MEASURING RISK IMPORTANCE IN A DYNAMIC PRA FRAMEWORK

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Risk importance measures are indexes that are used to rank systems, structures and components (SSCs) using risk-informed methods. The most used/known measures are: Risk Reduction Worth (RRW), Risk Achievement Worth (RAW), Birnbaum (B) and Fussell-Vesely (FV). Once obtained from classical Probabilistic Risk Analysis (PRA) analyses, these risk measures can be effectively employed to optimize component testing and maintenance. In contrast to classical PRA methods, Dynamic PRA methods couple stochastic methods with safety analysis codes to determine risk associate to complex systems such as nuclear plants. Compared to classical PRA methods, they can evaluate with higher resolution the safety impact of timing and sequencing of events on the accident progression. The objective of this paper is to present a series of algorithms that can be used to determine classical risk importance measures (RRW, RAW, B and FV) along with newly developed ones from a Dynamic PRA analysis.

I. INTRODUCTION

Risk Importance Measures (RIMs) [1] are indexes that are used to rank systems, structures and components (SSCs) based on their contribution to the overall risk. The most used measures [2] are:

- Risk Reduction Worth (RRW),
- Risk Achievement Worth (RAW),
- Birnbaum (B), and,
- Fussell-Vesely (FV).

Typically, this ranking is performed in a classical PRA framework, where risk is determined by considering probability associated to the minimal cut-sets generated by static logic structures [3] (e.g., Event-Trees, Fault-Trees). In a classical PRA analysis, each SSC is represented by a set of basic events; as an example emergency diesel generators can be represented by two basic events: *failure to start* and *failure to run*. The risk measures associated to each basic event are calculated from the generated cut-sets by determining:

- The nominal risk
- The increased risk assuming basic event failed
- The reduced risk assuming basic event perfectly reliable

In this context, the Nuclear Regulatory Commission (NRC) has issued the 10CFR50.69 document [4,5] designed to guide plant owners to perform a risk-informed categorization and treatment of SSCs in order to reduce operating and maintenance costs while preserving acceptable risk levels. The described categorization is based on a set of risk importance measures obtained from the plant classic PRA models.

In contrast to classical PRA methods, Dynamic PRA methods [6] couple stochastic methods (e.g., RAVEN [7], ADAPT [8], ADS [9], MCDET [10]) with safety analysis codes (RELAP5-3D [11], MELCOR [12], MAAP [13]) to determine risk associate to complex systems such as nuclear plants. Accident progression is thus determined by the simulation code and not set a-priori by the user. The advantage of this approach, compared to classical PRA methods, is that a higher fidelity of the results can be achieved since:

- No assumption of timing/sequencing of events is set by the user but dictated by the accident evolution
- No success criteria are defined but instead, the simulation stops if either a fail or a success state are reached
- There is no need to compute convolution integrals in order to specify probability of basic events that temporally depends from other basic events.

The scope of this paper is to present a method to determine classical RIMs from Dynamic PRA data. Few test cases will be presented in order to show how the calculation is performed. In addition, new margin-centric

RIMs that better capture the continuous aspect of a Dynamic PRA approach will be presented.

II. CLASSICAL RIMs IN CLASSICAL PRA

In classical PRA methods, for any basic event, the most used RIMs measures are: Risk Achievement Worth (RAW), Risk Reduction Worth (RRW), Birnbaum (B) and Fussell-Vesely (FV) [2]. All these RIMs are calculated by determining three values based on core damage frequency (CDF):

- R_o: nominal CDF
- R_i^-: CDF for basic event i assuming perfectly reliable
- R_i^+: CDF for basic event i assuming it has failed

Once these three values are determined, then the RIMs are calculated [2] as follows for each basic event i:

$$RAW_i = \frac{R_i^+}{R_o} \quad (1)$$

$$RRW_i = \frac{R_o}{R_i^-} \quad (2)$$

$$B_i = R_i^+ - R_i^- \quad (3)$$

$$FV_i = \frac{R_o - R_i^-}{R_o} \quad (4)$$

Note the four RIMs listed above is not exhaustive: in literature it is possible to find additional RIMs such as the Differential Importance Measure (DIM) [14]. Since, the scope of this paper is tight to risk-informed application of 10CFR50.69, we will focus this paper only on the four RIMs listed above.

III. DYNAMIC PRA: THE RISMC APPROACH

The RISMC PRA approach [15] is based on several Dynamic PRA methods in which the deterministic and stochastic modeling are merged in a single analysis framework (see Figure 1). In the deterministic model we include:

- Modeling of the thermal-hydraulic behavior of the plant [16]
- Modeling of external events such as flooding [17]
- Modeling of the operators responses to the accident scenario [18]

Note that deterministic modeling of the plant or external events can be performed by employing specific simulator codes but also surrogate models [19], known as reduced order models (ROM). ROMs would be employed in order to decrease the high computational costs of employed codes.

In addition, *multi-fidelity codes* can be employed to model the same system; the idea is to switch from low-fidelity to high-fidelity code when higher accuracy is needed (e.g., use low-fidelity codes for steady-state conditions and high-fidelity code for transient conditions)

In the stochastic modeling we include all stochastic parameters that are of interest in the PRA analysis such as:

- Uncertain parameters
- Stochastic failure of system/components

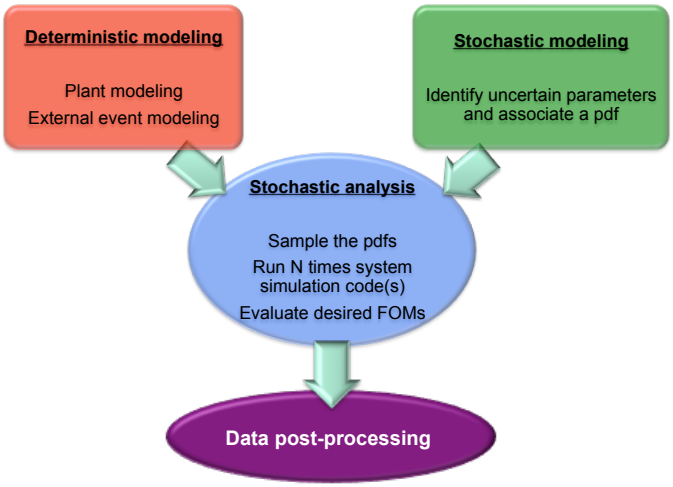

Figure 1. RISMC approach.

As mentioned earlier, Dynamic PRA methods heavily rely on multi-physics system simulator codes (e.g., RELAP5-3D [11]) coupled with stochastic analysis tools (e.g., RAVEN [7]). Each simulation run can be described by using two sets of variables:

- $\boldsymbol{c} = \boldsymbol{c}(t)$ represents the status of components and systems of the simulator (e.g., status of emergency core cooling system, AC system)
- $\boldsymbol{\theta} = \boldsymbol{\theta}(t)$ represents the temporal evolution of a simulated accident scenario, i.e., $\boldsymbol{\theta}(t)$ represents a single simulation run. Each element of $\boldsymbol{\theta}$ can be for example the values of temperature or pressure in a specific node of the simulator nodalization.

From a mathematical point of view, a single simulator run can be represented as a single trajectory in the phase space. The evolution of such a trajectory in the phase space can be described as follows:

$$\begin{cases} \dfrac{\partial \boldsymbol{\theta}(t)}{\partial t} = \boldsymbol{\mathcal{H}}(\boldsymbol{\theta}, \boldsymbol{s}, \boldsymbol{c}, t) \\ \dfrac{\partial \boldsymbol{c}(t)}{\partial t} = \boldsymbol{\mathcal{C}}(\boldsymbol{\theta}, \boldsymbol{s}, \boldsymbol{c}, t) \end{cases} \quad (5)$$

where:

- $\boldsymbol{\mathcal{H}}$ is the actual simulator code that describes how $\boldsymbol{\theta}$ evolves in time
- $\boldsymbol{\mathcal{C}}$ is the operator which describes how $\boldsymbol{c}$ evolves in time , i.e., the status of components and systems at each time step
- $\boldsymbol{s}$ is the set of N stochastic parameters s_i $(i = 1, \dots, S)$.

Starting from the system located in an initial state, $\boldsymbol{\theta}(t = 0) = \boldsymbol{\theta}(0)$, and the set of stochastic parameters

(which are generally generated through a stochastic sampling process), the simulator determine at each time step the temporal evolution of $\boldsymbol{\theta}(t)$. At the same time, the system control logic[1] determines the status of the system and components $\boldsymbol{c}(t)$. The coupling between these two sets of variables is shown in Figure 2.

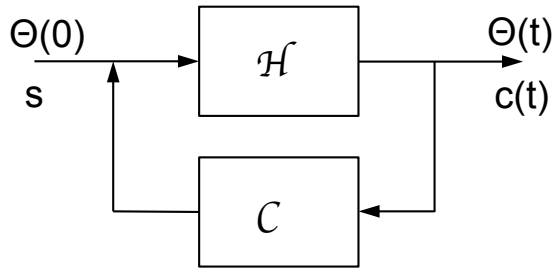

Figure 2. Relationship between simulator phisics code (*H*) and control logic (*C*).

A typical dynamic PRA analysis is performed by:

1. Associating a probabilistic distribution function (pdf) to the set of stochastic parameters $\boldsymbol{s}$ (e.g., timing of events)
2. Performing stochastic sampling of the pdfs defined in Step 1
3. Performing a simulation run given $\boldsymbol{s}$ sampled in Step 2, i.e., solve the system of equations (1)
4. Repeating Steps 2 and 3 *M* times and evaluating user defined stochastic parameters such as core damage (CD) probability (P_{CD}).

IV. CLASSICAL RIMs IN A DYNAMIC PRA CONTEXT

In a Dynamic PRA environment, R_o is obtained (e.g., through Monte-Carlo sampling) by:

- Running *N* simulation (e.g., RELAP5 runs)
- Counting the number N_{CD} of simulations that lead to core damage (CD) condition
- Calculating $R_o = \frac{N_{CD}}{N}$

Note that while basic events in classical PRA are mainly Boolean, in a Dynamic PRA environment the sample parameters can be, not only Boolean, but more often continuous. As an example, let consider two basic events:

1. Emergency Diesel Generator (EDG) failure to start, and,
2. EDG failure to run

In classical PRA analyses, a probability value is associated to each basic event. On the other side, in a Dynamic PRA framework, a Bernoulli distribution could be associated to the first basic event and a continuous distribution (e.g., exponential distribution) could be associated to the second basic event.

[1] Which is usually integral part of the system simulator

At this point a challenge arises: the determination of R_i^- and R_i^+ for each sampled parameter; two possible approaches can be followed[2]:

1. Perform a Dynamic PRA for R_o and each R_i^- and R_i^+
2. Determine an approximated value of R_i^- and R_i^+ from the simulation runs generated to calculate R_o

Regarding Approach 1, given the computational costs of each Dynamic PRA, it is unfeasible to determine R_i^- and R_i^+ for each sampled parameter. In fact, if we consider *M* sample parameters (i.e., *S* basic events), then the risk importance analysis would require $2S + 1$ Dynamic PRA analyses.

Regarding Approach 2, a method (implemented in RAVEN as an internal post-processor) was developed and it is here presented. This method requires an input from the user:

- Range, I_i^-, of the variable s_i that can be associated to "basic event with component perfectly reliable"
- Range, I_i^+, of the variable s_i that can be associated to "basic event in a failed status"

Given this kind of information, it is possible to calculate R_i^+ and R_i^- as follows[3]:

$$R_o = \frac{N_{CD}}{N} \tag{6}$$

$$R_i^+ = \frac{N_{CD,s_i \in I_i^+}}{N} \tag{7}$$

$$R_i^- = \frac{N_{CD,s_i \in I_i^-}}{N} \tag{8}$$

Note that this approach has an issue related to the choices of I_i^+ and I_i^-. Depending on their values, R_i^+ and R_i^- might change accordingly. In addition, the statistical error associated to the estimates of R_i^+ and R_i^- also changes.

An example is shown in Figure 1 for both cases (discrete and continuous) of a basic event x_i represented as a stochastic variable which is sampled (e.g., through a Monte-Carlo process) for each simulation run.

Lets consider the continuous case and assume s_i correspond to the basic event "EDG failure to run". The user might impose the following in order to determine R_i^+ and R_i^-:

- $I_i^- = [T_i^-, \infty]$ where T_i^- may be set equal to the simulation mission time (e.g., 24 hours). This implies that a sampled value for EDG failure to run greater than 24 hours implies that the EDG actually does not fail to run (reliability equal to 1.0)

[2] A possible approach would be to develop a new sampling strategy designed ad-hoc to maximize the amount of data that can be generated to determine more reliable values of R_i^- and R_i^+. However, research of effective algorithms is still under way.

[3] It is here indicated:

- $N_{CD,s_i \in I_i^+}$ as the number of simulations leading to core damage and with parameter $s_i \in I_i^+$
- $N_{CD,s_i \in I_i^-}$ the number of simulations leading to core damage and with parameters $s_i \in I_i^-$

- $I_i^+ = [0, T_i^+]$ where T_i^- may be set to an arbitrary small value (e.g., 5 min). This implies that a sampled value for EDG failure to run smaller than 5 min implies a reliability equal to 0.0

Note that while the definition of I_i^- is perfectly reasonable, one would argue that a smaller interval should be chosen for I_i^+ (e.g., 30 seconds or less).

Recall that ideally, a value of $s_i = 0.0$ should be theoretically chosen (and not an interval); however, given the nature of the distribution this is not allowed. Given the nature of the problem, we are bound to choose an interval I_i^+:

- A small interval in the neighbor of $s_i = 0.0$ would lead to a value of R_i^+ close to the theoretical one. However, the number of actual sampled values falling in I_i^+ would be very small, i.e., large stochastic error.
- A large interval in the neighbor of $s_i = 0.0$ would lead to a value of R_i^+ far from the theoretical one. However, the number of actual sampled values falling in I_i^+ would be very high, i.e., small stochastic error.

A solution to the large statistical error associated to a very small interval I_i^+ can be solved by employing different sampling algorithms other than the classical Monte-Carlo one.

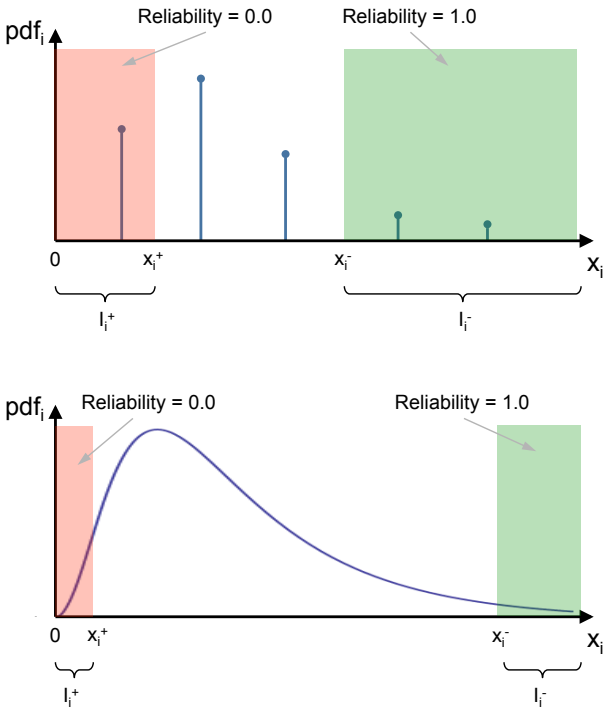

Figure 3. Treatment of discrete (top) and continuous (bottom) stochastic variables for reliability purposes.

As an example, a better resolution of the final value for R_i^+ can be achieved by sampling uniformly the range of variability of x_i and associate an importance weight to each sample. At this point the counting variable N_{CD} is weighted by the weight of each sample. By sampling uniformly the range of variability of x_i, the number of samples in the interval I_i^+ would be significantly higher.

V. EXAMPLES

In this section we presented three examples that will help the reader to understand how this method can be applied to fairly common cases.

I.A. Example I

The first example is shown in Figure 4: it consists of 3 components arranged in a series/parallel configuration. In this case the following probabilities of failures (on-demand) are provided:

- $p_A = 1.0\ 10^{-2}$
- $p_B = 5.0\ 10^{-2}$
- $p_C = 1.0\ 10^{-1}$

From a dynamic PRA point of view the analysis of this system is performed as follows:

1. Define 3 stochastic parameters (i.e., $S = 3$):
   a. s_1: status of component A
   b. s_2: status of component B
   c. s_3: status of component C
2. Assign a distribution to each stochastic parameter; in this case a Bernoulli distribution[4]
3. Define I_i^+ and I_i^- for each distribution: in this case we have chosen[5] $I_i^- = [0.0,0.1]$ and $I_i^+ = [1.0,1.1]$
4. Generate N samples, for example by Monte-Carlo sampling[6]
3. Determine R_o, R_i^- and R_i^+ for each component
5. Determine the desired RIMs for each component

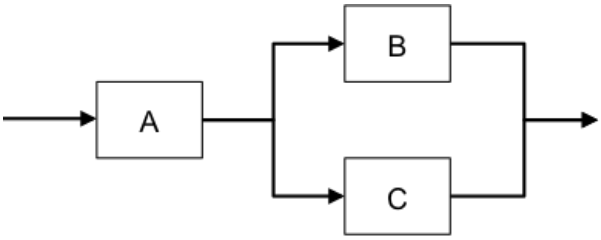

Figure 4. System for Example I and II.

Note that a Monte-Carlo sampling is not the best sampling strategy in terms of computational costs. This is

[4] It is here assumed this distribution is defined over two possible outcomes: 0 (component operating) with probability 1-p, and, 1 (component failed) with probability p.

[5] Note that the intervals I_i^+ and I_i^- chosen are including the two possible outcomes of the Bernoulli distribution.

[6] In this case the simulator returns 1 (system failure) if $s_1 = 1$ or if $s_2 = s_3 = 1$ and it returns 0 otherwise.

even more relevant if the value of p_A, p_B or p_C were several order of magnitude lower.

A more effective sampling strategy would be the Grid sampling: the stochastic variables are sampled over a fixed Cartesian grid and a probability weight is associated to each sample.

In this case, each stochastic variable s_i is sampled over two values, 0.0 and 1.0, and the probability weights w_i^0 and w_i^1 values associated to each sample coordinate are:

- $s_i = 0.0$: $w_i^0 = prob(s_i \in [-\infty, 0.5])$
- $s_i = 1.0$: $w_i^1 = prob(s_i \in [0.5, +\infty])$

Following this grid sampling strategy, only $2^N = 8$ are needed.

Below, the FV importance for all three components obtained by RAVEN (using a Grid sampling strategy) are shown compared with the analytical ones.

Table 1. Results obtained for Example I.

	Analytical	RAVEN
FV_A	0.6656	0.6656
FV_B	0.3311	0.3311
FV_C	0.3311	0.3311

I.B. Example II

The second example is similar to Example I but with different reliability data: a failure rate is provided for each component (mission time: 24 hours):

- $\lambda_A = 1.0\ 10^{-3}\ hr^{-1}$
- $\lambda_B = 5.0\ 10^{-3} hr^{-1}$
- $\lambda_C = 1.0\ 10^{-2} hr^{-1}$

Thus it is assumed that failure probability of each component is exponentially distributed: sampled value $\boldsymbol{s_i}$ from its own distribution is failure time of each component[7] ($\boldsymbol{t_A}$, $\boldsymbol{t_B}$ and $\boldsymbol{t_C}$).

In this case, I_i^+ and I_i^- can be defined as follows:

- $I_i^- = [24.0, +\infty]$: component is considered perfectly reliable if the failure time is greater than the mission time
- $I_i^+ = [0.0,1.0]$: component is considered unreliable if the failure time occurs within the first hour

As shown for Example I, a Grid sampling strategy has been employed. Table 2 shows the FV importance for all three components obtained by RAVEN (using a Grid sampling strategy) compared with the analytical ones.

[7] In this case the simulator returns 1 (system failure) if at a certain time $t \in [0,24]$ component A has failed or if both components B and C have failed.

Table 2. Results obtained for Example II.

	Analytical	RAVEN
FV_A	0.48957	0.48957
FV_B	0.4983	0.4983
FV_C	0.4983	0.4983

I.C. Example III

The third example considers a simplified ECCS model (see Figure 5) for a Pressurized Water Reactor (PWR). It consists of the following components and for a subset of them a value of mean time to failure (MTTF) is provided:

- Motor-operate valve M (MTTF = 24 h)
- Two redundant pumps, pump1 and pump2 (MTTF = 12 h)
- Heat exchanger HX (reliability = 1.0)

Pump1 is normally used while pump2 is on standby. If Pump1 fails then pump2 provide water flow. Pump2 cannot fail while in standby. Switch from pump1 to pump2 is perfectly reliable. The cooling is such that it takes 2 hours to reach vessel failure condition if the M-pump1-pump2 system has failed. Top event is: overheating of the vessel. Mission time is again equal to 24 hours.

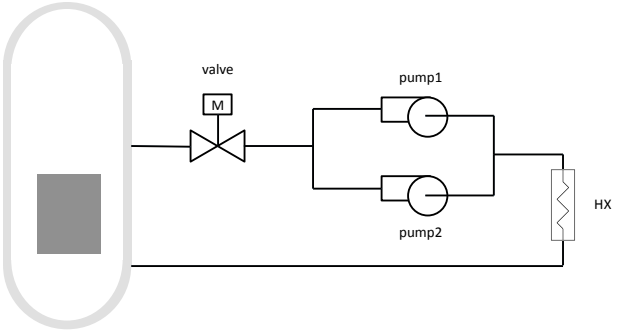

Figure 5. System for Example III.

Failure of the system occurs when temperature insider the core reaches a limit temperature. Note that the configuration is slightly different from the one presented in the first two examples (here a stand-by configuration is introduced) but also the condition of system failure is dictated by the dynamic behavior of the PWR. The system is designed such that a late failure of the ECCS may not lead to system failure (i.e., natural circulation is providing enough cooling). In other words, the ECCS is vital especially in the hours right after a reactor scram.

Note in this case classical PRA methods require few model simplifications in order to correctly determine system reliability.

In contrast, a dynamic PRA analysis follows the same steps presented for the first two examples; the only

difference is represented by the simulator that is actually employed.
Below are shown the FV importance for all three components obtained by RAVEN (using a Monte-Carlo sampling strategy) compared with the analytical ones.

Table 3. Results obtained for Example III.

	RAVEN
FV_{pump1}	0.25893
FV_{pump2}	0.25893
FV_{valve}	0.30331

VI. NEW SET OF RIMs IN A DYNAMIC PRA CONTEXT

Note that the RIMs described so far are tight to a binary logic of the outcome variable (e.g., OK vs. CD). Dynamic PRA approaches typically generate a continuous value of the outcome variables (e.g., peak clad temperature - PCT). In our application (see previous sections) we typically convert PCT to a discrete one as follows:

- $PCT > 2200\ F$: outcome = CD
- $PCT < 2200\ F$: outcome = OK

Given the different structure of the approach used in this paper to solve a PRA problem (i.e., Dynamic instead of classical PRA), the reader might think that a different set of RIMs should/could be developed in order to capture the nature of the problem solved using Dynamic PRA.

As a starting point, it would worth investigating the nominal probabilistic distribution (pdf) of PCT with the one obtained when reliability of each basic event (sampled parameter) is 0.0 or 1.0. So now we can indicate:

1. $pdf_o(T)$: nominal pdf of PCT
2. $pdf_i^-(T)$: pdf of PCT associated to basic event i assuming basic event is perfectly reliable
3. $pdf_i^+(T)$: pdf of PCT associated to basic event i assuming basic event has failed

An example is shown below for a hypothetical case where obtained $pdf_o(T)$ is indicated using an histogram while the limit value for PCT is shown using the red line passing at 2200 F.

In order to make a connection to what has been presented in the previous section, note that by looking at Figure 6:

$$R_o = \int_{2200}^{\infty} pdf_o(T)\, dT \qquad (9)$$

As part of the RISMC analysis, the user might want to supplement the results obtained in the previous section with the information associated to a more effective margin analysis.

In particular, of interest for RISMC applications is (see Figure 7) the concept of margin:

$$margin = 2200 - PCT \text{ given } (PCT < 2200)$$

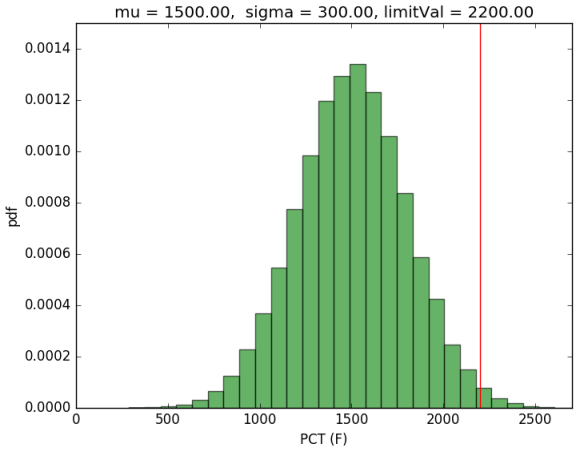

Figure 6. Plot of a hypothetical $pdf_o(T)$

Using the same philosophy indicated in the previous section for classical RIMs, we want to determine:

1. $margin_o$: pdf of the variable $2200 - PCT$ given that $PCT < 2200$
2. $margin_i^-$: pdf of the variable $2200 - PCT$ given that $PCT < 2200$ for basic event i assuming it is perfectly reliable
3. $margin_i^+$: pdf of the variable $2200 - PCT$ given that $PCT < 2200$ for basic event i when its assumed to be failed

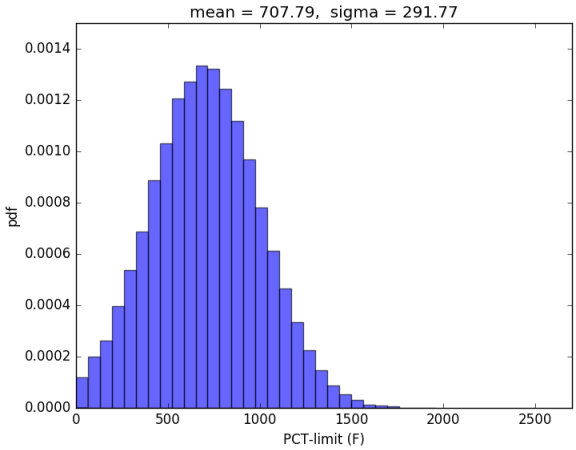

Figure 7. Plot of $margin_o$ for the case shown in Figure 2

Note now that $margin_o$, $margin_i^-$ and $margin_i^+$ are now pdfs and not numerical values. Hence, now the challenge arises on how to compare two pdfs:

- $margin_o$ vs. $margin_i^-$
- $margin_o$ vs. $margin_i^+$

Assume two pdfs are given: $pdf_1(x)$ and $pdf_2(x)$. Few approaches can be followed:

1. Z-test
2. Kolmogorov–Smirnov test

In the first approach (Z-test), the following variable Z is computed:

$$Z_{1,2} = \frac{mean(pdf_1) - mean(pdf_2)}{\sqrt{std\_dev^2(pdf_1) - std\_dev^2(pdf_2)}} \quad (10)$$

where:

- $mean(pdf)$ correspond to the mean of $pdf(x)$
- $std\_dev(pdf)$ correspond to the standard deviation of $pdf(x)$

In the second approach (Kolmogorov–Smirnov test [20]), instead of the pdf, the cumulative distribution functions (pdf) are considered: $cdf_1(x)$ and $cdf_2(x)$. In particular, the Kolmogorov-Smirnov statistic is calculated as:

$$KS_{1,2} = \sup_x (cdf_1(x) - cdf_2(x)) \quad (11)$$

Note that so far we have imposed clad failure temperature (CFT) to be a fixed value, i.e., 2200 F. In many RISMC applications CFT is no longer a numerical value but it can be un uncertain parameter, i.e., a pdf is associated to CDF: pdf(T). This link goes back to the original logo of RISMC where a pdf for "load" and "capacity" (see Figure 4).

A new definition of margin can be then defined:

$$margin = (\text{CFT} - \text{PCT})\ given\ (\text{CFT} - \text{PCT} > 0)$$

From here, once the pdf associated to the margin variable is determined it is possible to employ either the Z-tests or the Kolmogorov–Smirnov test in order to measure how this pdf changes when each basic event is considered perfectly reliable or failed.

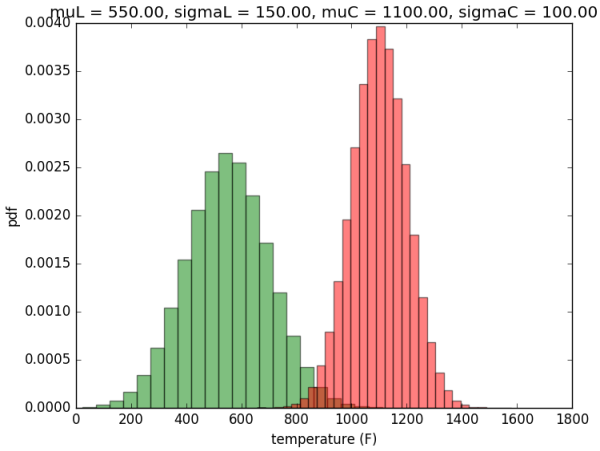

Figure 8. Plot of the pdfs for PCT (green) and CFT (red).

VII. CONCLUSIONS

This paper has presented a mathematical framework for determining risk importance measures in a simulation based, i.e. dynamic, PRA framework. We have shown how classical measures can be derived and we have provided few explanatory examples. We have also indicated how the data generation method is extremely important to maximize the amount of information generated by each simulation run. Lastly we have presented an additional set of risk importance measures that are not bounded by a Boolean logic but explore the continuity of the problem. The advantage of these measures is that they capture the idea of "safety margin"

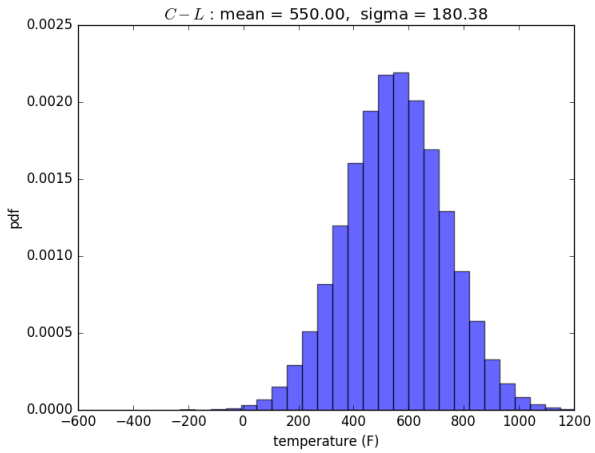

Figure 9. Plot of the pdf of the variable CFT − PCT.

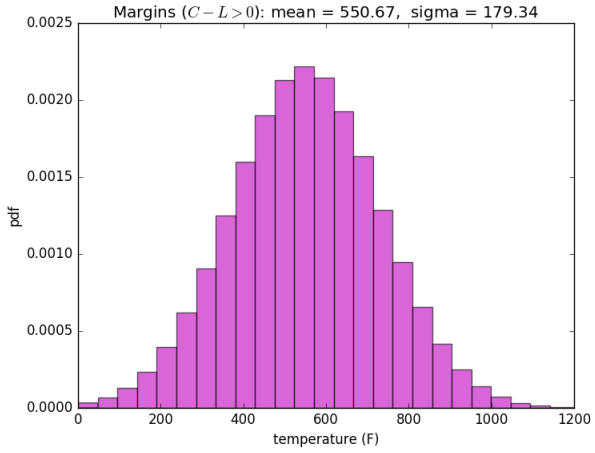

Figure 10. Plot of the pdf of the margin, i.e., CFT − PCT > 0.

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