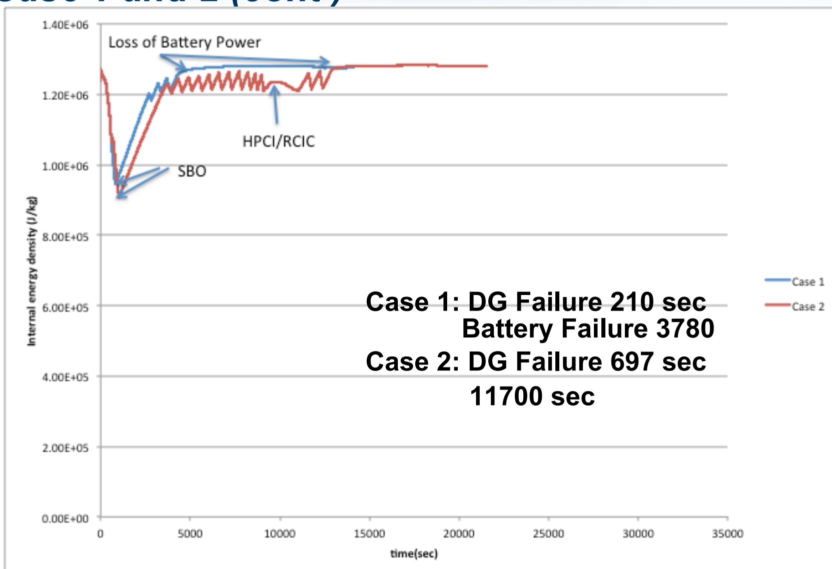
Case 1 and 2 SBO and Battery Loss Failure



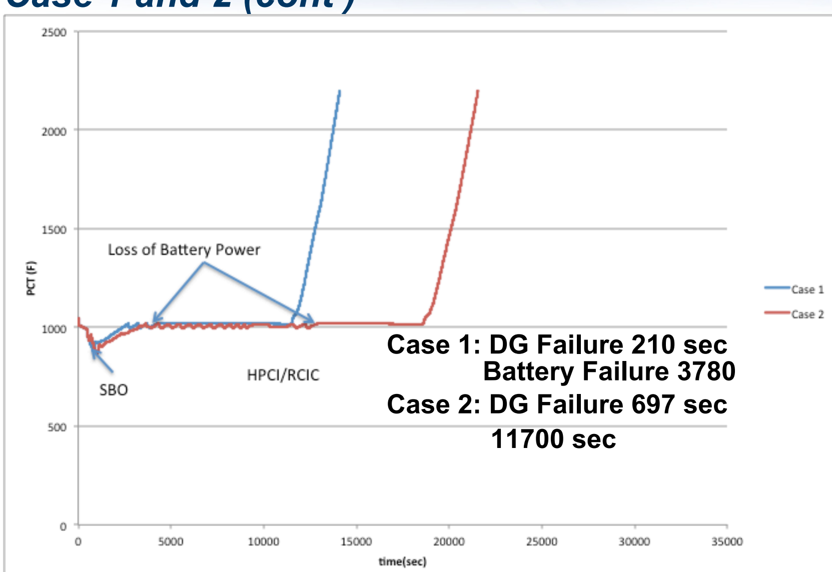
Case 1 and 2 (cont')

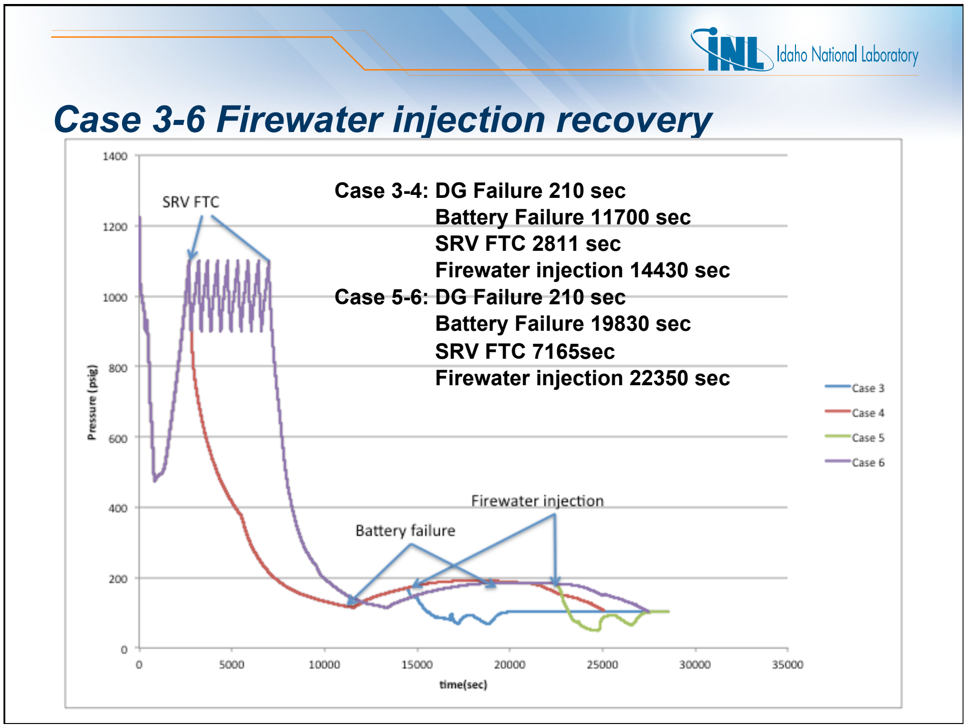


Case 1 and 2 (cont')



Case 1 and 2 (cont')

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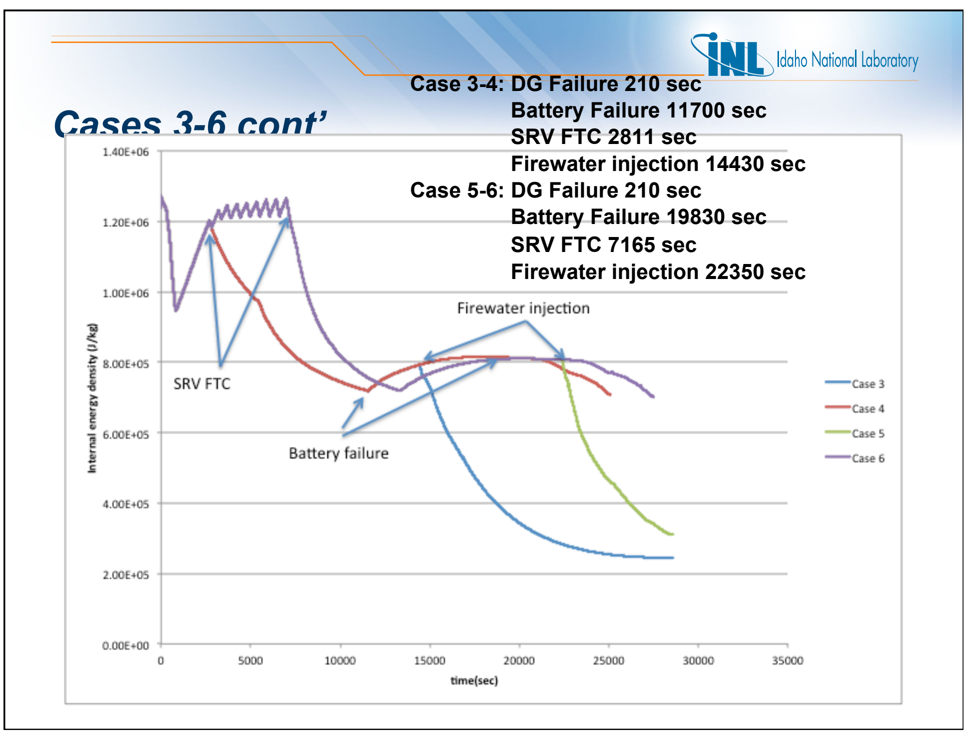
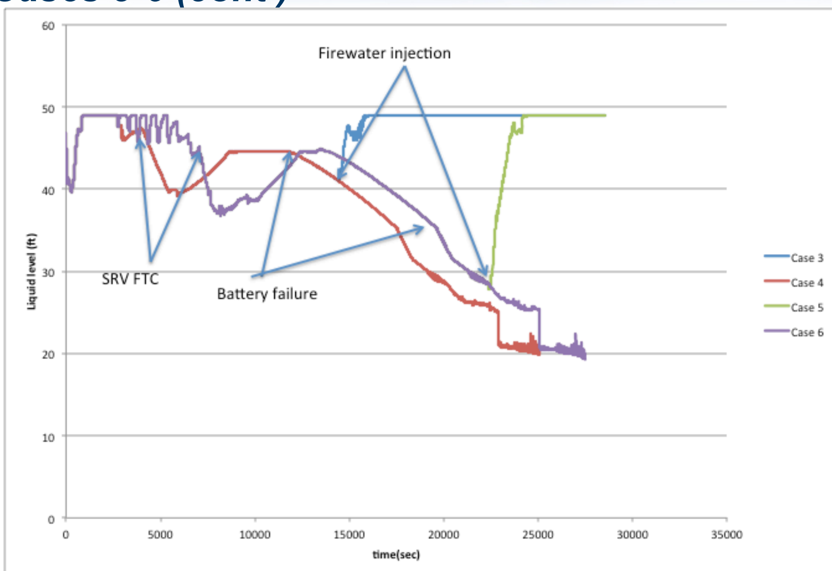
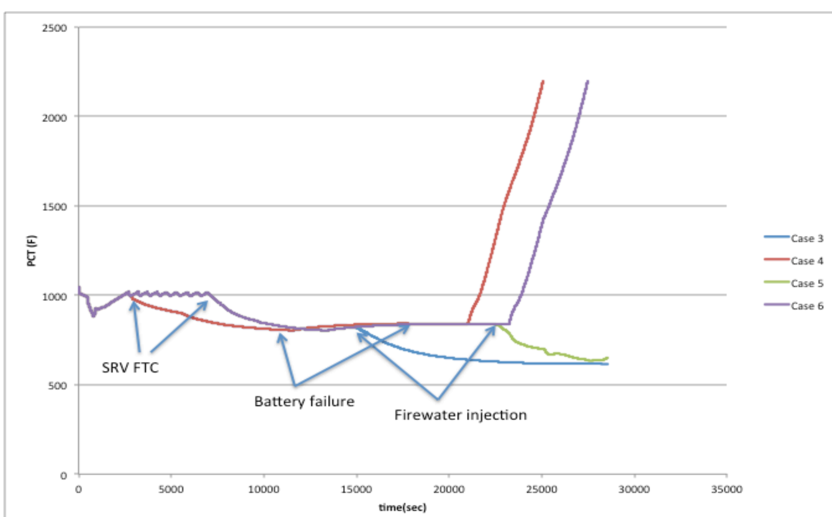
Case 3-6 Firewater injection recovery
Case 3-4: DG Failure 210 sec
Battery Failure 11700 sec
SRV FTC 2811 sec
Firewater injection 14430 sec
Case 5-6: DG Failure 210 sec
Battery Failure 19830 sec
SRV FTC 7165sec
Firewater injection 22350 sec
SRV FTC
Battery failure
Firewater injection
Pressure (psig)
time(sec)
Case 3
Case 4
Case 5
Case 6


Idaho National Laboratory
Cases 3-6 cont'
Case 3-4: DG Failure 210 sec
Battery Failure 11700 sec
SRV FTC 2811 sec
Firewater injection 14430 sec
Case 5-6: DG Failure 210 sec
Battery Failure 19830 sec
SRV FTC 7165 sec
Firewater injection 22350 sec
SRV FTC
Battery failure
Firewater injection
Internal energy density (J/kg)
time(sec)
Case 3
Case 4
Case 5
Case 6

Cases 3-6 (cont')



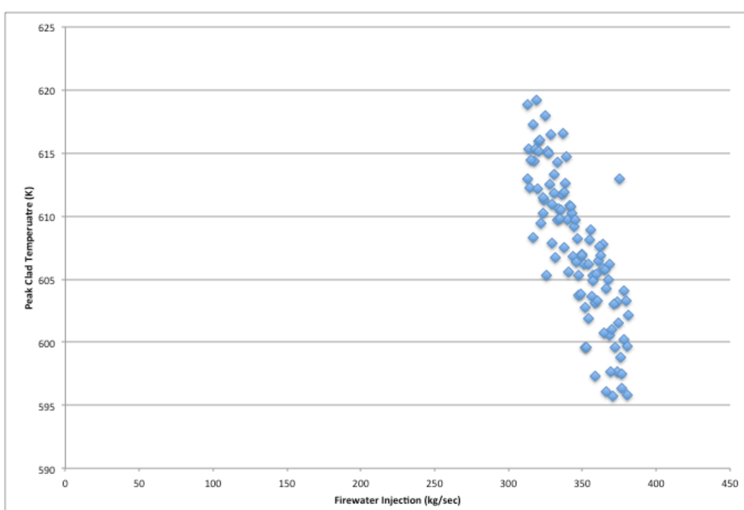
Cases 3-6 (cont')



BWR Sensitivity Analysis

Parameter	Nominal Value	Parameter	Nominal Value
SRV flow area	0.085 ft^2 (0.0079 m^2)	Zr thermal conductivity	0.00209 BTU/s/ft/F (13.02 W/ m^2K)
HPCI capacity	5600 gpm (424.3 l/s)	Zr heat capacity	35.18 BTU/ft^3/F (2.35 × 10^6 J/ m^3K)
RCIC capacity	5600 gpm (424.3 l/s)	U heat Conduction	3.906 × 10^{-4} BTU/ft^3F (2.43 W/m K)
Firewater capacity	2500 gpm (189.4 l/s)	U heat capacity	56.55 BTU/ft^3/F (3.82×10^6 J/m^3 K)
Power	3293 MW		

Sensitivity Analysis Case 3 Firewater Injection



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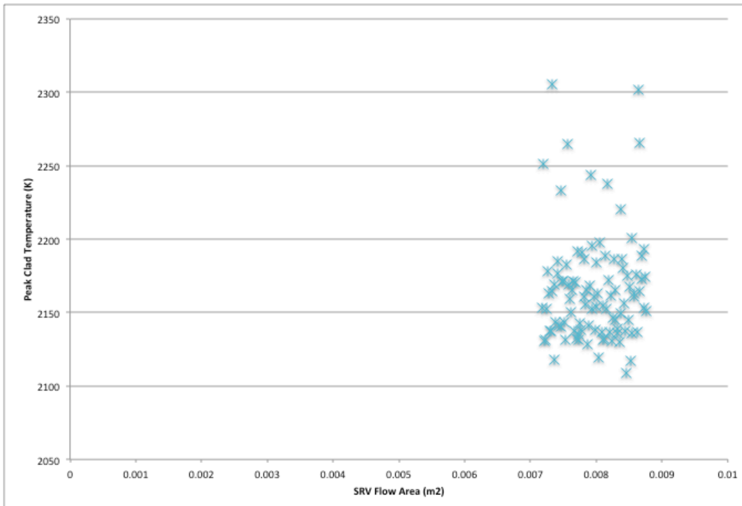
Case 3 Sensitivity Analysis SRV



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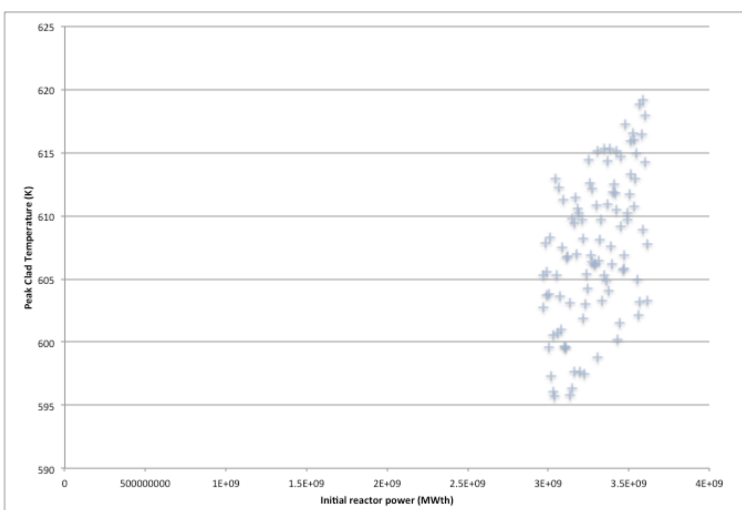
Sensitivity Analysis Case 3 Reactor Power



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Conclusions

- DET can provide useful insight risk analysis for complex dynamic system
- State or combinatorial explosion greatly impacts the ability to evaluate complex system
- Branch-and-Bound algorithm provides an optimization tool to reduce state explosion and reduce simulation in identifying high risk scenarios.
- Utilize the Branch-and-Bound algorithm to perform sensitivity analysis on various modeling parameters and identify those parameters that directly impact risk
  - Provide insight into modeling improvements and validations experiments that can reduce risk and improve safety margin
  - Reduction in safety margin allows for an increase in operating power

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Conclusions (cont')

- Methods presented in this research provide a unique method for optimizing dynamic event trees that has not been employed
- The algorithm provides a significant contribution to the field by allowing for more rigorous analysis using DET and reducing computational costs
  - These contributions include computational efficiency in evaluating risk
  - Methodology to identify modeling uncertainty such that a reduction in uncertainty can be used to improve safety margin
  - Improvement of the safety margin and quantification can be used to allow for power uprates and life extension of the current fleet of nuclear plants