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# Quantifying Safety Margin using the Risk-Informed Safety Margin Characterization (RISMC)

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# QUANTIFYING SAFETY MARGIN USING THE RISK-INFORMED SAFETY MARGIN CHARACTERIZATION (RISMC)

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*The Risk-Informed Safety Margin Characterization (RISMC), developed by Idaho National Laboratory as part of the Light-Water Reactor Sustainability Project, utilizes a probabilistic safety margin comparison between a load and capacity distribution, rather than a deterministic comparison between two values, as is usually done in best-estimate plus uncertainty analyses. The goal is to determine the failure probability, or in other words, the probability of the system load equaling or exceeding the system capacity. While this method has been used in pilot studies, there has been little work conducted investigating the statistical significance of the resulting failure probability. In particular, it is difficult to determine how many simulations are necessary to properly characterize the failure probability.*

*This work uses classical (frequentist) statistics and confidence intervals to examine the impact in statistical accuracy when the number of simulations is varied. Two methods are proposed to establish confidence intervals related to the failure probability established using a RISMC analysis. The confidence interval provides information about the statistical accuracy of the method utilized to explore the uncertainty space, and offers a quantitative method to gauge the increase in statistical accuracy due to performing additional simulations.*

## I. INTRODUCTION

Recently, the Risk-Informed Safety Margin Characterization (RISMC)[1] has been proposed as the next step in realistic safety margin calculations. However, with increased dependence on computer code simulations for the assessment of safety, questions arise not only related to the quality of the selected model and uncertainties, but also the methods used to explore the uncertainty space. Since the first question is usually addressed through standards[2] and regulation[3], this research focuses on the second aspect, which is the approach to covering the range of uncertainties through multiple computer code simulations. This work summarizes a recent effort by Argonne National Laboratory to improve the quantification of safety margins during nuclear power plant safety analyses utilizing mechanistic modeling[4].

In particular, this work seeks to provide statistical methods to assist in uncertainty quantification that must meet the following criteria. First, the statistical methods developed must be applicable to the RISMC (as described in Section II.B). Second, the methods must be able to quantify the increase in statistical accuracy that is associated with increasing the number of simulations during a RISMC analysis.

In addition to these goals, the proposed methods should also have the following properties. First, the techniques should be intuitive and straightforward to apply. Second, they should retain the ability to add additional simulations at a later time. Finally, the methods should provide a pathway for more advanced sampling techniques in the future.

## II. BACKGROUND

The Best Estimate Plus Uncertainty (BEPU) technique marked a major step forward in reactor safety assessment. Of particular interest here is the method utilized to quantify safety margin during BEPU calculations. Section II.A reviews the BEPU methods. This is followed by a review of the RISMC approach in Section III.A, including a review of pilot applications.

### II.A. Best Estimate Plus Uncertainty (BEPU)

In 1988, an amendment to 10 CFR 50.46[5] allowed the realistic modeling of loss of coolant accidents (LOCAs), and signified the first transition to best-estimate plus uncertainty (BEPU) analyses. Unlike the non-mechanistic, conservative models that formed the basis of reactor safety analysis at the time, BEPU focused on the use of realistic simulations of reactor accidents. However, questions arose related to its implementation. In particular, the original regulatory amendment simply stated that the analysis should demonstrate a "high level of probability that the criteria would not be exceeded."

In RG 1.157[6], the NRC clarified this requirement, stating that a 95% probability level is considered acceptable to NRC for comparisons to safety limits. Thanks to works by Gubá, Pál, and Makai[7], and Nutt and Wallis[8], the use of the 95% one-sided confidence interval for the 0.95-quantile (95% percentile) became the accepted approach for satisfying NRC requirements. Together, these metrics are now colloquially known as the 95/95 criterion.

Of particular interest here is not the methods used to calculate the 95/95 value, but the implications of the metrics. As shown in Table I, the 0.95-quantile can be considered a conservative value in respect to the input parameter uncertainties. Utilizing the 0.95-quantile value to represent the output distribution of an analysis means there's a 95% probability of the simulation result being less than that value. Therefore, it can be considered conservative in comparison to choosing the mean or median value, for example.

The 95% one-sided confidence interval, on the other hand, simply provides an interval where the chosen statistic (in this case the 0.95-quantile) is likely to fall. It does not imply the same conservatism in respect to the input parameter uncertainties as does the use of the 0.95-quantile. It is a measure of the statistical accuracy of the chosen sampling method utilized to explore the uncertainty space.

TABLE I. Implications of the 95/95 Criterion

| **Metric** | **Implication** |
|---|---|
| 0.95-quantile (a.k.a. 95$^{th}$ percentile) | A conservative measure of the impact of parameter uncertainty. The 0.95-quantile signifies the value that 95% of results will fall *below*. In other words, there is a 95% probability of the result of the analysis being less than the 0.95-quantile. |
| 95% one-sided confidence interval | In frequentist statistics, a 95% confidence interval implies that the estimated parameter in question (for example, the 0.95-quantile value) will fall within the bounds of the confidence interval 95 out of 100 times. It is a measure of the accuracy of the sampling scheme's estimator, not a direct measure of the parameter uncertainties. |

Since the use of the confidence interval has been accepted by the NRC for BEPU analyses, it has been selected here to provide information regarding the statistical accuracy of RISMC analyses. Unlike BEPU analyses, the confidence interval will not be used in conjunction with a conservative statistic (like the 0.95-quantile), but with the mean failure probability.

### II.B. Risk-Informed Safety Margin Characterization (RISMC)

The RISMC, developed by Idaho National Laboratory as part the of the Light Water Reactor Sustainability Program, utilizes a probabilistic margin comparison between a load and capacity distribution, rather than a deterministic comparison between two values, as with BEPU. As Fig. 1 shows, the failure probability for the system is calculated by determining the probability of the load distribution exceeding (or equaling) the capacity distribution. The distributions themselves are usually determined through uncertainty analysis using computer model simulations.

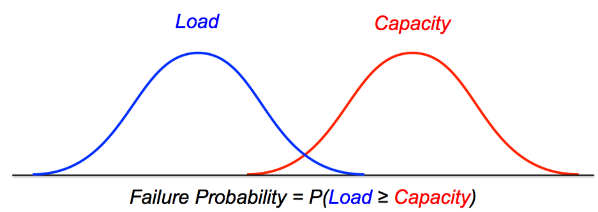


Fig. 1. RISMC Failure Probability

Recently, a RISMC pilot application study[9] demonstrated the approach for analyzing a loss of feedwater event at a commercial pressurized water reactor. In this study, 100 computer model simulations were conducted for each branch of the loss of feedwater event tree to explore the range of uncertainties. Utilizing the peak cladding temperature (PCT) from each simulation, the probability of fuel failure was calculated using a triangular distribution representing the capacity distribution of the fuel. After each simulation, the PCT was compared to a random value selected from the capacity distribution. If the simulated PCT was higher than the sampled capacity value, then the simulation was considered to experience core damage. It should be noted that there was no analysis of the implied statistical accuracy when using 100 simulations per event tree branch, compared to other values.

## III. STATISTICAL METHODS

This section reviews two methods for assessing the statistical accuracy associated with a RISMC evaluation through the use of upper confidence limits (UCLs). Unlike the use of confidence limits in BEPU analyses, where they are used in conjunction with a conservative statistic (the 0.95-quantile), the use of confidence limits in this regard simply provides statistical information for the mean failure probability. The first method described is perhaps the most intuitive and straightforward, while the second method offers a reduction in variance.

### III.A. Simple Random Sampling (SRS)

The first statistical approach, referred to as Simple Random Sampling (SRS) is based on the procedure used in the RISMC pilot study. In that work, the PCT from a simulation was compared to a capacity value chosen at random from the capacity distribution. SRS builds on this method and calculates an UCL for the resulting failure probability. The follow section describes the application procedure, with a walk-through provided in Fig. 2.

The first step to establishing the UCL for the failure probability when using SRS is to estimate the failure probability $p$. For this work, the hat notation ($\hat{p}$) will be used to distinguish the estimator from the true value. The SRS failure probability estimator, referred to as $\hat{p}_{SRS}$, is the sum of the number of simulations that violated the capacity $n_{fail}$, divided by the total number of simulations $n$, as seen in Eq. (1).

$$\text{estimated failure probability} = \hat{p}_{SRS} = \frac{n_{fail}}{n}. \quad (1)$$

From there, the standard deviation of the failure probability is found using Eq. (2), the sample standard deviation formula,

$$\text{Standard dev. of failure probability estimator} = st.dev = \sqrt{\left(\frac{1}{n-1}\right) \times \sum_{i=1}^{n} (I_i - \hat{p}_{SRS})^2}, \quad (2)$$

where $I_i$ is the indicator function for each simulation $i$. On the $i$-th simulation, if the observed load exceeds the sampled capacity, then $I_i = 1$; otherwise $I_i = 0$. Finally, the 95% one-sided UCL is found using Eq. (3),

$$\text{95\% UCL for estimated failure probability} = \hat{p}_{SRS} + z_{95\%}\left(\frac{st.dev.}{\sqrt{n}}\right), \quad (3)$$

where $z_{95\%}$ is the standard normal critical point for a one-sided 95% confidence interval (*i.e.*, 1.645). Fig. 2 provides an overview of the application using example values.

### III.B. Conditional Monte Carlo (CMC)

The second statistical method, referred to as Conditional Monte Carlo, contains the same initial steps as the SRS approach. The difference is the comparison to the capacity value. In SRS, a random value for the capacity was chosen from the capacity distribution, then compared to the result of the simulation. However, if the capacity distribution is already known, then the simulation result can be used to calculate the failure probability directly, using the cumulative distribution function of the capacity.

As the example in Fig. 3 shows, using the result of the simulation (in this case, a PCT of $X = 2369$ °F), the conditional failure probability is found using the capacity's cumulative distribution function $G$.

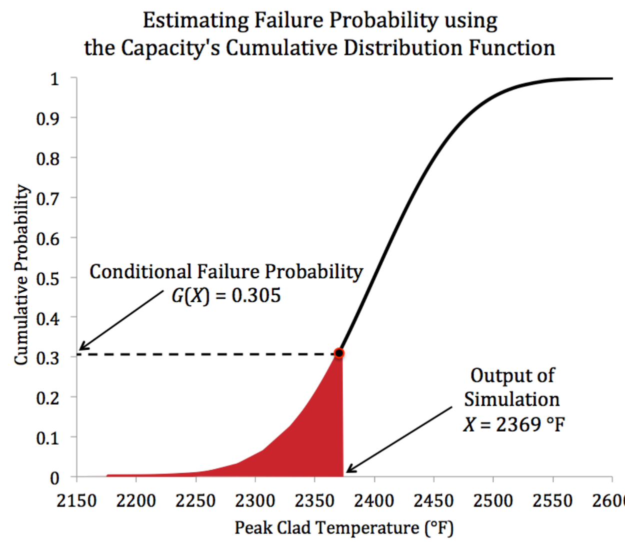


Fig. 3. Determining Failure Probability

This process can be repeated for each simulation that was conducted to explore the uncertainty space. Using the conditional failure probability results from the individual simulations, the estimated failure probability can be found using Eq. (4)

$$\text{estimated failure probability} = \hat{p}_{CMC} = \frac{1}{n}\sum_{i=1}^{n} G(X_i), \quad (4)$$

where $n$ is the total number of simulations. From there, the standard deviation of the estimated failure probability is found using the sample standard deviation formula shown in Eq. (5),

$$\text{Standard dev. of failure probability estimator} = st.dev. = \sqrt{\left(\frac{1}{n-1}\right) \times \sum_{i=1}^{n} (G(X_i) - \hat{p}_{CMC})^2}, \quad (5)$$

Finally, the 95% one-sided UCL is found using the same formula as with SRS, shown in Eq. (3). By removing the random selection of the capacity value for each simulation, the variance of the result is reduced and there could be a small computational time-savings. Fig. 4 provides an overview of the CMC approach using example values.

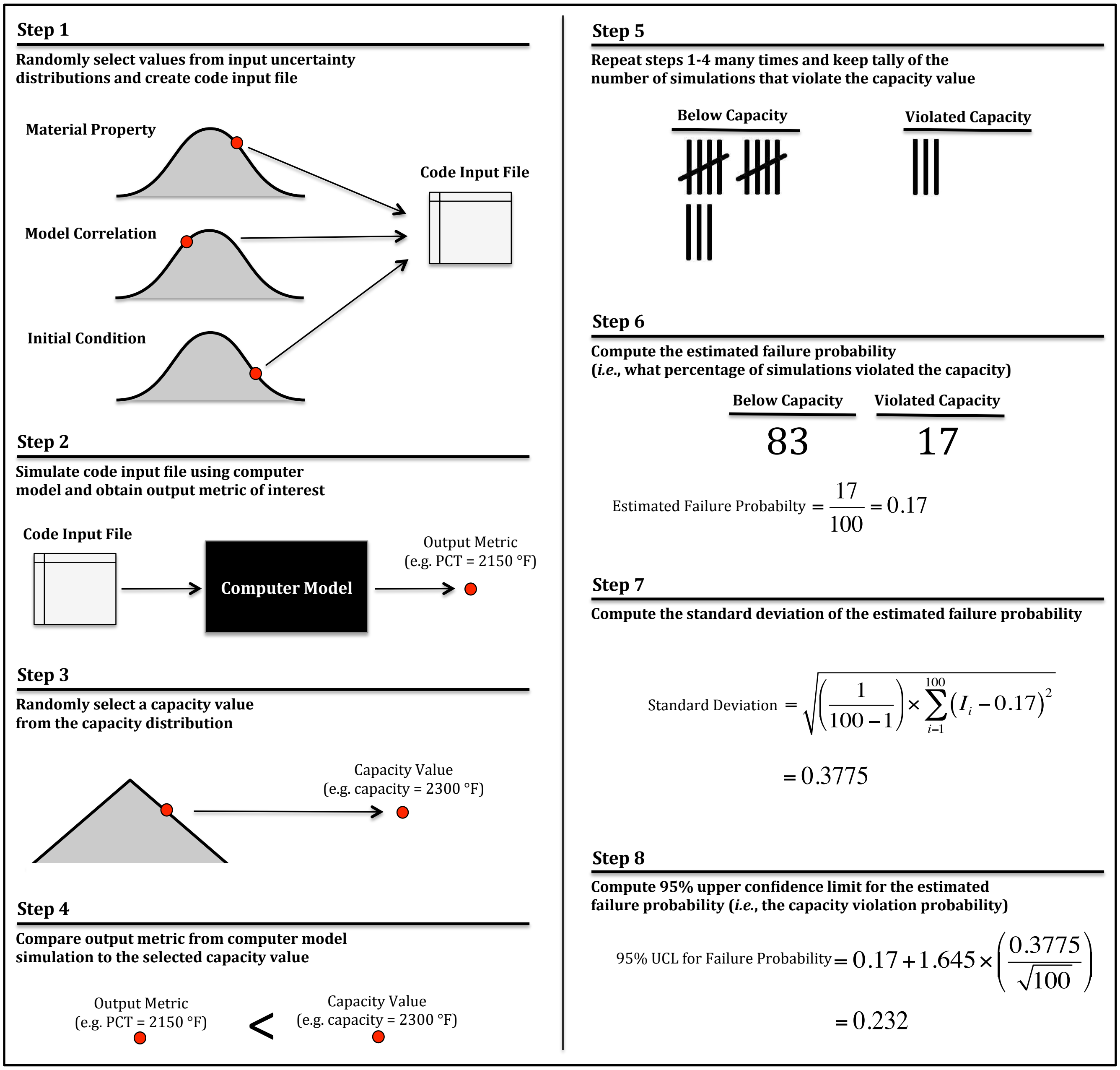


Fig. 2. SRS Approach Overview

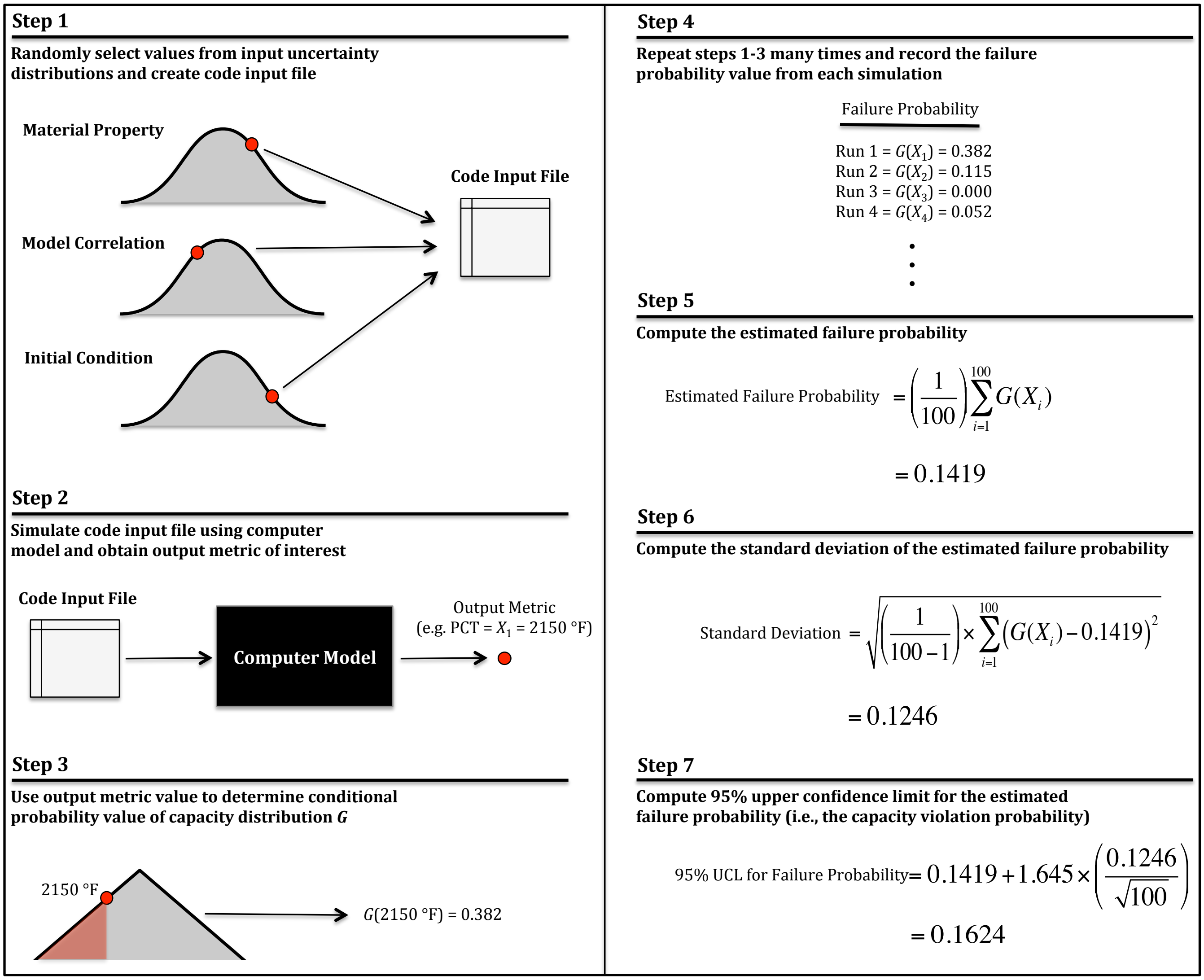


Fig. 4. CMC Approach Overview

## IV. PRA EXAMPLE APPLICATION

The following section provides an example application of the CMC approach for an event tree analysis of a small LOCA, seen in Fig. 5. For this example, each branch of the event tree is simulated multiple times utilizing a computer model to explore the range of input parameter uncertainties. The PCT for each simulation is recorded and compared to a capacity distribution (the triangular distribution seen in Fig. 6), which depicts the range of PCTs where fuel failure may be encountered.

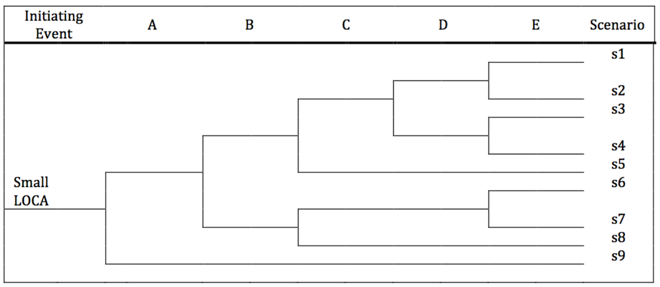


Fig. 5. Example Small LOCA Event Tree

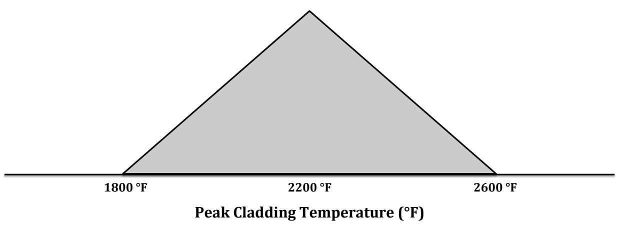


Fig. 6. Probability Density Function of Capacity Distribution

Fig. 7 depicts the steps in the analysis, and is reviewed here. First, input values are chosen at random (using Monte Carlo sampling) from the parameter uncertainty distributions. These values are utilized to create the code input file. Next, each branch of the small LOCA event tree is modeled using the selected input parameter values, and the PCT from each simulation is recorded.

Using the CMC method, the PCT from each simulation is utilized to calculate the failure probability of that simulation using the capacity's cumulative distribution function. As can be seen, most scenarios have a failure probability of zero, since the PCT falls below 1800°F, which is the lower bound of the capacity distribution.

The probability of each branch (scenario) of the event tree is used in conjunction with the failure probability to determine the core damage frequency (CDF) of that scenario, as seen in Step 4 of Fig. 7. Then, the total CDF of the event tree can be calculated by summing the CDF of the individual scenarios. The first four steps are then repeated many times, and the total CDF of the event tree is recorded for each iteration utilizing new input uncertainty values.

In step 6, the mean CDF of the event tree is found utilizing the CDF results from each iteration. Step 7 uses the same results to determine the standard deviation of the event tree CDF. Lastly, step 8 calculates the 95% UCL of the event tree CDF based on the results of step 6 and 7.

## V. OBSERVATIONS

One of the goals of this work was to establish statistical methods that can demonstrate the improvement in statistical accuracy that accompanies an increased number of simulations. The SRS method can be utilized to demonstrate this fact. For example, Fig. 8 shows the results for the 95% UCL failure probability when 20% of the simulations conducted violate the capacity. If ten simulations are conducted, and two violate the system capacity, then the estimated failure probability is 20%. However, taking into account the 95% UCL, then the failure probability is almost 42%. However, if the calculation is repeated with 100 simulations and 20 violate the capacity, the estimated failure probability is still 20%, but the failure probability with a 95% UCL is now only 26%. As can be seen, increasing the number of simulations greatly increases the implied statistical accuracy.

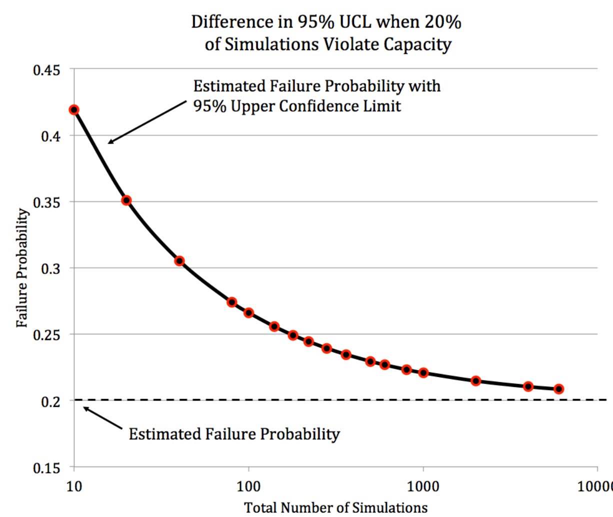


Fig. 8. Improvement with Increased Simulation

Another goal of the research was to provide statistical methods that are intuitive and can accept additional simulations at a later time. Both of the methods reviewed here utilize Monte Carlo random sampling, which is not only straightforward to apply, but allows simulations to be added later, as long as Monte Carlo sampling is employed.

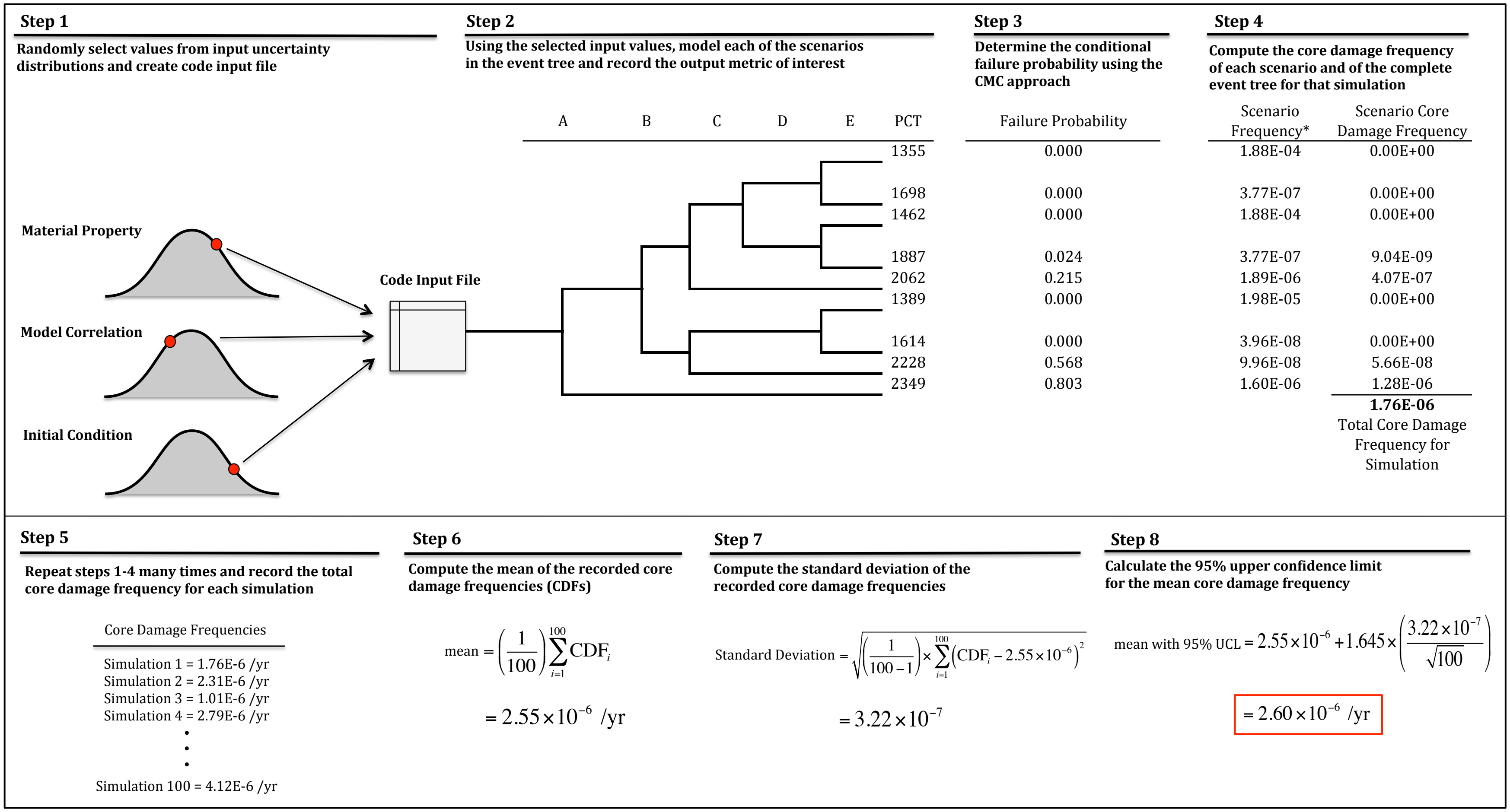


Fig. 7. Utilizing CMC for a RISMC Event Tree Analysis

*The scenario frequency is determined using the failure probabilities of each top event and the initiating event frequency, as is customary for event tree analysis.

## VI. CONCLUSION

This work presents two options to assess the statistical accuracy associated with a RISMC analysis. Both methods utilize Monte Carlo sampling and UCLs. The SRS approach is preferred if the capacity distribution is not known, but can be sampled. On the other hand, the CMC is better if the capacity distribution is known, and can be computed analytically or numerically.

Both approaches are seen as initial steps at addressing the statistical accuracy related to RISMC analyses. Far more advanced sampling methods exist, including many variance reduction techniques and adaptive sampling. Also, alternative statistical approaches are available, such as the use of Bayesian analyses, which are usually considered more conducive to use in risk assessments since it is often easier to propagate results.

## ACKNOWLEDGMENTS

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## REFERENCES

1. C. SMITH, C. RABITI, and R. MARTINEAU, “Risk Informed Safety Margin Characterization (RISMC) Pathway Technical Program Plan," Idaho National Laboratory, INL/EXT-11- 22977, (2012).
2. American Society of Mechanical Engineers, “NQA-1 Quality Assurance Requirements for Nuclear Facility Applications," NQA-1a-2009, (2009).
3. U.S. Code of Federal Regulations, "Quality Assurance Criteria for Nuclear Power Plants and Fuel Reprocessing Plants," 10 CFR 50 Appendix B, 2007.
4. D. GRABASKAS, et al., Argonne National Laboratory, unpublished information, (2014).
5. U.S. Code of Federal Regulations, " Acceptance Criteria for Emergency Core Cooling Systems for Light-water Nuclear Power Plants,” 10 CFR 50.46, (Amended 2007).
6. U.S. Nuclear Regulatory Commission, "Best-Estimate Calculations of Emergency Core Cooling System Performance," R.G. 1.157, (1989).
7. L. PÁL, M. MAKAI, and A. GUBÁ, "Statistical aspects of Best Estimate Method - I," *Reliability Engineering and System Safety*, vol. 80, pp. 217-232, (2003).
8. W. NUTT and G. WALLIS, "Evaluation of Nuclear Safety from the Outputs of Computer Codes in the Presence of Uncertainties," *Reliability Engineering and System Safety*, vol. 83, pp. 57- 77, (2004).
9. R. R. SHERRY, J. R. GABOR, and S. M. HESS, "Pilot Application of Risk Informed Safety Margin Characterization to a Total Loss of Feedwater Event," *Reliability Engineering and System Safety*, vol. 117, pp. 65-72, (2013).