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The RISMC Approach to Perform Advanced PRA Analyses

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Abstract – *The existing fleet of nuclear power plants is in the process of extending its lifetime and increasing the power generated from these plants via power uprates. In order to evaluate the impact of these two factors on the safety of the plant, the RISMC Pathway aims to develop simulation-based tools and methods to assess risks for existing nuclear power plants in order to optimize safety. This pathway, by developing new methods, is extending the state-of-the-practice methods that have been traditionally based on logic structures such as Event-Trees and Fault-Trees. These static types of models mimic system response in an inductive and deductive way respectively, yet are restrictive in the ways they can represent spatial and temporal constructs. RISMC analyses are performed by using a combination of thermal-hydraulic codes and a stochastic analysis tool currently under development at the Idaho National Laboratory, i.e. RAVEN. This paper presents a case study in order to show the capabilities of the RISMC methodology to assess impact of power uprate of a boiling water reactor system during a station blackout accident scenario. We employ the system simulator code, RELAP5-3D, coupled with RAVEN which perform the stochastic analysis. Our analysis is in fact performed by: 1) sampling values of a set of parameters from the uncertainty space of interest, 2) simulating the system behavior for that specific set of parameter values and 3) analyzing the set of simulation runs. Results obtained give a detailed investigation of the issues associated with a plant power uprate including the effects of station blackout accident scenarios. We are able to quantify how the timing of specific events was impacted by a higher nominal reactor core power. Such safety insights can provide useful information to the decision makers to perform risk informed margins management.*

I. INTRODUCTION

In the RISMC [1,2] approach, under the Light Water Reactor Sustainability Program (LWRS) LWRS campaign [3], what we want to understand is not just the frequency of an event like core damage, but how close we are (or not) to key safety-related events and how might we increase our safety margin through proper application of Risk Informed Margin Management. In general terms, a “margin” is usually characterized in one of two ways:

- A deterministic margin, typically defined by the ratio (or, alternatively, the difference) of a capacity (i.e., strength) over the load.
- A probabilistic margin, defined by the probability that the load exceeds the capacity.

A probabilistic safety margin is a numerical value quantifying the probability that a safety metric (e.g., for an important process observable such as clad temperature) is exceeded under accident conditions.

The RISMC Pathway uses the probabilistic margin approach to quantify impacts to reliability and safety. As part of the quantification, we use both probabilistic (via risk simulation) and mechanistic (via physics models) approaches. Probabilistic analysis is represented by the stochastic risk analysis while mechanistic analysis is represented by the plant physics calculations. Safety margin and uncertainty quantification rely on plant physics (e.g., thermal-hydraulics and reactor kinetics) coupled with probabilistic risk simulation (see Fig. 1). The coupling, which we call Computational PRA (CPRA), also know as Dynamic PRA [4], takes place through the interchange of physical parameters (e.g., pressures and temperatures) and operational or accident scenarios (e.g., the series of successes and/or failures representing a sequence of events).

This paper presents a case study in order to show the capabilities of the RISMC methodology [5] to assess limitations and performances of a Boiling Water Reactor (BWR) system during a Station Black Out (SBO) accident scenario using a simulation-based environment also known as dynamic PRA [4]. Such assessment cannot be naturally performed in a classical Event Tree/Fault Tree (ET/FT) based environment.

We employ a system simulator code, one of the RELAP series of codes [6], coupled with a CPRA code, RAVEN [7,8], that monitors and controls the simulation. The latter code, in particular, introduces both deterministic (e.g., system control logic, operating procedures) and stochastic (e.g., component failures, variable uncertainties, human actions) elements into the simulation.

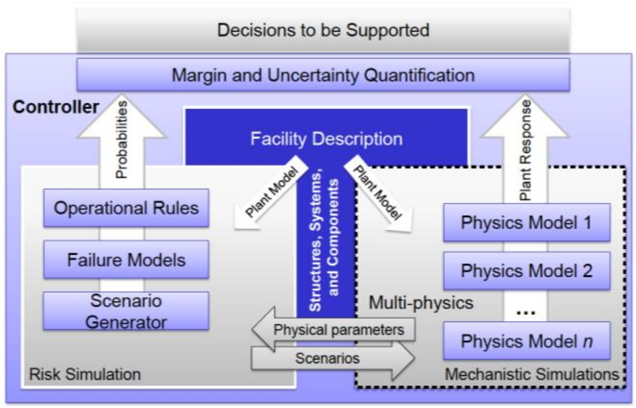


Fig. 1. Overview of the RISMC approach [5].

II. THE RISMC APPROACH

In Section I we have shown the main reasons behind the choice of moving from an ET-FT logic structure and employing directly system simulator codes to perform PRA analyses. A simulator code is, per se, a tool that can be represented as [9,10]:

$$\frac{\partial \boldsymbol{\theta}(t)}{\partial t} = \boldsymbol{\mathcal{H}}(\boldsymbol{\theta}, \boldsymbol{p}, \boldsymbol{s}, t) \tag{1}$$

where:

- $\boldsymbol{\theta} = \boldsymbol{\theta}(t)$ represents the status of the system as function of time t, i.e., $\boldsymbol{\theta}(t)$ represents a single simulation
- $\boldsymbol{\mathcal{H}}$ is the actual simulator code that describes how $\boldsymbol{\theta}$ evolves in time
- $\boldsymbol{p}$ is the set of parameters internal to the simulator code (e.g., pipe friction coefficients, pump flow rate, reactor power)
- $\boldsymbol{s} = \boldsymbol{s}(t)$ represents the status of components and systems of the simulator (e.g., status of emergency core cooling system, AC system)

By using the RISMC approach, the PRA is performed by following these steps:

1. Associating a probabilistic distribution function (pdf) to the set of parameters $\boldsymbol{p}$ and $\boldsymbol{s}$ (e.g., timing of events)
2. Performing sampling of the pdfs defined in Step 1
3. Performing a simulation run given the $\boldsymbol{p}$ and $\boldsymbol{s}$ sampled in Step 2
4. Repeating Steps 2 and 3 N times and evaluate user defined stochastic parameters such core damage (CD) probability (P_{CD}) as the ratio between the number of simulations that lead to CD divided by N (the total number of simulations).

Strictly speaking, the sampling associated to the vector of parameters $\boldsymbol{p}$ is usually defined as uncertainty quantification while sampling the timing of events $\boldsymbol{s}$ is usually called PRA. In our applications, we include in the definition of PRA the sampling of both $\boldsymbol{p}$ and $\boldsymbol{s}$.

III. RISMC TOOLKIT

In order to perform advanced safety analysis, the RISMC Pathway has a toolkit that was developed internally at INL using MOOSE [11] as the underlying numerical solver framework. This toolkit consists of the following software tools:

- RELAP (both RELAP5-3D [6] and RELAP-7 [12]): the code responsible for simulating the thermal-hydraulic dynamics of the plant.
- RAVEN [7,8]: it has two main functions: 1) act as a controller of the RELAP-7 simulation and 2) generate multiple scenarios (i.e., a sampler) by stochastically changing the order and/or timing of events.
- PEACOCK: the Graphical User Interface (GUI) that allows the user to create/modify input files of both RAVEN and RELAP-7 [13] and to monitor the simulation in real time while it is running.
- GRIZZLY: the code that simulates the thermal-mechanical behavior of components in order to model component aging and degradation. Note that for the analysis described in this article, aging was not considered in the accident scenarios.

For the scope of this article, we used RELAP5-3D and RAVEN to show advanced PRA analyses.

III.A. RAVEN

The RAVEN statistical framework is a recent add-on of the RAVEN package that allows the user to perform generic statistical analysis. By statistical analysis we include:

- Sampling of codes: either stochastic (e.g., Monte-Carlo [14] and Latin Hypercube Sampling [15]) or deterministic (e.g., Dynamic Event Tree [16])
- Generation of Reduced Order Models (ROMs) [17] also known as surrogate models or emulators
- Post-processing of the sampled data and generation of statistical parameters (e.g., mean, variance, covariance matrix)

Figure 2 shows an overview of the elements that comprise the RAVEN statistical framework:

- *Model*: it represents the pipeline between the input and output spaces. It is comprised of both mechanistic codes (e.g., RELAP-7) and ROMs
- *Sampler*: it is the driver for any specific sampling strategy (e.g., Monte-Carlo [18], Latin Hypercube Sampling [19], dynamic event trees [20])
- *Database*: the data storing entity
- *Post-processing*: module that perform statistical analyses and visualizes results

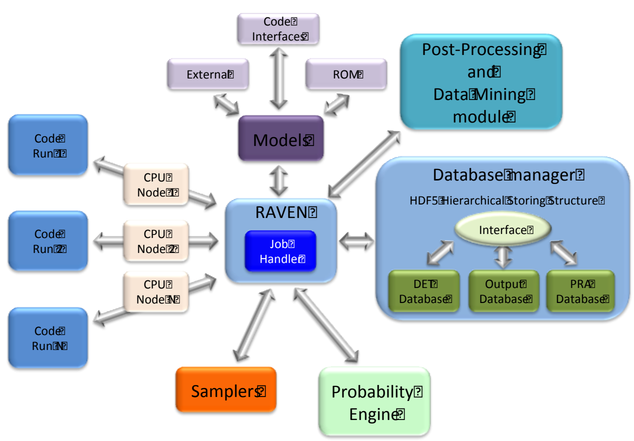


Fig. 2. Structure of RAVEN statistical framework components.

III. BWR SBO TEST CASE

As mentioned in the introduction, the test case chosen to show the RISMC approach is a SBO accident scenario for a BWR system. In Section III.A we describe the BWR model that we implemented while Section III.B shows the accident progression.

III.A. BWR Model

The system considered in this test case is a generic BWR power plant with a Mark I containment as shown in Fig. 3 [5]. The three main structures are the following:

1) Reactor Pressure Vessel (RPV), it is the pressurized vessel that contains the reactor core.
2) Primary containment includes:
   a. Drywell (DW): it contains the RPV and circulation pumps
   b. Pressure Suppression Pool (PSP) also known as wetwell: a large torus shaped container that contains a large amount of water; it is used as ultimate heat sink.
   c. Reactor circulation pumps

While the original BWR Mark I includes a large number of systems, we consider a subset of it:

- RPV level control systems: provide manual and automatic control of the RPV water level:
  1. Reactor Core Isolation Cooling System (RCIC): Provide high-pressure injection of water from the CST to the RPV. Water flow is provided by a turbine driven pump that takes steam from the main steam line and discharges it to the suppression pool. Alternatively, the water source can be shifted from the CST to the PSP.
  2. High Pressure Coolant Injection (HPCI): similar to RCIC, it allows greater water flow rates
- Safety Relief Valves (SRVs): DC powered valves that control and limit the RPV pressure.
- Automatic Depressurization System (ADS): separate set of relief valves that are employed in order to depressurize the RPV.
- Cooling water inventory:
  1. Condensate Storage Tank (CST) that contains fresh water that can be used to cool the reactor core.
  2. PSP water: PSP contains a large amount of fresh water that is used to provide ultimate heat sink when AC power is lost.
  3. Firewater system: water contained in the firewater system can be injected into the RPV when other water injection systems are disabled and when RPV is depressurized.
- Power systems (see Fig. 4):
  1. Two independent power grids that are connected to the plant station thorough two independent switchyards. Loss of power from both switchyards disables the operability of all system except: ADS, SRV, RCIC and HPCI (which require only DC battery).

2. Diesel generators (DGs) which provide emergency AC power
3. Battery systems: instrumentation and control systems need DC power.

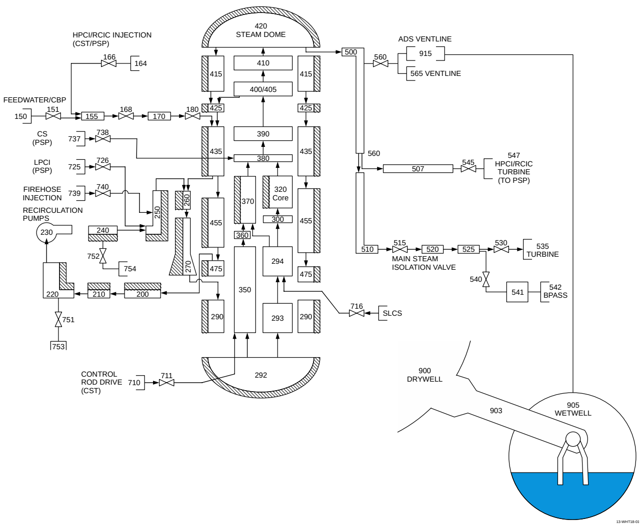


Fig. 3. RELAP-5 nodalization scheme for the BWR system.

III.B. SBO Scenario

The accident scenario under consideration is a loss of off-site power followed by loss of the DGs, i.e. SBO initiating event [5]. In more details, at time t = 0 LOOP condition occurs due to external events (i.e., power grid related) which triggers the following actions:

- Operators successfully scram the reactor and put it in sub-critical conditions by fully inserting the control rods in the core
- Emergency DGs successfully start, i.e., AC power is available
- Core decay heat is removed from the RPV through the RHR system
- DC systems (i.e., batteries) are functional

At a certain time, SBO condition occurs: due to internal failure, the set of DGs fails, thus removal of decay heat is impeded. Reactor operators start the SBO emergency operating procedures and perform:

- RPV level control using RCIC or HPCI
- RPV pressure control using SRVs
- Containment monitoring (both drywell and PSP)

Plant operators start recovery operations to bring back on-line the DGs while the recovery of the power grid is underway by the grid owner emergency staff.

Due to the limited life of the battery system and depending on the use of DC power, battery power can deplete. When this happens, all remaining control systems are offline causing the reactor core to heat until clad failure temperature is reached, i.e., core damage (CD).

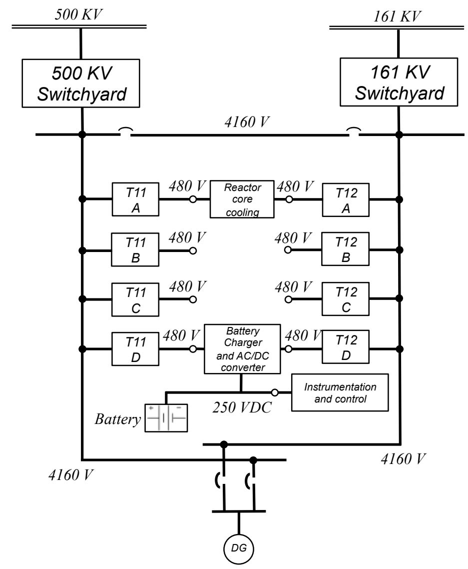


Fig. 4. BWR AC/DC power system schematics.

If DC power is still available and one of these conditions are reached:

- Failure of both RCIC and HPCI
- HCTL limits reached
- Low RPV water level

then the reactor operators activate the ADS system in order to depressurize the RPV .

As an emergency action, when RPV pressure is below 100 psi plant staff can connect the firewater system to the RPV in order to cool the core and maintain an adequate water level. Such task is, however, hard to complete since physical connection between the firewater system and the RPV inlet has to made manually.

When AC power is recovered, through successful re-start/repair of DGs or off-site power, RHR can be now employed to keep the reactor core cool

V. STOCHASTIC ANALYSIS

For this analysis we considered several uncertain parameters:

- **Failure time of DGs**: regarding the time at which the DGs fail to run we chose an exponential distribution with a value of lambda equal to 1.09 10^{-3} h^{-1} as indicated by NRC published data [21].
- **Recovery time of DGs**: Regarding time needed to recover the DGs, we used as a reference the NUREG/CR-6890 vol.1 [22]. This document uses a

Weibull distribution[1] with α = 0.745 and β = 6.14 h (mean = 7.4 h and median = 3.8 h). Such distribution represents the pdf of repair of one of the two DGs (choosing the one easiest to repair).

- **Offsite AC power recovery**: For the time needed to recover the off-site power grid, we used as reference NUREG/CR-6890 vol.2 [22] (data collection was performed between 1986 and 2004). Given the four possible LOOP categories (plant centered, switchyard centered, grid related or weather related), severe/extreme events (such as earthquake) are assumed to be similar to these events found in the weather category (these are typically long-term types of recoveries). This category is represented with a lognormal distribution (from NUREG/CR-6890 [22]) with $\mu = 0.793$ and $\sigma = 1.982$.
- **Battery life**: For the amount of DC power available, when AC power is not obtainable, we chose to limit battery life between 4 and 6 hours using a triangular distribution (see NUREG/CR-6890 vol.2 [22]).
- **Battery failure time**: As basic event in the PRA model, the probability value associated with battery failure is equal to 1.4 10^{-5} for an expected life of 4 hours. We have assumed an exponential distribution for the battery failure time distribution. The value of λ for this distribution has been calculated by imposing that the CDF of this distribution ($1 - e^{-\lambda t}$) at 4 hours (i.e., the probability that battery fails within 4 hours is 1.4 10^{-5}):

$$\int_0^4 \lambda\, e^{-\lambda t}\, dt = \left[1 - e^{-\lambda t}\right]_0^4 = 1.4\, 10^{-5}$$

This leads to a value of $\lambda = 3.5\, 10^{-6}$/hr.

- **SRVs fails open time**: the SPAR model indicates a probability value of 8.56 10^{-4}.
- **Clad Fail temperature**: Uncertainty in failure temperature for the clad is characterized by a triangular distribution [23] having:
  - Lower limit = 1800 F (982 C): PRA success criterion
  - Upper limit = 2600 F (1427 C): Urbanic-Heidrick transition temperature
  - Mode = 2200 F (1204 C): 10 CFR regulatory limit
- **RCIC fails to run**: Regarding the distribution of RCIC to fail to run we assumed an exponential distribution with $\lambda = 4.43\, 10^{-3} h^{-1}$ as indicated in the SPAR model.
- **HPCI fails to run**: Identical distribution for RCIC fails to run distribution (see above)
- **Firewater flow rate**: The value of firewater flow rate is between 150 and 300 gpm [5]. For the scope of this article we also considered the possibility of very low firewater flow rates. Thus we assumed a triangular distribution defined in the interval $[0,300]$ gpm with mode at 200 gpm.

Regarding the pdfs related to human related actions we looked into the SPAR-H [24] model contained in SAPHIRE. SPAR-H characterizes each operator action through eight parameters – for this study we focused on the two important factors:

- Stress/stressors level
- Task complexity

These two parameters are used to compute the probability that such action will happen or not; these probability values are then inserted into the ETs that contain these events. However, from a simulation point of view we are not seeking if an action is performed but rather when such action is performed. Thus, we need a probability distribution function that defines the probability that such action will occur as function of time.

Table 1. Correspondence table between task complexity and stress/stressor level and time values

Complexity	μ (min)
High	45
Moderate	15
Nominal	5

Stress/stressors	σ (min)
Extreme	30
High	15
Nominal	5

Since modeling of human actions is often performed using lognormal distributions [5], we chose such a distribution where its characters parameters (i.e., μ and σ) that are dependent on the two factors listed above (Stress/stressors level and Task complexity). We used Table 1 [5] to convert the three possible values of the two factors into numerical values for μ and σ.
For our specific case we modeled two human related actions as indicated below:

- **Battery repair time**: DC battery system restoration is performed by recovering batteries from nearby vehicles and connecting them to the plant DC system. We assumed that this task has high complexity with extreme stress/stressors level. This leads to $\mu = 45\ min$ and $\sigma = 15\ min$
- **Firewater availability time**: The operations to align the firewater system to the RPV are considered a very complex operation. This time is measured after

[1] Weibull distribution $pdf(x)$ is here defined as: $pdf(x) = \frac{\alpha}{\beta^\alpha} x^{\alpha-1} e^{-\left(\frac{x}{\beta}\right)^\alpha}$

the ADS has been activated, i.e., after the RPV has been depressurized. Also for this case we assumed that this task has a high complexity with extreme stress/stressors level. This leads to $\mu = 45\ min$ and $\sigma = 30$.

A summary of the uncertain parameters and their associated distribution is listed in Table 2.

Table 2. Summary of the uncertain parameters considered and their associated distribution

Stochastic variable*	Distribution	Distribution parameters
DGs Failure time (h)	Exponential	$\lambda = 1.09\ 10^{-3}$
DGs Recovery time (h)	Weibull	$\alpha = 0.745, \beta = 6.14$
Battery life (h)	Triangular	(4, 5, 6)
SRV1 failure	Bernoulli	$p = 8.56\ 10^{-4}$
PG recovery (h)	Lognormal	$\mu = 0.793, \sigma = 1.982$
Clad Fail temp. (F)	Triangular	(1800, 2200, 2600)
HPCI fails to run (h)	Exponential	$\lambda = 4.43\ 10^{-3}$
RCIC fails to run (h)	Exponential	$\lambda = 4.43\ 10^{-3}$
Battery failure time (h)	Exponential	$\lambda = 3.5\ 10^{-6}$
Batt. rec. time (min)	Lognormal	$\mu = 45$, $\sigma = 15$
FW avail. time (min)	Lognormal	$\mu = 45$, $\sigma = 30$
FW flow rate (gpm)	Uniform	(0, 200, 300)

VI. RESULTS

In [25] we presented several analyses which included limit surface [26] evaluations and uncertainty quantifications using advanced data analysis and data visualization techniques. In this article we focused more on the probabilistic side of the analysis.

We performed two series of Latin Hypercube Sampling analysis for the two levels of reactor power (100% and 120%) using 10,000 samples for each case. The scope of this analysis is to evaluate how core damage (CD) probability changes when reactor power is increased by 20%. We also performed this comparison by identifying importance of specific events by performing the following for each case:

1. Building an ET based logic structure that queries the following events: SRV status, DG, PG and FW recovery (see Fig. 5)
2. Associate each of the 10,000 simulations to a specific branch of the ET by querying the status of the SRV, PG, DG and FW components in the simulation run
3. Evaluate the probability and the outcome associated to each branch

A summary of the core damage probability for the cases is shown in Table 3: the probability value almost doubled for a 20% power increase. The summary of the branch probabilities represented in Fig. 5 is shown in Table 4. As expected, all branches that lead to CD have a probability increase while the ones leading to OK decrease.

Table 3. Core damage probability for two different power levels (100% and 120%).

Outcome	100%	120%
OK	0.9902	0.9804
CD	9.82 E-3	1.95 E-2

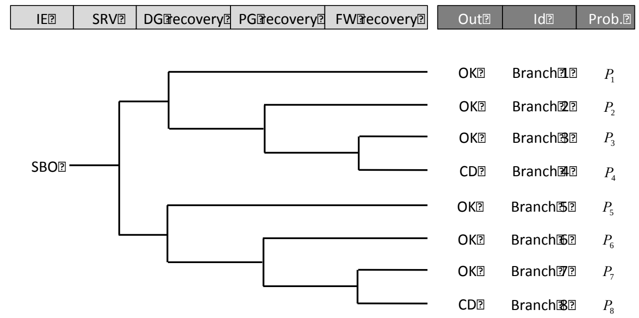


Fig. 5. Simplified ET logic structure for a BWR SBO.

Table 4. Branch probabilities associated to the ET shown in Fig. 5 for both cases (100% and 120% power level).

Branch	Out	100%		120%		ΔP
		Count	Prob.	Count	Prob.	(%)
1	OK	3146	0.375	3238	0.353	-6
2	OK	4549	0.618	4440	0.606	-2
3	OK	847	0.00931	985	0.00926	-0.6
4	CD	557	0.00982	691	0.0196	+99
5	OK	333	7.32E-6	223	6.29E-6	-14
6	OK	254	1.53E-5	189	3.96E-6	-74
7	OK	251	5.92E-6	175	2.39E-6	-60
8	CD	63	2.12E-6	59	2.54E-6	+20

Regarding the FW flow rate, we were able to determine that a minimum value of 50 gpm is enough to assure an OK outcome. Note that branches 4 and 8 (in Fig. 5) include also the simulations characterized by FW align before core damage condition is met but with FW flow rate insufficient to keep the core cooled.

IV.A. Impact of auxiliary AC power systems (FLEX system)

In addition to the analysis reported above we evaluated the impact of auxiliary AC system generators as additional sources of AC power. The U.S. nuclear industry, as a measure after the Fukushima accident [28], developed a FLEX system to counterattack the risks associated with external events (e.g., earthquakes or flooding). Such a system employs portable AC and DC emergency generators located not only within the plant perimeter but also at strategic locations within the US borders in order to quickly supply affected NPPs with both AC and DC power. For our case, we assumed a new distribution associated with the AC recovery time within the plant instead of the DG recovery time distribution. Since FLEX operations can be considered as human-related events, we followed the same approach described in Section V for human related events. In fact, we assumed that the AC recovery can be considered to be of moderate complexity and high levels of stress/stressors. Note that this model may not be indicative of any actual NPP FLEX strategies – for an actual FLEX evaluation, plant specific information would need to be considered. The new AC recovery distribution that replaces the DG recovery distribution is then a lognormal having a mean and a standard deviation values as follows:

- mean = 15.0
- standard deviation = 15.0

We then performed a new Latin Hypercube Sampling analysis in order to estimate the new core damage probability value (see Table 5) and the branch probabilities associated with the ET structure shown in Fig. 5 as shown in Table 6. Note that from Table 6 it is possible to evaluate the impact of the FLEX system using a familiar ET structure. In particular, it is possible to note that Brach 1 in largely impact by the FLEX system (via a new AC recovery strategy).

Table 5. Core damage probability for two different test cases (120% with and without FLEX system)

Outcome	120% w/o FLEX	120% w/ FLEX
OK	0.981	0.995
CD	1.95 E-2	4.59 E-3

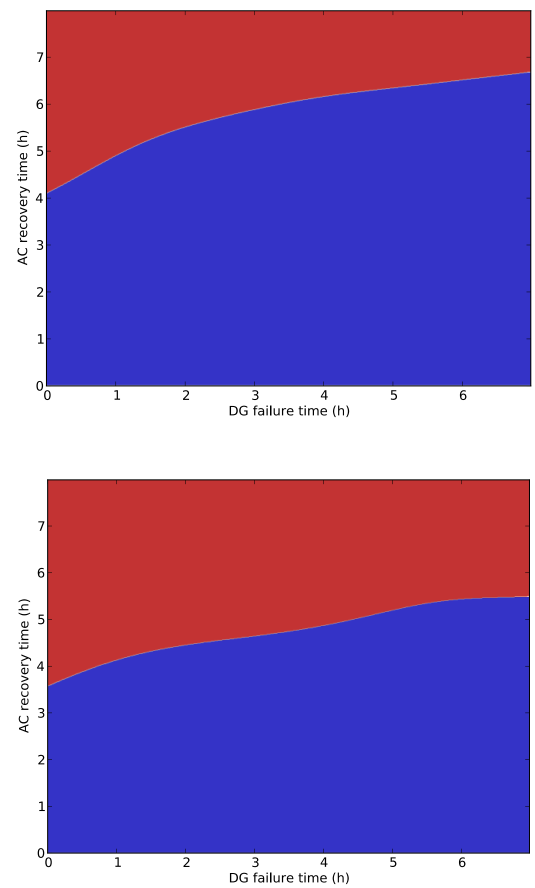
Table 6. Branch probabilities associated to the ET shown in Fig. 5 for two different test cases (120% with and without FLEX system)

Branch	Outcome	Probability (120%)		ΔP (%)
		w/o FLEX	w/ FLEX	
1	OK	0.353	0.505	43
2	OK	0.606	0.490	-21
3	OK	0.00926	3.49E-05	-100
4	CD	0.0196	0.00459	-77
5	OK	6.29E-06	2.87E-06	-54
6	OK	3.96E-06	1.79E-09	-100
7	OK	2.39E-06	6.77E-10	-100
8	CD	2.54E-06	1.09E-09	-100

As second step in the analysis, we focused on the concept of limit surfaces [26]: the boundaries in the space of the sample parameters that separate failure from success. The advantage of limit surfaces is that they allow us to physically visualize how system performances are reduced due to, for example, a power uprate. By system performance, we mainly refer to both reduction in recovery timings (e.g., AC power recovery) and time reduction to perform steps in reactor operating procedures (e.g., time to reach HCTL).

For the scope of this article, we focused on a safety relevant case: DG failure time vs. DG recovery time as shown in Fig. 6. These limit surfaces are obtained using Support Vector Machines (SVM) [27] based.

As expected the failure region (red area) is expanding when reactor power is increased by 20%. This power increase on average reduces AC recovery time by about one hour.



(a) (b)

Fig. 6. Limit surface obtained in a two dimensional space (DG failure time vs. AC recovery time) for two different power level: 100% (left) and 120% (right).

VII. CONCLUSIONS

In this article we have shown the RISMC approach in order to evaluate the impact of power uprate on a BWR SBO accident scenario. We have employed RELAP5-3D as system simulator code and the RAVEN code to perform the accident sequence generation and statistical analysis. The BWR system, the system control logic and the accident scenario have been directly implemented in the RELAP5-3D input file. We evaluate the increase of CD probability of such power uprate and its decrease due to the implementation of FLEX system to provide emergency power to the plant. In particular, we have shown how the RISMC approach to perform PRA analyses can overcome limitations of classical ET-FT based methodologies and provide the user to a much larger amount of information such as time reduction for plant recovery strategies.

NOMENCLATURE

AC	Alternating Current
ADS	Automatic Depressurization System
BWR	Boiling Water Reactor
CDF	Cumulative Distribution Function
DC	Direct Current
DG	Diesel generator
DW	Drywell
EOP	Emergency Operating Procedures
ET	Event-Tree
FT	Fault-Tree
FW	Firewater
HPCI	High Pressure Core Injection
IE	Initiating Event
LOOP	Loss Of Offsite Power
NPP	Nuclear Power Plant
PDF	Probability Distribution Function
PG	Power Grid
PRA	Probabilistic Risk Assessment
PSP	Pressure Suppression Pool
RCIC	Reactor Core Isolation Cooling
RPV	Reactor Pressure Vessel
SRV	Safety Relief Valve

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