Charles R. Pierce
Regulatory Affairs Director

Southern Nuclear
Operating Company, Inc.
40 Inverness Center Parkway
Post Office Box 1295
Birmingham, AL 35242

Tel 205.992.7872
Fax 205.992.7601

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Vogtle Electric Generating Plant, Units 1 & 2
Supporting Documents for Upcoming SNC NRC Public Meeting
Regarding the Resolution of GSI-191

Ladies and Gentlemen:

A Nuclear Regulatory Commission (NRC) public meeting is being scheduled for later this year to discuss Vogtle Electric Generating Plant's planned resolution to GSI-191. In support of this upcoming public meeting, Southern Nuclear Operating Company (SNC) is submitting the attached reports to the NRC. While SNC is not requesting formal NRC review and approval of these reports, these reports help form a significant portion of the planned technical discussion for the meeting. To facilitate meaningful discussion, it is suggested that the NRC staff that plan on attending the meeting familiarize themselves with the content of these reports prior to the meeting. Because of the size of Enclosure 2, only the relevant portions to the upcoming meeting are provided. A full version of Enclosure 2 can be provided upon request.

This letter contains no NRC commitments. If you have any questions, please contact Ken McElroy at (205) 992-7369.

Respectfully submitted,

C. R. Pierce

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Regulatory Affairs Director

CRP/RMJ

Enclosures:
1. Risk-Informed GSI-191 Uncertainty Quantification
2. Head Loss Testing of a Prototypical Vogtle 1 and 2 Strainer Assembly

A001
NRR

cc: Southern Nuclear Operating Company (w/o Enclosures)
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Mr. D. G. Bost, Executive Vice President & Chief Nuclear Officer
Mr. D. R. Madison, Vice President – Fleet Operations
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Mr. R. E. Martin, NRR Senior Project Manager – Vogtle 1 & 2
Mr. S. S. Koenick, NRR Senior Project Manager – Vogtle GSI-191
Mr. V. Cusumano, Chief, Safety Issue Resolution Branch
Mr. L. M. Cain, Senior Resident Inspector – Vogtle 1 & 2

Vogtle Electric Generating Plant, Units 1 & 2
Supporting Documents for Planned November 5, 2015 SNC NRC Public Meeting
Regarding the Resolution of GSI-191

Enclosure 1

Risk-Informed GSI-191 Uncertainty Quantification

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Risk-Informed GSI-191 Uncertainty Quantification

This document discusses two methods that can be used to quantify the uncertainty associated with a risk-informed GSI-191 evaluation. The first method is a detailed statistical approach for sampling input parameter probability distributions and propagating the uncertainties. The second method is a simplified approach for selecting bounding input parameter values and calculating the uncertainty range using sensitivity analysis.

Over the past year, the industry has been moving in the direction of using simplified methods for risk-informed GSI-191 evaluations [1, 2]. Implementing simplified methods is beneficial since it allows the ECCS strainer performance issue to be resolved more efficiently and reduces the time and effort required for NRC technical review. Therefore, this document focuses primarily on the simplified approach for uncertainty quantification.

1. Introduction

Uncertainty quantification is a key requirement in Regulatory Guide (RG) 1.174 for a risk-informed evaluation [3]. As defined in RG 1.174 and explained in more detail in NUREG-1855 [4] and two corresponding EPRI reports [5, 6], there are three types of epistemic uncertainty that should be addressed:

1. Parametric uncertainty
2. Model uncertainty
3. Completeness uncertainty

Parametric uncertainty refers to the variability in input parameters that are used in the risk assessment. Due to the wide range of plant-specific post-LOCA conditions related to GSI-191 phenomena, this is a very important aspect for understanding the overall uncertainty.

Model uncertainty refers to the potential variability in an analytical model when there is no consensus approach. A consensus approach is a model that has been widely adopted or accepted by the NRC for the application for which it is being used [4]. For example, the use of a spherical zone of influence (ZOI) to model the debris quantity generated by a high energy break is a consensus model that has been widely adopted and accepted by the NRC [7, 8]. In general, plants implementing a simplified risk-informed approach are using standard models that have been widely accepted for deterministic evaluations (e.g., accepted insulation and qualified coatings ZOI sizes, the use of WCAP-16530 [9] to model chemical effects, and prototypical strainer module testing for head loss and penetration). By using these consensus approaches, the effort to address model uncertainty is minimized.

Completeness uncertainty refers to 1) the uncertainty associated with scenarios or phenomena that are excluded from the risk evaluation, and 2) the uncertainty associated with unknown phenomena. Although it is not practical to quantify the uncertainty associated with factors that are not explicitly modeled (e.g., secondary side breaks, or breaks downstream of the first isolation valve), their potential impact can be qualitatively assessed. Uncertainties associated with unknown phenomena, on the other hand, cannot even be qualitatively assessed. Uncertainties associated with unknown phenomena are the reason that it is important to maintain defense-in-depth and safety margins.

This document primarily focuses on the method for quantifying parametric uncertainty, since this is the most important uncertainty for a simplified risk-informed GSI-191 evaluation that can be quantified. The uncertainty quantification will ultimately be used to define the confidence in the calculated mean values for the change in core damage frequency (ΔCDF) and change in large early release frequency (ΔLERF) due to GSI-191 effects.

2. Method for Parametric Uncertainty Quantification

There are two methods that can be used for quantifying parametric uncertainty. The first method is a detailed statistical approach for sampling input parameter probability distributions, propagating the uncertainties, and producing probability distributions for the results. This is a rigorous and commonly used method for uncertainty quantification.

However, the preferred method for the simplified risk-informed approach is to calculate mean ΔCDF and ΔLERF values using a combination of bounding and nominal/realistic input values, and define the uncertainty as the maximum change in ΔCDF and ΔLERF when the nominal input values are all changed to bounding values. Although this approach does not show the shape of the ΔCDF and ΔLERF probability distributions, or the weight of the tails, it does provide a good indication of the overall uncertainty in the evaluation.

The simplified uncertainty quantification method fits very well with the overall simplified GSI-191 approach. At a high level, the evaluation methodology would include the following steps:

1. Select appropriate models for debris generation, transport, chemical effects, strainer head loss, etc. based on models that have been generally used and accepted for past GSI-191 evaluations.
2. Select input values (for calculating the mean ΔCDF and ΔLERF) where each input is either:
    a. A bounding value similar to a value that would be used in a deterministic evaluation (e.g., a maximum latent debris quantity based on plant walkdowns)
    b. A nominal value based on realistic plant design and operation (e.g., an initial RWST level that is above the low level alarm based on historical operating conditions).
3. Execute the integrated models with the specified inputs to determine which breaks lead to success and failure.
4. Use the conditional failure probability to calculate the mean ΔCDF and ΔLERF.
5. Evaluate a set of sensitivity cases where each nominal input value is changed to a bounding input value (minimum and/or maximum) to determine the minimum[1] and maximum ΔCDF and ΔLERF values.

[1] Note that the minimum ΔCDF and ΔLERF are generally not as important as the maximum ΔCDF and ΔLERF, and wouldn't necessarily have to be calculated. Also, the use of some bounding input values in Step 2.a biases the mean ΔCDF and ΔLERF toward the maximum.

3. Input Parameter Selection

Determining whether to use a bounding or realistic value for each input parameter (for the purpose of calculating the mean ΔCDF and ΔLERF) is a plant-specific process. This process involves a consideration of the level of conservatism that can be tolerated, the confidence in the test or analysis used to determine the value, how the overall analysis will affect the plant design and licensing basis, and other factors. Some plants may choose to use a set of inputs that are mostly bounding, while other plants may choose to use realistic values for more of the input parameters to get a more accurate prediction of the post-LOCA conditions.

If a bounding value is selected for an input parameter, it is essentially equivalent to a consensus model where the uncertainty does not need to be quantified. This is consistent with the guidance in Draft Regulatory Guide (DG) 1322 (e.g., Paragraph C.10.d) [10]. For example, a plant may use a latent debris quantity that is 50% higher than what is measured in a plant walkdown in order to bound any uncertainty in the measurements and provide operating margin for potential changes in containment cleanliness. In this case, since the latent debris quantity exceeds the expected maximum value, it is not necessary to quantify the uncertainty. However, another plant may choose to perform their analysis using the actual results of the latent debris measurements without including additional margin. In this case, it is necessary to evaluate the uncertainty associated with the latent debris quantity based on uncertainties in the walkdown measurements and potential future changes based on the level of rigor in the containment cleanliness program.

Depending on the models that are used, the worst-case direction for some input parameters may not be intuitively obvious. For example, a minimum water temperature could be worse with respect to strainer head loss, but a maximum temperature could be worse with respect to degasification. Similarly, a minimum pool volume could be worse with respect to NPSH margin, but either a minimum or maximum pool volume could be worse with respect to the quantity of chemical precipitates predicted using the WCAP-16530 methodology. For these types of parameters, the best approach may be to select realistic mean conditions to calculate the mean ΔCDF and ΔLERF values. Sensitivity analyses with each possible combination of bounding values could then be used to determine the best and worst case scenarios that would provide the uncertainty bounds showing the minimum and maximum ΔCDF and ΔLERF values (e.g., for the two parameters described above, a 2x2 simulation matrix could be run to evaluate the combinations of min/max pool temperature and min/max pool volume).

Table 1 shows a summary of several important input parameters for a GSI-191 evaluation with an indication of which direction is more limiting in terms of strainer or core failures. This table illustrates the logic for determining the worst-case conditions. However, the worst case (or best case) set of input parameters is highly dependent on plant-specific configurations as well as the models that are implemented. Therefore, the bounding direction shown in this table would not be applicable for every plant.

Table 1: Bounding direction for important input parameters

Parameter	Bounding Direction for Strainer Failures	Bounding Direction for Core Failures	Comments
Fiber Insulation Debris Quantity	Maximum	Maximum	
Qualified Coatings Debris Quantity	Maximum	N/A	Core acceptance criteria only a function of fiber quantity
Microporous Insulation Debris Quantity	Maximum	N/A	
Unqualified Coatings Debris Quantity	Maximum	N/A	
Latent Debris Quantity	Maximum	Maximum	
Miscellaneous Debris Quantity	Maximum	Minimum	Miscellaneous debris blocks strainer area, which could be "beneficial" for reducing penetration
Debris Transport Fractions	Maximum	Maximum	
Pool Volume/Level	Minimum or Maximum	Minimum or Maximum	Affects NPSH margin, degasification, partial submergence, time-dependent transport, pH, chemical release, and chemical solubility
Containment Pressure	Minimum	N/A	Affects degasification and NPSH margin
Pool Temperature	Minimum or Maximum	Minimum or Maximum	Affects NPSH margin, degasification, pool volume/level, chemical release, chemical solubility, head loss
ECCS Flow Rate	Minimum or Maximum	Minimum or Maximum	Affects head loss, NPSH margin, time-dependent transport, penetration, core accumulation, pool volume, and degasification
CS Flow Rate	Minimum or Maximum	Minimum	Affects head loss, washdown transport, time-dependent transport, penetration, pool volume, and core accumulation
ECCS/CS Switchover Time	Minimum or Maximum	Minimum or Maximum	Affects pool volume, NPSH margin, and core accumulation
Hot Leg Switchover Time	N/A	Maximum	
Secure CS Time	Maximum	Minimum	
Boil-off Flow Rate	N/A	Maximum	
Boron Concentration	Minimum or Maximum	N/A	Affects pH
Buffer Quantity	Minimum or Maximum	N/A	Affects pH
pH	Minimum or Maximum	N/A	Affects chemical release and chemical solubility
Head Loss	Maximum	N/A	

Parameter	Bounding Direction for Strainer Failures	Bounding Direction for Core Failures	Comments
Structural Margin	Minimum	N/A	
NPSH Margin	Minimum	N/A	
Degasification	Maximum	N/A	
Void Fraction Limit	Minimum	N/A	
Penetration	Minimum	Maximum	
Core Fiber Limit	N/A	Minimum	

4. Example Calculation with RWST Injection Model

To compare the rigorous and simplified uncertainty quantification methodology, a calculation was performed to determine the volume and timing for water injected from a refueling water storage tank (RWST). Each input parameter was specified using a probability distribution defining the mean, minimum, and maximum values[2]. The mean values for the output parameters were then calculated by a) sampling the input parameter distributions and propagating the uncertainties, and b) a simple hand calculation using only the mean input parameter values. The minimum and maximum values for the output parameters were calculated in a similar manner with the two methods described above.

The input parameter values are shown in Table 2. For the first approach, these values were fit using beta distributions, and each distribution was sampled 1,000 times to calculate the mean output values. For this calculation, the output parameters are defined as a) the volume of water injected at RHR switchover, b) the total volume of water injected from the RWST, c) the time to RHR switchover, and d) the time to CS switchover.

Table 2: Simple RWST injection model input parameter values

Parameter	Minimum	Mean	Maximum
Initial RWST Volume (gal)	210,000	250,000	310,000
RHR Switchover Volume (gal)	55,000	60,000	65,000
CS Switchover Volume (gal)	12,000	21,000	25,000
RHR Pump Flow Rate (gpm)	1,000	5,000	7,000
CS Pump Flow Rate (gpm)	3,000	4,000	7,500

The simple hand calculation equations for calculating the mean injected volume and switchover time output values are shown below along with the mean input parameter values:

$$V_{RHR\ Injected} = V_{initial} - V_{RHR\ Switchover} = 250{,}000gal - 60{,}000gal = 190{,}000gal$$

$$V_{Total\ Injected} = V_{initial} - V_{CS\ Switchover} = 250{,}000gal - 21{,}000gal = 229{,}000gal$$

$$t_{RHR\ Switchover} = \frac{V_{RHR\ Injected}}{Q_{RHR} + Q_{CS}} = \frac{190{,}000gal}{5{,}000gpm + 4{,}000gpm} = 21.1min$$

$$t_{CS\ Switchover} = t_{RHR\ Switchover} + \frac{V_{Total\ Injected} - V_{RHR\ Injected}}{Q_{CS}}$$
$$= 21.1min + \frac{229{,}000gal - 190{,}000gal}{4{,}000gpm} = 30.9min$$

Figure 1 through Figure 5 show the probability distributions with the sampled water volume or flow rate values for each input parameter. The mean value of the input parameter is also shown with a vertical line on each figure.

[2] The inputs used for the example calculations are hypothetical. For a real evaluation, these values would be determined based on realistic conditions and constraints. For example, the minimum and maximum values for the initial RWST level might be defined based on the low level and high level alarm setpoints, and the mean value might be defined based on operating history.

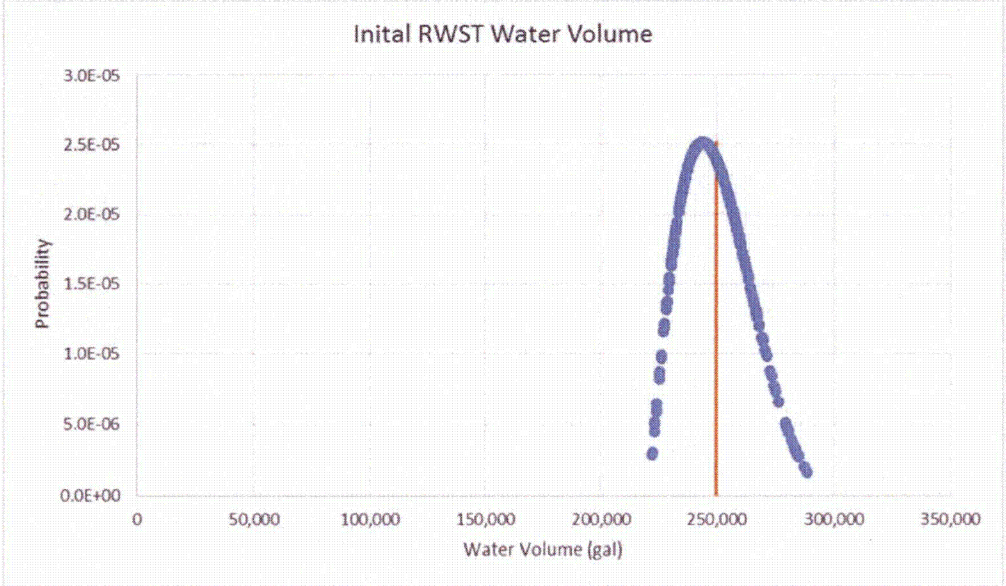

Figure 1: Sampled values for initial RWST water volume

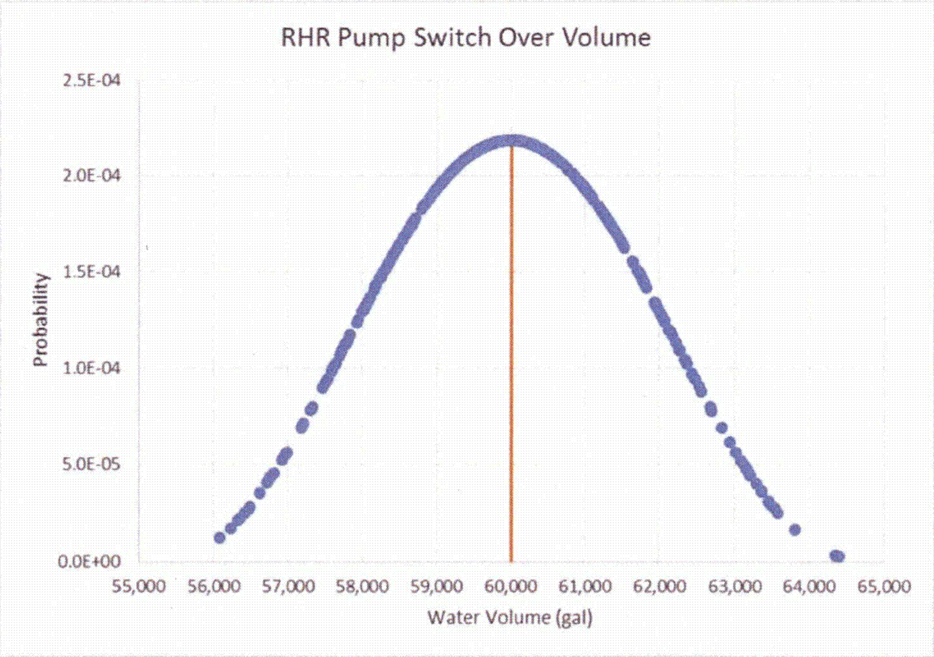

Figure 2: Sampled values for RWST water volume at RHR pump switchover

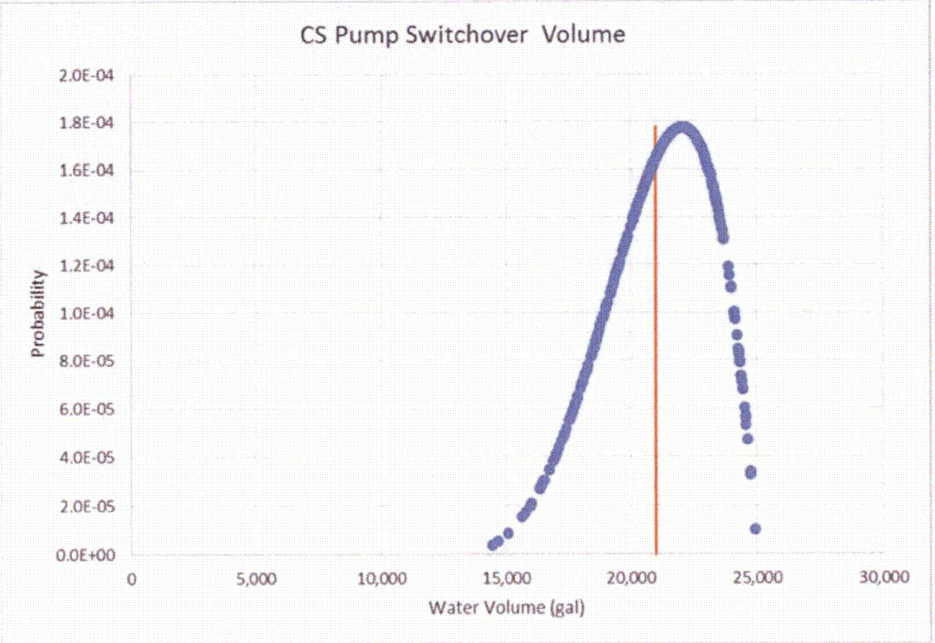

Figure 3: Sampled values for RWST water volume at CS pump switchover

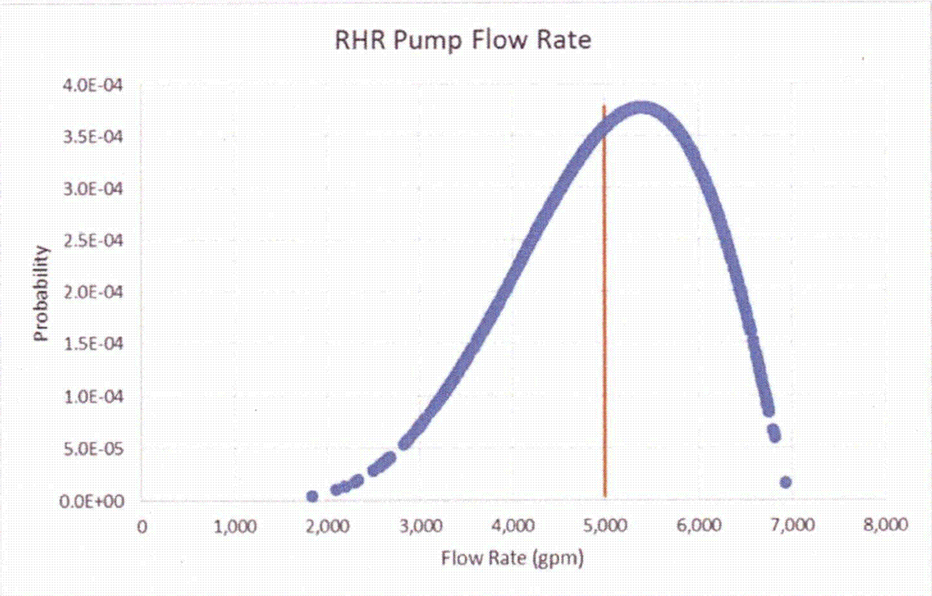

Figure 4: Sampled values for RHR pump flow rate

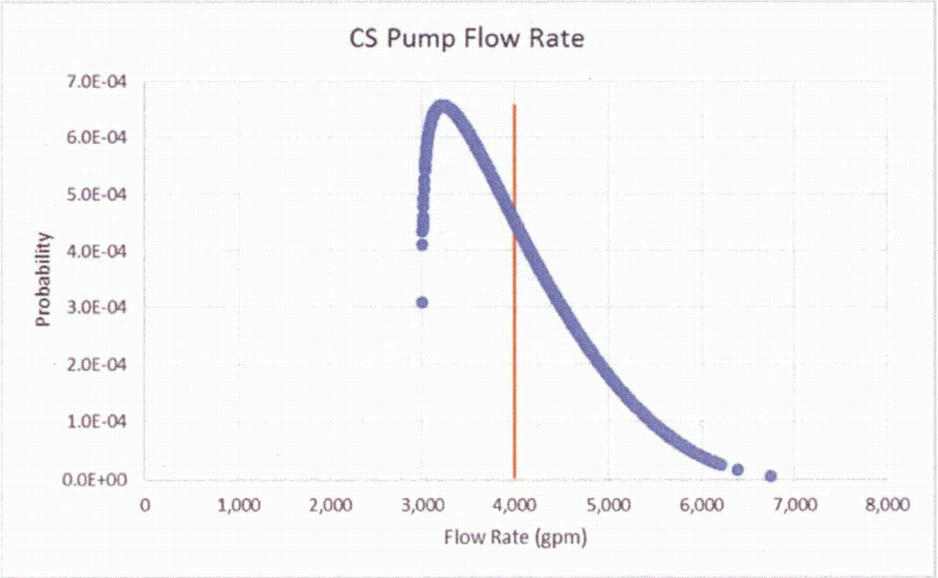

Figure 5: Sampled values for CS pump flow rate

The mean output values based on the two methods are shown in Table 3.

Table 3: Mean output parameter values from the simple RWST injection model

Parameter	Mean Output Calculated Using Input Parameter Probability Distributions	Mean Output Calculated Using Mean Input Parameter Values	Difference
Volume of water injected at RHR switchover (gal)	189,684	190,000	0.17%
Total volume of water injected (gal)	228,695	229,000	0.13%
Time to RHR switchover (minutes)	21.5	21.1	-1.86%
Time to CS switchover (minutes)	31.5	30.9	-1.90%

Although these two methods don't produce exactly the same result, the simplified method provides a reasonable approximation of the mean output parameter values.

Similarly, by plugging in bounding values for the various input parameters, the absolute minimum and maximum output values can be compared to the sampled minimum and maximum values. These results are shown in Table 4 and Table 5. Note that the absolute minimum and maximum values are always bounding compared to the values calculated using the probability distributions due to the fact that a large number of samples or a stratified sampling scheme would be necessary to fully capture the low probability tails.

Table 4: Maximum output parameter values from the simple RWST injection model

Parameter	Maximum Output Calculated Using Input Parameter Probability Distributions	Maximum Output Calculated Using Bounding Input Parameter Values	Difference
Volume of water injected at RHR switchover (gal)	234,941	255,000	8.5%
Total volume of water injected (gal)	274,103	298,000	8.7%
Time to RHR switchover (minutes)	26.1	63.8	144%
Time to CS switchover (minutes)	36.4	78.9	117%

Table 5: Minimum output parameter values from the simple RWST injection model

Parameter	Minimum Output Calculated Using Input Parameter Probability Distributions	Minimum Output Calculated Using Bounding Input Parameter Values	Difference
Volume of water injected at RHR switchover (gal)	160,739	145,000	-9.8%
Total volume of water injected (gal)	198,626	185,000	-6.9%
Time to RHR switchover (minutes)	17.9	16.1	-10.0%
Time to CS switchover (minutes)	27.1	24.7	-8.9%

5. Example Calculation with Detailed GSI-191 Model

A second, more detailed example calculation was performed using a GSI-191 model incorporating plant-specific inputs and phenomenological models (including debris generation, debris transport, chemical effects, strainer head loss, degasification, strainer structural margin, NPSH margin, pump gas void limits, fiber penetration, core fiber accumulation, and core fiber limits). In this example calculation, 13 of the input parameters were defined using probability distributions. (All other inputs were defined using fixed values or time-dependent profiles.) The parameters used to define the distributions are shown in Table 6.

Table 6: Detailed GSI-191 model input parameter values

Parameter	Minimum	Mean	Maximum
Initial RWST Mass (lb_m)	5,711,564	5,898,959	6,025,231
RWST Mass at RHR Switchover (lb_m)	751,547	1,650,000	2,049,981
RWST Mass at CS Switchover (lb_m)	167,685	700,000	840,121
RWST Boron Concentration (ppm)	2,100	2,537	2,900
Break Size-Dependent RHR Pump Flow Rate Variability	80%	100%	110%
CS Pump Flow Rate (gpm)	2,597	2,700	2,900
Containment Spray Termination Time (minutes)	150	180	240
Break Size and Time-Dependent Pool Temperature Variability (°F)	-5	0	+15
Latent Fiber Quantity (lb_m)	0	9	65
Strainer Structural Margin (ft)	22	24.7	30
Pump Gas Void Fraction Limit	1.5%	2%	4%
Fiber Penetration Fraction	2%	5%	8%
Core Fiber Accumulation Limit for Cold Leg Breaks (g/FA)	6	7.5	15

Each of the probability distributions were independently sampled (using simple Monte Carlo sampling), and the sampled inputs were used to evaluate the range of potential breaks to determine which breaks would pass or fail the long term core cooling acceptance criteria. A total of 235 iterations of sampled input parameters were run in the simulation. For each iteration, approximately 28,000 breaks (including a range of ½ inch partial breaks to double-ended guillotine breaks at each weld location) were evaluated.

The simulated failures were used to calculate conditional failure probabilities for small, medium, and large breaks, and these conditional failure probabilities were subsequently used to estimate ΔCDF. Also, similar to the simple RWST injection calculation, the mean ΔCDF output was estimated using the mean input parameter values, and the minimum and maximum ΔCDF was calculated using the best case and worst case bounding values. Figure 6 shows a histogram of the ΔCDF values calculated from the Monte Carlo simulation, and Table 7 shows a comparison between the mean, minimum, and maximum values determined using the Monte Carlo simulation and the simplified approach.

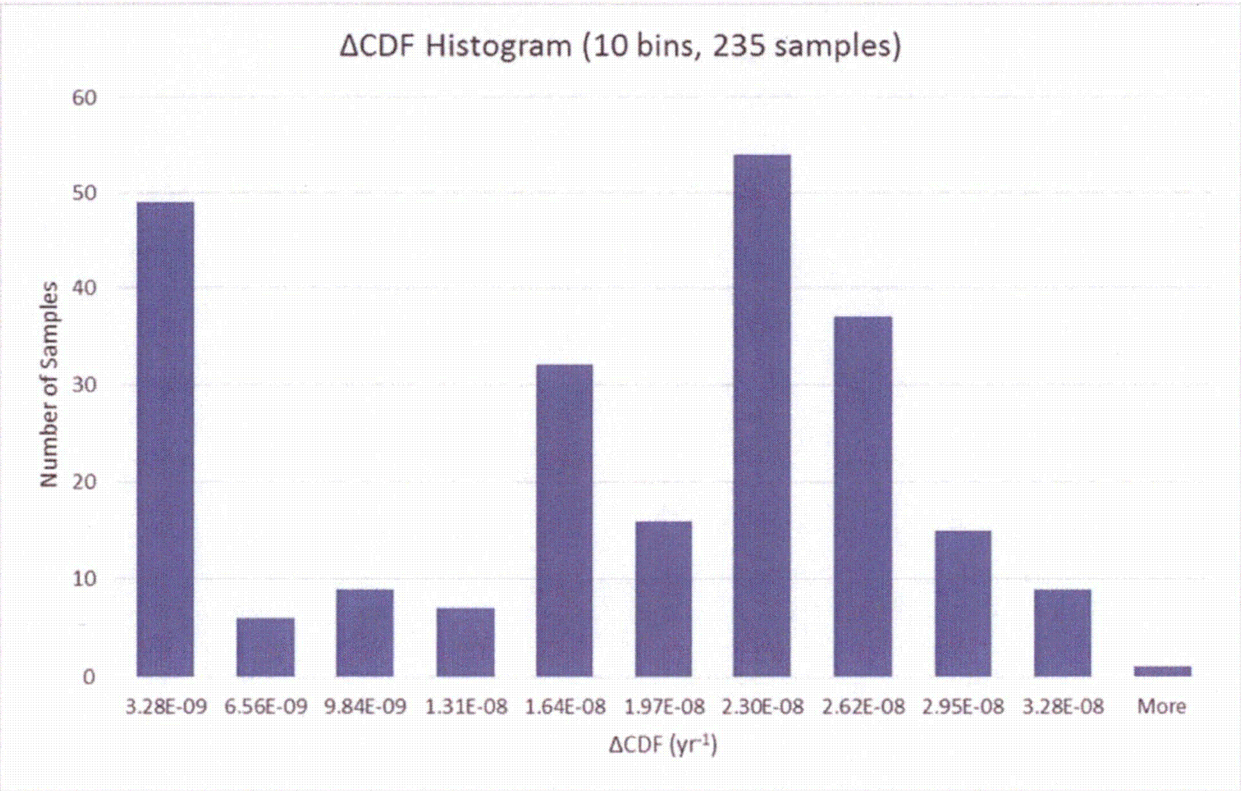

Figure 6: ΔCDF histogram based on simulation with sampled input parameters

Table 7: Output parameter values from the detailed GSI-191 model

Parameter	Calculated Output Using Sampled Input Probability Distributions	Calculated Output Using Fixed Mean and Bounding Input Values	Difference
Maximum ΔCDF	3.3E-08	3.6E-07	991%
Mean ΔCDF	1.6E-08	1.4E-08	-13%
Minimum ΔCDF	0E-00	0E-00	0%

As shown in this more detailed example, using the mean values for the input parameters provides a reasonable approximation of the mean ΔCDF. In this particular example, the bounding maximum ΔCDF value is an order of magnitude higher than the mean value. However, since the bounding maximum represents an extremely low probability scenario (i.e., it is based on worst case bounding input values using the simplified approach), and is still within Region III of RG 1.174 (very low risk), there is high confidence that the mean risk is very low as defined by Region III of RG 1.174 [3]. This is illustrated in Figure 7. The three points show the best-case, mean, and worst-case ΔCDF values calculated using the simplified approach, and the dashed line illustrates the ΔCDF probability distribution that would be calculated using the rigorous approach. A plot of ΔLERF would look very similar to the ΔCDF plot.

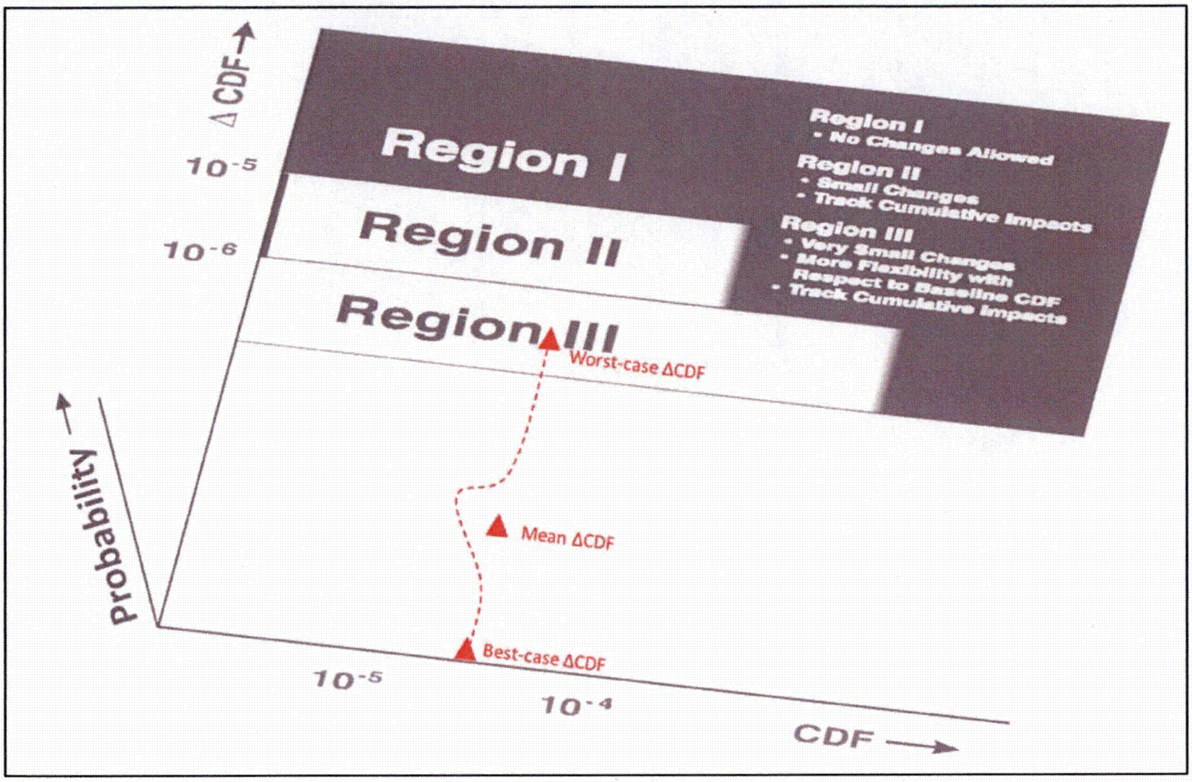

Figure 7: Illustration of uncertainty quantification results using the bounding input values from the simplified approach overlaid on RG 1.174 risk figure

6. Conclusions

Parametric uncertainty is the primary type of uncertainty that must be quantified for a simplified GSI-191 evaluation.

Using a combination of mean and bounding input values, the mean ΔCDF/ΔLERF as well as the ΔCDF/ΔLERF uncertainty range can be estimated. This is a simplified approach for uncertainty quantification that reduces the overall effort required to evaluate uncertainties.

Although the simplified approach sacrifices some accuracy in the calculated mean ΔCDF and ΔLERF values, the use of consensus models (which are generally conservative), and a mixture of bounding input parameters, skews the results in a conservative direction (i.e., higher ΔCDF and ΔLERF).

This document primarily focuses on the calculation of ΔCDF and the associated uncertainty. However, it is important to note that CDF, LERF, and ΔLERF are also important parameters in determining whether the overall GSI-191 risk meets the RG 1.174 acceptance guidelines.

Using a simplified approach is beneficial for both the NRC and industry to work toward a more rapid and resource-efficient resolution of GSI-191.

7. References

[1] NEI Presentation to the NRC (ML14204A233), GSI-191 (GL 2004-02) Issue Resolution Strategy, A Simplified Risk-Informed Approach, July 22, 2014.

[2] STP Presentation to the NRC (ML15034A114), STP Risk-Informed Approach to GSI-191, February 4, 2015.

[3] Regulatory Guide 1.174, An Approach for Using Probabilistic Risk Assessment in Risk-Informed Decisions on Plant-Specific Changes to the Licensing Basis, Revision 2: May 2011.

[4] NUREG-1855, Guidance on the Treatment of Uncertainties Associated with PRAs in Risk-Informed Decisionmaking, Revision 1 DRAFT: March 2013.

[5] EPRI Report 1016737, Treatment of Parameter and Model Uncertainty for Probabilistic Risk Assessment, Final Report: December 2008.

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[8] NEI 04-07 Volume 2, Safety Evaluation by the Office of Nucelar Reactor Regulation Related to NRC Generic Letter 2004-02, Revision 0: December 2004.

[9] WCAP-16530-NP-A, Evaluation of Post-Accident Chemical Effects in Containment Sump Fluids to Support GSI-191, March 2008.

[10] Draft Regulatory Guide DG-1322, Risk-Informed Approach for Addressing the Effects of Debris on Post-Accident Long-Term Core Cooling, DRAFT: April 2015.