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Results of a Demonstration Assessment of Passive System Reliability Utilizing the Reliability Method for Passive Systems (RMPS)

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Advanced small modular reactor designs include many advantageous design features such as passively driven safety systems that are arguably more reliable and cost effective relative to conventional active systems. Despite their attractiveness, a reliability assessment of passive systems can be difficult using conventional reliability methods due to the nature of passive systems. Simple deviations in boundary conditions can induce functional failures in a passive system, and intermediate or unexpected operating modes can also occur. As part of an ongoing project, Argonne National Laboratory is investigating various methodologies to address passive system reliability. The Reliability Method for Passive Systems (RMPS), a systematic approach for examining reliability, is one technique chosen for this analysis. This methodology is combined with the Risk-Informed Safety Margin Characterization (RISMC) approach to assess the reliability of a passive system and the impact of its associated uncertainties. For this demonstration problem, an integrated plant model of an advanced small modular pool-type sodium fast reactor with a passive reactor cavity cooling system is subjected to a station blackout using RELAP5-3D. This paper discusses important aspects of the reliability assessment, including deployment of the methodology, the uncertainty identification and quantification process, and identification of key risk metrics.

I. INTRODUCTION

The most recent iteration of advanced small modular reactor designs has many new design features that are intended to result in reduced capital costs, shorter construction timeframes, higher uptimes, and increased reliability. Many of these advantages result from the inclusion of passive safety systems, where the primary benefit of passive safety systems is a significant increase in plant safety. While not novel, these systems are unique compared to conventional active systems in that they rely on passive phenomena to achieve the desired safety function. These passive systems rely on no operator intervention for actuation and often do not contain any moving parts.

Because these systems are largely driven by passive phenomenology (e.g. natural circulation, gravity, etc.), the operating capacity and mode is directly affected by the boundary conditions associated with the system. If the existing boundary conditions are beyond the expected design envelope, the system can exhibit unanticipated behavior that may prevent completion of its planned safety function. This is true even when no physical obstructions or failures exist within the system, thereby allowing the system to fail functionally without actively failing. Additionally, if implemented in the near-term, these systems can operate under large uncertainties, due in part to lack of previous operating experience and the large operating margin for passive phenomenology; reliability and failure modes are typically not well-understood in first-of-a-kind systems with limited operating experience.

While passive systems may eliminate some typical failure modes (e.g. operator error, or component/signal failure leading to overall system failure), integration of passive systems into a conventional risk assessment can prove to be challenging due to their failure characteristics and intermediate operating modes. Traditional event trees are not well-equipped to handle the non-binary operating states of passive systems without substantial branch generation and tree growth, nor are these event trees capable of addressing the time-dependent boundary conditions affecting passive system performance. However, conventional event trees are very efficient at capturing the correlated effects of uncertainties on system behavior.

As part of an ongoing effort to address the aforementioned issues, Argonne National Laboratory is examining various techniques for the assessment of the reliability of a passive system coupled with an advanced small modular reactor. Several candidate techniques have been identified in previous work,[1] but the focus of this paper is on the use of mechanistic methods, specifically the Reliability Method for Passive Systems (RMPS) coupled with the Risk-Informed Safety Characterization

(RISMC) approach. A companion paper[2] describes the application of simulation-based methods to the same demonstration problem.

For this analysis, a metal-fueled pool-type sodium-cooled fast reactor (SFR) paired with a reactor cavity cooling system (RCCS) relying on natural convection is subjected to a station blackout with the potential for early to late power recovery. A demonstration problem with two passive systems (the primary sodium pool and RCCS) was intentionally chosen to examine the potential interaction between the two systems, particularly when an active system (such as intermediate system heat removal) is utilized to influence one of the passive systems. All simulations are performed using an integrated RELAP5-3D (Ref. 3) model of the reactor and RCCS deployed under an in-house job server on a distributed Windows system.

Section II of this paper describes the RMPS utilized for this analysis. Section III describes the demonstration problem, including the system model, scenario and identification of important parameters and uncertainty quantification. The results of the analysis are presented in Section IV, with concluding remarks being made in Section V.

II. RELIABILITY METHOD FOR PASSIVE SYSTEMS (RMPS)

While several mechanistic methodologies exist[4,5,6], the Reliability Method for Passive Systems (RMPS)[7] has been selected for use in this work. The RMPS, which provides a systematic approach for examining passive system reliability using deterministic codes and models, is a relatively mature mechanistic technique, with development beginning in 2001 by the European Union contracting with the Atomic Energy and Alternative Energies Commission (CEA).[8] The full methodology requires nearly a dozen discretized steps, but the process can be divided into three fundamental phases, as described in Table I. These three phases include preprocessing and model development, simulation and propagation, and analysis/post-processing.

While the RMPS enables a rigorous and structured assessment of passive system reliability by mechanistically incorporating expert judgment into deterministic simulations, the RMPS is very similar to conventional reliability methods. Despite the robust framework of a mechanistic analysis, traditional event trees introduce some fairly well known limitations to the analysis. Scenario progression through accident space must be prespecified; this includes event ordering and relative timing. For phenomena that are not well understood, consideration of the full range of uncertainties associated with these events can change the ordering of events. However, the rigid structure of static event trees prevents any modification of event order. Inclusion of non-binary branching events in a static event tree is also difficult due to the tendency of the size of the tree to explode. In this case, scenario monitoring and data management become difficult and are often more cumbersome than the development of the analysis itself.

TABLE I. The three phases of RMPS.

Phase 1	• Identify a system, its intended mission, and possible failure modes • Select or develop a best-estimate code to perform the analysis • Identify important system variables, characterize their associated uncertainties
Phase 2	• Conduct sensitivity analysis • Determine failure probability of the system using best-estimate code • Assess the impact of the uncertainties of the important system variables
Phase 3	• Incorporate the failure probability into the PRA

III. DEMONSTRATION PROBLEM

This section will discuss the demonstration problem developed for this analysis. The RELAP5-3D model of the reactor is described in Section III.A. A description of the scenario is presented in Section III.B, and uncertainties relevant to the demonstration problem are identified in Section III.C.

III.A. System Model

Because the primary objective of this work is to examine various reliability assessment techniques for passive systems, a generic advanced small modular reactor (advSMR) design was selected for this analysis. A simplified model of a metal-fuel pool-type SFR was developed in RELAP5-3D as part of this effort; the fundamental design characteristics of the reactor are shown in Table II. The primary system model contains representation of the four primary electromagnetic (EM) pumps, the intermediate heat exchanger (IHX), inlet/outlet plenums, and the core region. During normal operation, the IHX would typically be utilized to reject heat to a secondary/tertiary loop and ultimate heat sink; however, during accident scenarios, the IHX can also be used to reject decay heat to a heat sink such as the condenser while bypassing the power conversion system. A schematic of the primary system components and simplified nodalization diagram of the RELAP5-3D model are shown in Figures 1 and 2, respectively.

TABLE I. Design characteristics for demonstration SFR.

Feature	
Power rating	250 MWth/100 MWe
Primary coolant	Sodium
Primary system type	Pool
Fuel type	Metallic
Coolant pump type	Electromagnetic
Coolant pump number	4
Primary vessel height	10 m
Core inlet/outlet temperature	400°C/550°C

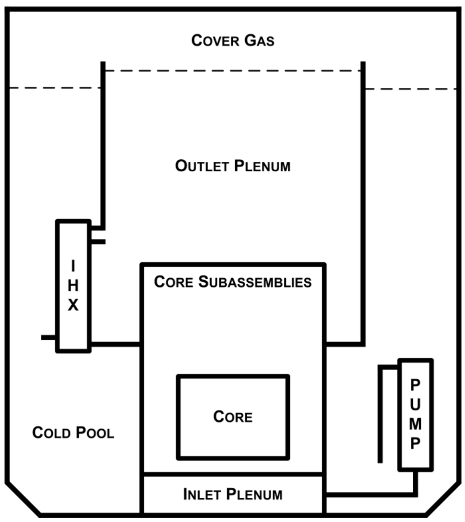

Fig. 1. Schematic of primary system for demonstration SFR showing model components (not to scale).

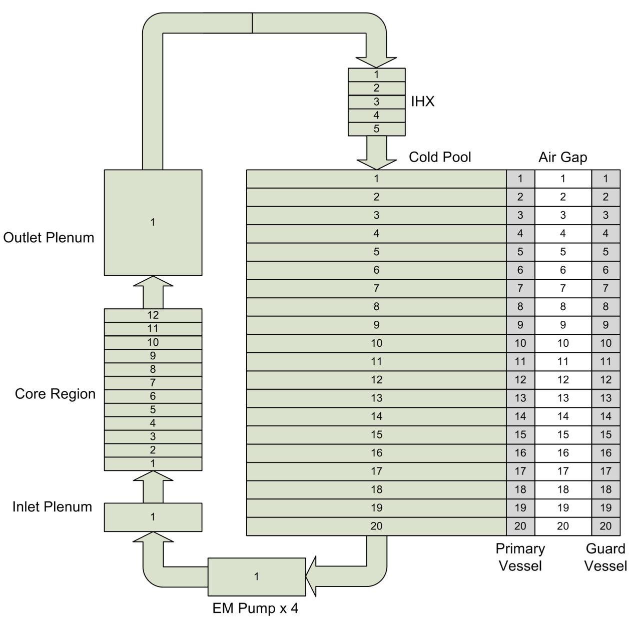

Fig. 2. Simplified nodalization diagram of primary system in RELAP5-3D (not to scale).

At this time, RELAP5-3D does not contain detailed metal fuel models that adequately consider both feedback kinetics and failure mechanisms; therefore, the core is not explicitly modeled in this analysis. Instead, in protected transients where the reactor successfully scrams, a programmed reactivity component considering both fission power and decay heat is used to treat heat generation in the core region. The programmed reactivity was derived from SAS4A/SASSYS-1 (Ref. 9) analyses for a similar reactor and scenario. In unprotected scenarios where the reactor is not scrammed, an integral solution[10] to the space-averaged reactor kinetics equations is utilized to control fission power. A programmed reactivity component derived from SAS4A/SASSYS-1 analyses is utilized to treat decay heat in the unprotected scenarios.

A passive heat removal system that operates at decay heat levels has also been coupled with the primary system model for this analysis. Typically, an SFR would be paired with a system similar to a reactor vessel auxiliary cooling system (RVACS). However, for this demonstration analysis, a reactor cavity cooling system (RCCS) was selected for inclusion due to the availability of the experimental Natural convection Shutdown heat removal Test Facility (NSTF) at Argonne. The NSTF is a half-scale representation of the RCCS that is conducting ongoing tests; thus far, preliminary results have been used for benchmarking analyses of the existing RCCS RELAP5-3D model.[11]

The RCCS design originated from the General Atomics Modular High Temperature Gas cooled Reactor (GA-MHTGR) design[12], and utilizes natural convection and radiation to remove decay heat from the reactor guard vessel and reject it to the atmosphere. A plan view of RCCS is shown in Fig. 3 and an overall system view is shown in Fig. 4. The system consists of a series of hot riser tubes and chimneys enclosed within the reactor cavity. Heat is rejected from the guard vessel to the hot riser tubes via radiation. The hot riser tubes are then cooled by naturally convecting air that enters the system from the atmosphere via a downcomer. This air is then vented to the atmosphere once it exits the riser tubes and travels through outlet chimneys. The RCCS is entirely passive, meaning no baffles or valves are present in the system to modify flow. This also means that the system is functioning during normal operation, removing some fraction (decay heat levels) of the total energy produced.

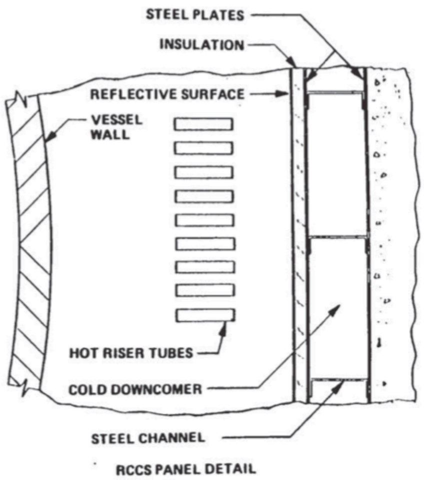

Fig. 3. Plan view of RCCS.[12]

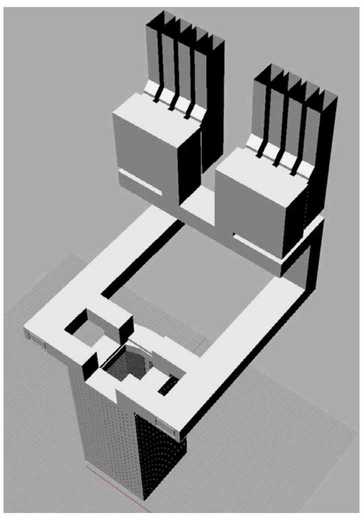

Fig. 4. Overall system view of RCCS.[13]

III.B. Scenario Description

A prolonged grid-induced station blackout (SBO) has been selected as the accident scenario for this demonstration analysis. An SBO was chosen for this analysis due in part to the recent increase in regulatory attention to SBOs (as a result of the events at Fukushima in 2011) and because it is an ideal scenario for analysis of passive system performance in the absence of active systems. The top events selected for inclusion in the mechanistic event tree were derived from the SBO event tree from the PRISM Preliminary Safety Information Document (PSID),[14] and probabilities of these events were determined using information from the PSID and engineering judgment. The top events and their associated likelihoods are shown in Table II.

TABLE II. Top events considered in SBO analysis.

Top Event	Probability	Source/ Comment
SBO (IE)	9.19E-2 per ry	95^{th} percentile from Ref. 15
RPS Signal to RSS	P(fail) = 2.4E-5	Ref. 14 and 16
Enough Control Rods Inserted	P(fail) = 5.8E-5	Ref. 14 and 16
Pump Trip	P(trip) = 1.0	All EM pumps trip due to IE
Pump Coastdown	P(1/4 fail) = 5.0E-5 P(2/4 fail) = 1.63E-6 P(3/4 fail) = 5.54E-7 P(4/4 fail) = 4.21E-7	Single failure probability derived from Ref. 14; Remaining probabilities calculated using alpha factor model with staggered testing for CCF[17]
Operating Power Heat Removal	P(fail) = 1.0	All active heat removal systems fail due to IE
RCCS Operating	P(operating) = 1.0	Assume no physical damage of RCCS; IE does not affect system
Delayed Active Heat Removal	Dependent on power recovery, where P(power recovery within 24 hr following IE) = 0.5	Active heat removal is used if power is recovered
Sampling	Determined by sampling uncertain parameters *(see Section III.C)*	Sampled values feed directly into model input

* IE = initiating event, RPS = reactor protection system, RSS = reactor shutdown system, CCF = common cause failure

The initiating event (IE) chosen for this analysis is an SBO in which all onsite and offsite AC power is lost. It is important to note that this SFR design does not include safety grade diesel generators as it is assumed that use of passive heat removal will be adequate to maintain core integrity; this design option is prevalent in advanced reactor designs, particularly SFRs.[14] For this work, it is assumed that the SBO is caused by a massive grid disruption rather than a naturally occurring external event (in a true risk assessment, the treatment of recovery likelihoods would be strongly dependent on the IE). The frequency of the initiating event was conservatively derived from NUREG/CR-6890 (Ref. 15) using the 95th percentile value.

The next top events in Table II correspond to the ability to scram the reactor. Successful scram is dependent on the reactor protection system (RPS) successfully sending a signal to the reactor shutdown system (RSS), and for enough control rods to be inserted if the signal is successfully sent. Because there is no explicit core model which can be used to assess shutdown neutronically, it is assumed in this analysis that either all or none of the six available control rods are inserted.

The top events for pump trip, operating power heat removal failure and operation of RCCS are all assumed to have likelihoods of unity due to the structure of this analysis and the nature of the initiating event. The primary pumps trip and active operating heat removal fails due to the loss of power from the SBO initiator. It is assumed that RCCS operates successfully with no physical obstructions. In fiscal year 2015, some degradation of RCCS capacity will be considered.

Because it can significantly affect primary system heat levels, coastdown of all four primary EM pumps is considered in this analysis. Due to their design, EM pumps add a unique failure mode to the tree. Because the pumps have almost no inertial force, a separate flywheel and synchronous machine are required to simulate the gradual decrease in flow rate typically experienced by mechanically impelled pumps. When power is lost, the inertial energy of the flywheel is used to simulate pump coastdown and prevent abrupt changes in flow. The failure probability of a single coastdown mechanism is taken from the PRISM PSID, while failure of multiple mechanisms is treated as the result of common cause failures (CCF). In these cases, the likelihoods were calculated using an alpha factor model with staggered testing.[17]

Delayed active heat removal is entirely dependent on recovery of offsite power. The method by which power is recovered (e.g. grid reconnection, use of mobile diesel generators) is not a relevant component of this analysis, so it was assumed that power recovery is equally likely between 4 hr and 24 hr following the IE. However, power recovery is questioned only at 9 hr and 19 hr following the onset of the accident; the limited times were selected to cover the accident space of interest without creating computational burden. It is conservatively assumed that the likelihood of power restoration within 24 hr is 50%, although this probability is likely higher now given post-Fukushima coping requirements. Table III shows the power recovery options and associated probabilities used in this analysis.

TABLE III. Power recovery options for SBO analysis.

Option	Probability	Comment
No power recovery	P(no recovery) = 0.5	Assumed no equipment or staff available
Early power recovery (9 hr after IE)	P(recovery at 9 hr) = 0.25	Discrete time chosen to represent first half of timeframe
Late power recovery (19 hr after IE)	P(recovery at 19 hr) = 0.25	Discrete time chosen to represent latter half of timeframe

The last top event shown in Table II is considered to be a sampling branch that represents uncertainty propagation in the scenario. The likelihood of this branch is determined by the fraction of total scenarios within each end state (e.g. the plant is in a safe state, or core damage is sustained). Values for uncertain parameters are determined using Monte Carlo sampling, and the selected values are then used as direct inputs to the model. Incorporation of risk results directly into the event tree has previously been applied to a Risk Informed Safety Margin Characterization (RISMC) for a total loss of feedwater.[18]

III.C. Parameter Identification and Uncertainty Quantification

Identification of important parameters and quantification of the associated uncertainties is a key component to the RMPS, where nearly 50% of the methodology is concerned with parameter selection, uncertainty quantification and screening. Because this is a demonstration analysis of the reliability of passive systems, the focus of this work was on those parameters which are expected to affect passive system performance. Some uncertainties related to the primary system were also selected, but only those expected to have a significant effect on heat levels in the primary pool. Typically, however, this process should identify any parameter that is expected to have a significant effect on the end state of the plant.

The important parameters and their associated uncertainties are shown in Table IV. Engineering judgment and information provided in the PRISM PSID were used to quantify the majority of the uncertainties. Because the plant model used in this analysis does not identify any specific component or material, most uncertainties are assumed to be normally distributed.

TABLE IV. Quantified uncertainties used in this work.

Uncertainty	Characterization
Ambient temperature, °C	$U(-30.0,45.0)$
Primary vessel emissivity	$N(0.77,0.35)$
Primary vessel thermal conductivity	$N(1.0,0.0125)$
Guard vessel emissivity	$N(0.77,0.35)$
Guard vessel thermal conductivity	$N(1.0,0.0125)$
Hot riser tubes emissivity	$N(0.77,0.35)$
Hot riser tubes thermal conductivity	$N(1.0,0.0125)$
Steel liner emissivity	$N(0.77,0.35)$
Duct surface roughness	$\ln N(3.45,0.70)$
Initial power level	$N(1.0,0.025)$
Decay heat curve	$N(1.0,0.025)$
Active heat removal actuation time	$U(4.0,24.0)$

With regard to parameters affecting the primary system, heat generation in the core and timing of active heat removal actuation were identified as important inputs. The initial power level at which the accident occurs and the decay heat curve were applied as scaling factors to the existing inputs, where it is assumed that they vary by up to 5% of their mean value. Activation of decay heat removal is dependent on power recovery, where it is assumed that active heat removal systems will be utilized if power is recovered. Power restoration is assumed to be equally likely between 4 hr and 24 hr following the initiating event, but is only questioned in the event tree at 9 hr and 19 hr following the onset of the SBO (as discussed in Section III.B).

The remaining uncertainties shown in Table IV relate to the performance of RCCS. Uncertainty in the primary vessel, guard vessel, hot riser tube and steel liner emissivites was determined using assumptions reported in the PRISM PSID, where the conservative value listed in the PSID was chosen as the 95th percentile value. Variance in the primary vessel, guard vessel and hot riser tube thermal conductivities is assumed to be the result of deviations in manufacturing. The thermal conductivities, applied as a scaling factor to the existing RELAP5-3D correlations, are assumed to vary by up to 2.5% of the mean value. Duct surface roughness is assumed to vary significantly over the lifetime of the facility due to accumulation of particulate and debris in the cavity region. Bounding values of 10 μm and 100 μm are selected as the 5th and 95th percentiles, respectively, based on engineering judgment, where the roughness is assumed to be lognormally distributed. The final selected parameter affecting RCCS performance is the temperature of ambient air being drawn into the passive system. It is assumed the air temperature is uniformly distributed between -30°C and 45°C, where these values are meant to be representative of conservative seasonal changes in populated climates where nuclear facilities may be installed.

IV. RESULTS

This section will present the results of this work. The solution methodology is described in Section IV.A. System metrics used to quantify core damage are described in Section IV.B. The numerical results and corresponding discussion are in Section IV.C.

IV.A. Solution Methodology

Determination of model inputs, execution of the simulations and core damage probability quantification were accomplished using a simple and straightforward method. Monte Carlo sampling is first used to determine the model inputs from the quantified uncertainty distributions identified in Table IV; here, a single draw of values from each uncertain parameter is considered to be a set. The selected set is then input to the model, and the RELAP5-3D simulation is launched. The simulation proceeds (and branches) until either a core damage metric is achieved, or completion of the mission time. This entire process generates a single event tree; additional trees are generated by repeating the process, beginning with the selection of new uncertain parameters via Monte Carlo sampling.

During the simulations, state variables pertaining to fuel integrity were tracked; these values were used to determine the core damage frequency during post-processing. First, the core damage frequency for each event tree was determined, then a cumulative core damage frequency for all event trees was determined with and without a 95% confidence interval. A total of 70 complete event trees were created for this analysis.

IV.B. Core Damage Metrics

To qualify core damage in the absence of an explicit, detailed core model, two temperatures in the core region were used: peak sodium temperature and peak cladding temperature. The peak sodium temperature, and more specifically the threshold at which sodium boiling occurs (883°C), in the core region is often used as a core damage indicator in SFR safety analyses. While localized clad failure in the presence of sodium voids is not necessarily a rigorously modeled phenomenon, this simple, binary metric is considered to adequately represent the occurrence of some level of core damage due to reduced heat transfer in the voided regions.

The peak cladding temperature was also used as a core damage metric for this work. Typically, clad failure via fuel/clad eutectic formation is the primary failure mechanism considered in metal fuel SFRs. Under this phenomenon, which occurs when elements from the fuel (uranium, plutonium and rare-earth fission products) and cladding (iron) diffuse into one another at high temperature, a mixture possessing a lower melting point than any of its individual constituents is formed. Melting of this material is highly dependent on time-at-temperature for the material; at 650°C (924 K), the exposure time required for failure is on the order of hundreds of hours, while at 850°C (1124 K), the time to failure is on the order of minutes.[19] Despite this, a cumulative damage function that determines the integral stress on the clad was not implemented for this analysis, as it was beyond the scope of this work, and the core was coarsely modeled. Instead, the likelihood of fuel failure (i.e. core damage) was treated as a function of cladding temperature using a one-sided normal distribution. This distribution assumes that below 700°C (974 K), eutectic penetration of the cladding barrier will not occur (i.e. the likelihood is approximately zero), and as the cladding temperature approaches the sodium boiling point of 883°C (1157 K), the likelihood of fuel damage approaches 0.5. At 883°C, the likelihood of core damage is assumed to be 1.0, as this is the sodium boiling criterion.

Use of peak cladding temperature and sodium boiling, independently or in conjunction with one another, is a very conservative core damage metric. The criteria for core damage in a metal fuel SFR may not be limited to clad failure; it is commonly believed that ejection of molten fuel from a failed pin can hypothetically prevent further fuel damage by reducing the critical mass of the core and therefore core temperature. In a true risk assessment, mechanistic core damage models, or a regulatory-accepted surrogate metric, should be employed to determine the end state of the core. In the absence of these models, cumulative damage functions developed from empirical correlations should be utilized.

IV.C. Numerical Results and Discussion

The quantified core damage frequency produced from this mechanistic analysis is shown in Table V. Results are shown using the sodium boiling indicator combined with the simplified eutectic penetration model, and the sodium boiling indicator alone, to assess the effect of the simplified eutectic penetration model. Results in Table V are presented both with and without application of the 95% confidence interval (CI) to determine the adequacy of the sample size.

TABLE V. Final results of the mechanistic analysis.

Core Damage Metric	Core Damage Frequency (yr^{-1})	Core Damage Frequency w/ 95% CI (yr^{-1})
Sodium boiling and eutectic penetration	1.334E-6	1.346E-6
Sodium boiling only	2.130E-12	2.425E-12

The results from Table V show that use of the simple eutectic penetration core damage metric increase the core damage frequency by six orders of magnitude. The reason for this is largely based on the number of scenarios that experience pump coastdown failure in all four pumps, the number of unprotected scenarios and the likelihoods of these events. Sodium boiling occurs only in scenarios where the reactor fails to scram, and all four primary pumps fail to coastdown normally; the number of scenarios that experience this is a fairly small fraction of the event tree, and sodium boiling does not necessarily occur in all of these scenarios. On the other hand, the simple eutectic penetration model does not predict non-negligible failure probabilities until the peak cladding temperature reaches 700°C. Temperatures of this magnitude are experienced in nearly all unprotected scenarios, which constitute two-thirds of the event tree (where half of these scenarios depend on the success of the RPS, which has a reliability on the order 1.0E-5), thereby producing a significantly higher core damage frequency.

As shown in Table V, application of the 95% confidence interval introduces negligible changes to the core damage frequency, indicating that the sample size of 70 complete event trees was sufficient for this analysis. The confidence interval margin is slightly larger for the sodium boiling only metric relative to the sodium boiling metric combined with the simple eutectic penetration model; this is a result of the slightly larger variance in the sodium boiling only metric, which is a binary indicator.

While quantification of a performance metric is an important ability of a reliability assessment, this work also demonstrated the importance of capturing the influence of uncertainty on the final results. Table VI contains the linear correlation between sodium boiling and each uncertainty sampled for this analysis for unprotected cases with pump coastdown failure in all four primary pumps. The Pearson product-moment correlation coefficient was used to determine the linear dependence between sodium boiling and each parameter, where ±1 indicates perfect correlation (positive or negative) and 0 indicates no relationship. A wide variety of correlation and regression analysis techniques are available; this analysis is intended to demonstrate the significance of uncertainty correlations.

TABLE VI. Pearson coefficient for sodium boiling.

Uncertainty	Pearson Coefficient
Ambient temperature	-0.094
Primary vessel emissivity	-0.178
Primary vessel thermal conductivity	-0.206
Guard vessel emissivity	-0.055
Guard vessel thermal conductivity	-0.047
Hot riser tubes emissivity	0.117
Hot riser tubes thermal conductivity	0.224
Steel liner emissivity	-0.064
Duct surface roughness	-0.106
Initial power level	0.486
Decay heat curve	0.558

The results in Table VI show that uncertainties in the initial power level and decay heat curve had the greatest effect on the occurrence of sodium boiling. Thermal conductivities of the primary vessel and hot riser tubes and the primary vessel emissivity also had a noticeable influence on sodium boiling. For this application, the Pearson coefficients have limited value due to the generic problem design, but in a true risk analysis, these results are invaluable to a vendor or designer because correlation coefficients such as these can be used to target important characteristics or components of the system with the largest effect on performance. Correlation analyses can also be used to check for unintuitive performance or model features. In this case where sodium boiling occurs shortly after the initiating event, the initial energy source (initial power level and decay heat) had the greatest effect on the primary coolant in the short term, meaning the initial operating power and decay heat level should have the largest effect on sodium boiling.

The importance of developing coupled system models to examine feedback between passive systems is also demonstrated in this work. For example, consider the coupled behavior of core power, core temperature and the RCCS, as shown in Figures 5 and 6 for unprotected scenarios from a single event tree (i.e. all scenarios use the same epistemic uncertainty parameters). The results in Fig. 5 show that core temperature begins to decrease immediately following power recovery (at 9 hr or 19 hr following the IE); in the absence of power recovery, core temperature peaks at nearly 950 K and then decreases due to the RCCS). Core power (Fig. 5) also increases shortly following recovery of AC power; this is due to the gradual decrease in negative reactivity (i.e. slow insertion of positive reactivity as the core cools) which is the result of the negative feedback coefficients of metal fuel. For cases with power recovery, core temperature asymptotically goes to normal operating levels (a property of the RELAP5-3D model; in reality, core temperature would be lower at decay heat levels if normal safety systems were utilized), and accordingly, core power goes to a new equilibrium value. Additionally, behavior of the RCCS is tied to changes in the primary system, as shown in Fig. 6. In cases with power recovery, the decrease in core temperature leads to an immediate drop in RCCS mass flow rate. Development of a new equilibrium flow rate in the RCCS requires several hours, with stabilized, decreased flow rates being developed approximately 10 hr following the disruption produced by power recovery and use of active heat removal systems.

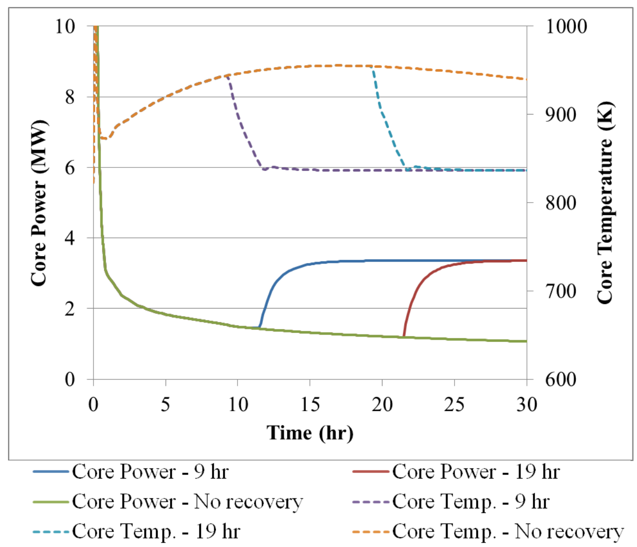

Fig. 5. Core power (solid lines) and core temperature (dashed lines) in cases with no primary pump coastdown failures. Cases for all power recovery options (recovery at 9 hr, 19 hr and no recovery) are shown from a single event tree.

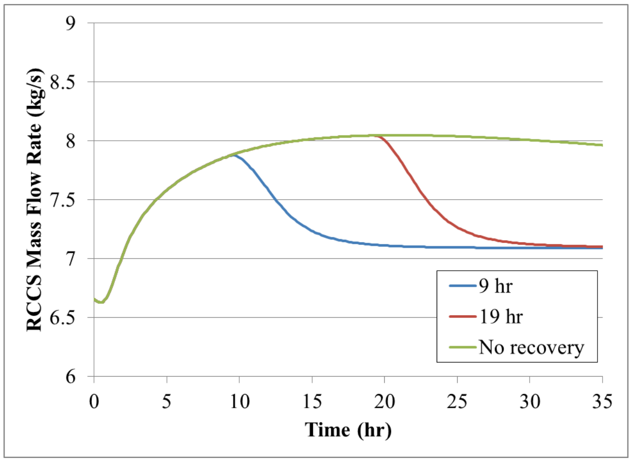

Fig. 6. Mass flow rate through RCCS for cases with no primary pump coastdown failure. All power recovery options (recovery at 9 hr, 19 hr and no recovery) are shown from a single event tree.

V. CONCLUSIONS

The analysis presented in this paper outlined a mechanistic methodology for addressing passive system reliability within a probabilistic framework. As a part of this process, significant components of the mechanistic technique were highlighted, including the importance of parameter identification/screening, uncertainty quantification/propagation, selection of success/failure criteria (e.g. a core damage metric), importance of sample size and analysis of the correlation of results with the uncertain parameters. The importance of coupled, deterministic models of passive systems was also demonstrated as part of this analysis. The effect of active cooling systems on primary system temperature, core power and the efficiency of the RCCS was explicitly shown in the results of this work.

Components of the methodology presented in this work may also satisfy early regulatory requirements for advanced reactors as these designs enter the licensing phase. The recently issued ASME/ANS PRA standard for Advanced Non-LWRs[20] requires the mechanistic modeling of passive safety systems that are to be utilized to fulfill safety functions, with empirically developed models and correlations to support modeling of the passive system. An additional requirement of the standard is the identification and quantification of uncertainties in the models, where the level of detail is dependent on the maturity of the reactor design. The mechanistic RMPS described in this work satisfies these requirements of the standard, which may become a foundation of future licensing requirements.

Lastly, it is important to note that this work is not a comment on the reliability of the RCCS, SFRs or the viability of the pairing of the two systems. While effort was made to create a realistic problem using real-world systems, specific materials or components were not explicitly identified as part of this work. The primary intention of this analysis was to demonstrate a methodology for addressing passive system reliability within a probabilistic risk assessment, not to perform a true risk analysis of any actual system. Additionally, many key components of the model were simplified to reduce model complexity and decrease runtimes. In an actual risk assessment, the level of model fidelity would need to be based on the requirements of the analysis.

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