A Dynamic Safety Margins Estimation with a Limited Number of PWR Large Break LOCA Simulations

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The development of methodologies for Risk-Informed Safety Margin Characterization (RISMC) in presence of stochastic and epistemic uncertainties affecting the system dynamic behavior is one of the objectives of the Light Water Reactor Sustainability (LWRS) Program.
In the present work, the characterization of safety margin uncertainties is handled by Order Statistics (OS) (with both Bracketing and Coverage approaches) to jointly estimate percentiles of the distributions of the safety parameter and of the time required for it to reach these percentiles values during its dynamic evolution. The novelty of the proposed approach consists in the integration of dynamic aspects (i.e., timing of events) into the definition of a dynamic safety margin for a probabilistic quantification of margins.
The methodology is applied to a pilot case study of a TRACE model of a Large Break Loss of Coolant Accident (LBLOCA) occurring in the Zion Nuclear Power Plant (NPP).

1. INTRODUCTION

Risk-Informed Safety Margin Characterization (RISMC) is aimed at supporting decision-making regarding newer reactor technologies implementation and lifetime extension of older nuclear fleets [US D.O.E, 2009].
Dynamic reliability approaches [Siu, 1994; Devooght, 1997; Marseguerra et al., 1998; Labeau et al., 2000; Dufour et al., 2002; Di Maio et al., 2009; Aldemir, 2013] have been developed, aimed at giving explicit account to the interactions among the physical parameters of the process (such as temperature, pressure, speed, etc.), the human operators actions and the failures of the hardware and software components. As a by-product, this creates the opportunity for the quantification of operational safety margins within a dynamic reliability scheme [Zio et al., 2010[b]].
Traditionally, a safety margin is defined as the minimum distance between the system “loading” and its “capacity” [US D.O.E., 2009]. The challenge is the effective representation of the uncertainties inherent in the TH code parameters, correlations and approximations.
Uncertainty is typically distinguished into two types: randomness due to inherent variability in the system behavior and imprecision due to lack of knowledge and

information on the system [Apostolakis, 1990]. The former type of uncertainty is often referred to as objective, aleatory, stochastic, whereas the latter is often referred to as subjective, epistemic, state of knowledge [Apostolakis 1990; Helton, 2011]. To deal with these uncertainties, traditional safety margins quantification has implied conservatism in both the analysis of the TH code outputs and the evaluation criteria [Nutt et al., 2004]. Best Estimate (BE) methodologies have reduced the amount of conservatism for the evaluation of safety margins, but do not take into account all aleatory and epistemic uncertainties in the physical models stochastic behavior and model parameter values [US D.O.E., 2009].

In order to more realistically quantify the uncertainty of TH code outcomes, a probabilistic safety margin definition has been proposed, which better deals with epistemic uncertainties [Zio et al., 2010]. However, the effect of timing, order and magnitude of the component failures on the system dynamics is not considered.

In this respect, a dynamic probabilistic safety margin approach is proposed in this paper, based on time-dependent phenomenological models of stochastic system evolution including possible dependencies between failure events [Aldemir, 2013]. For this, we introduce a novel definition of a dynamic probabilistic safety margin by the combined quantification of a percentile (e.g., 95th) of the safety parameter distribution (e.g., oil temperature, peak cladding temperature) and a percentile (e.g., 5th) of the distribution of the earliest time required to the safety parameter to reach the given percentile value. The uncertainties affecting the dynamic probabilistic safety margin are treated using Order Statistics (OS) (i.e., bracketing and coverage approach) [Nutt et al., 2004]. By so doing, we are able to compute the confidence that, for a selected accidental scenario of a Dynamic Event Tree (DET) obtained by a IDPSA analysis, the estimated 95th percentile of the safety parameter cannot be reached before the 5th percentile of the estimated time: if these estimated percentiles meet the safety criteria with the required confidence, the NPP can be licensed as “safe”” to withstand the selected accidental scenario.

Furthermore, the proposed definition of dynamic probabilistic safety margin provides the analyst with the additional resilience information on the available time for counteracting the occurrence of an accidental scenario, rather than only quantifying to which extent the selected combination of failure events can be harmful for the NPP.

The proposed framework of analysis, initially presented in [Di Maio et al., 2016] is here applied to a pilot case study based on a TRACE model of a Zion Nuclear Power Plant (NPP): the distributions of the Peak Cladding Temperature (PCT) and of the time for reaching the PCT values during a Loss Of Coolant Accident (LOCA) in the cold leg of one of the loops of the plant with a varying break diameter are obtained and the dynamic probabilistic safety margin is quantified.

The paper is organized as follows. In Section 2, the concept of probabilistic safety margin is explored and that of dynamic probabilistic safety margin is introduced. In Section 3, a brief explanation is given of the OS approaches (bracketing and coverage) used for the definition of the number of TH code runs for uncertainty analysis with a required confidence (e.g., 95%) in the quantification of the dynamic probabilistic safety margin. In Section 4, the methodology is applied to a Zion NPP accidental scenario. Conclusions of the whole study are drawn in Section 5.

2. DYNAMIC PROBABILISTIC SAFETY MARGIN

Traditionally, for an accidental scenario 'a', safety margin $M(y_j, a)$ is defined as the difference between the conservatively computed values reached by a selected safety parameter $y_j(a)$, j=1,2,…J, and a predefined upper (lower) threshold U_j (L_j) during an accidental scenario [Nutt et al., 2004; Martorell et al., 2009; Secchi et al., 2008].
For the upper threshold U_j, it is defined as:

$$M\left(y_j, a\right) = \begin{Bmatrix} \frac{U_j - y_j(a)}{U_j - y_{j\,ref}} & if\ y_j(a) \le U_j \\ 0 & if\ U_j < y_j(a) \\ 1 & if\ y_j(a) < y_{j\,ref} \end{Bmatrix} \tag{1}$$

and for the lower threshold L_j as:

$$M\left(y_j, a\right) = \begin{Bmatrix} \frac{y_j(a) - L_j}{y_{j\,ref} - L_j} & if\ L_j \le y_j(a) \\ 0 & if\ y_j(a) < L_j \\ 1 & if\ y_j(a) > y_{j\,ref} \end{Bmatrix} \tag{2}$$

where $y_{j\,ref}$ is a reference value for $y_j(a)$, which can also be considered as the nominal value of the safety parameter y_j. However, a safety margin so defined ends up to be too conservatively computed not accounting explicitly for the uncertainties in the estimation of safety margin [Martorell et al., 2006; Zio et al., 2008[b]].
To overcome this conservatism, the safety margin can be defined in probabilistic terms as the difference between U_j (L_j) and the value of a specific γ_1 percentile of the distribution of the safety parameter $y_j(a)$, accounting for both the aleatory and epistemic uncertainties that effect y. Without loss of generality, we only refer to an upper threshold U_j, the extension to L_j being straightforward. By regulation, γ_1 is usually set equal to the 95th percentile.
Despite that, the estimation of the probability density function of y, $f(y)$, and of its γ-th percentile y_{γ_1}, $f(y_{\gamma_1})$, is a non-trivial task that requires guaranteeing a confidence β_1 (e.g., 95% confidence), viz [Nutt et al., 2004; Zio et al., 2010]:

$$\gamma_1 = \Pr\{y < y_{\gamma_1}\} \tag{3}$$

$$\beta_1 = Pr\{y_{\gamma_1} < \hat{y}_{\gamma_1}\} \tag{4}$$

Figure 1 shows that $M\left(y_j, a\right) > 0$ if $y_{\gamma_1} < U_j$. Since $\hat{y}_{\gamma_1} > y_{\gamma_1}$ with confidence β_1, if $y_{\gamma_1} < U_j$, then $M\left(y_j, a\right) > 0$. After the distribution of the values of the safety parameter y and the point estimates of the percentiles (i.e., y_{γ_1} (real) and $\hat{y}_{\gamma_1}$ (estimated)) are obtained, the probabilistic safety margin can be calculated from equation (5) [Nutt et al., 2004; Zio et al., 2008[a]], as given:

$$M(\gamma_1, \beta_1) = \begin{Bmatrix} \frac{U_j - \hat{y}_{\gamma_1}}{U_j - y_{j\,ref}} & if\ \hat{y}_{\gamma_1} \le U_j \\ 0 & if\ U_j < \hat{y}_{\gamma_1} \\ 1 & if\ \hat{y}_{\gamma_1} < y_{j\,ref} \end{Bmatrix} \tag{5}$$

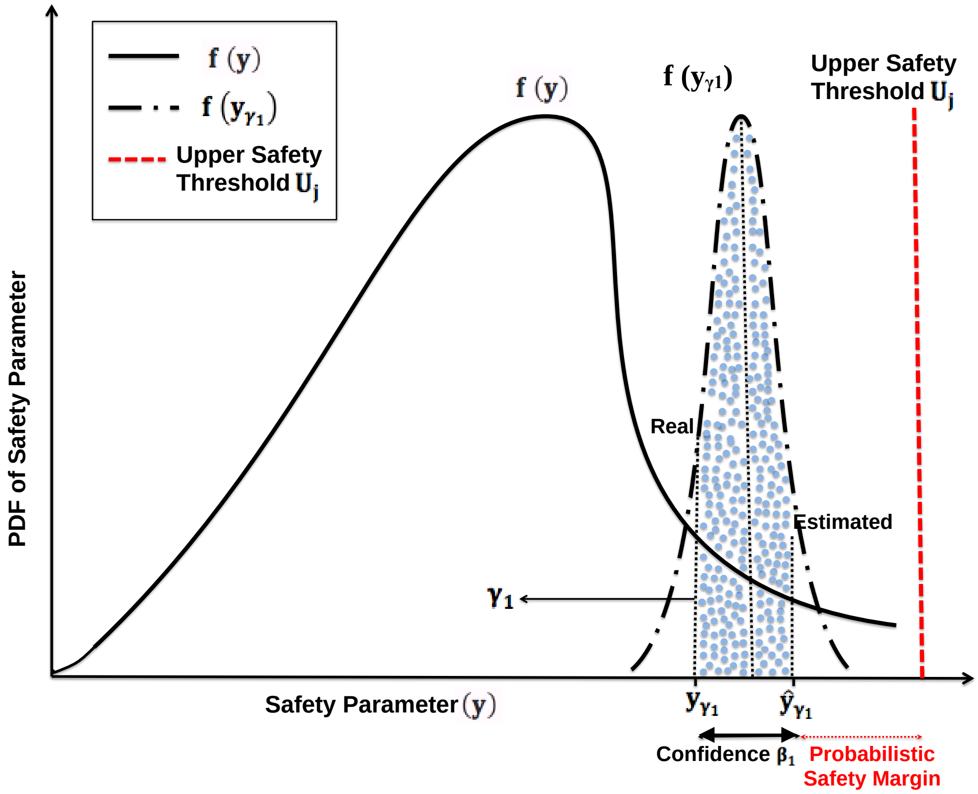

Figure 1 Sketch of the probability distribution of the values of safety parameter y, the probabilistic safety margin, the real y_{γ_1} and estimated $\hat{y}_{\gamma_1}$ values of a given percentile (e.g., 95$^{\text{th}}$)

The definition of probabilistic safety margin of equation (5) can be enriched by taking into account the resilience information related to the time required for reaching y_{γ_1}. Similarly to y, if we consider the pdf $f(y_t)$ of time y_t required to reach y_{γ_1}, $y_{t_{\gamma_2}}$ a specific percentile (e.g., 5$^{\text{th}}$ percentile) of y_t and $\hat{y}_{t_{\gamma_2}}$ its estimate, then we can define (see Figure 2):

$$\gamma_2 = \Pr\left\{y_t < y_{t_{\gamma_2}}\right\} \tag{6}$$

$$\beta_2 = Pr\left\{y_{t_{\gamma_2}} > \hat{y}_{t_{\gamma_2}}\right\} \tag{7}$$

The dynamic probabilistic safety margin can, thus, be defined as a probabilistic safety margin with respect to the safety parameter y together with the information on the earliest (grace) time t required to reach that margin (i.e., the available time for counteracting the occurrence of an accidental scenario a).

$$M(\gamma_1, \gamma_2, \beta_1, \beta_2) = \left\{ \begin{array}{cc} \frac{U_j - \hat{y}_{\gamma_1}}{U_j - y_{j\,ref}} & if\ \hat{y}_{\gamma_1} \leq U_j \\ 0 & if\ U_j < \hat{y}_{\gamma_1} \\ 1 & if\ \hat{y}_{\gamma_1} < y_{j\,ref} \end{array} \right\} \text{ with grace time } \hat{y}_{t_{\gamma 2}} \tag{8}$$

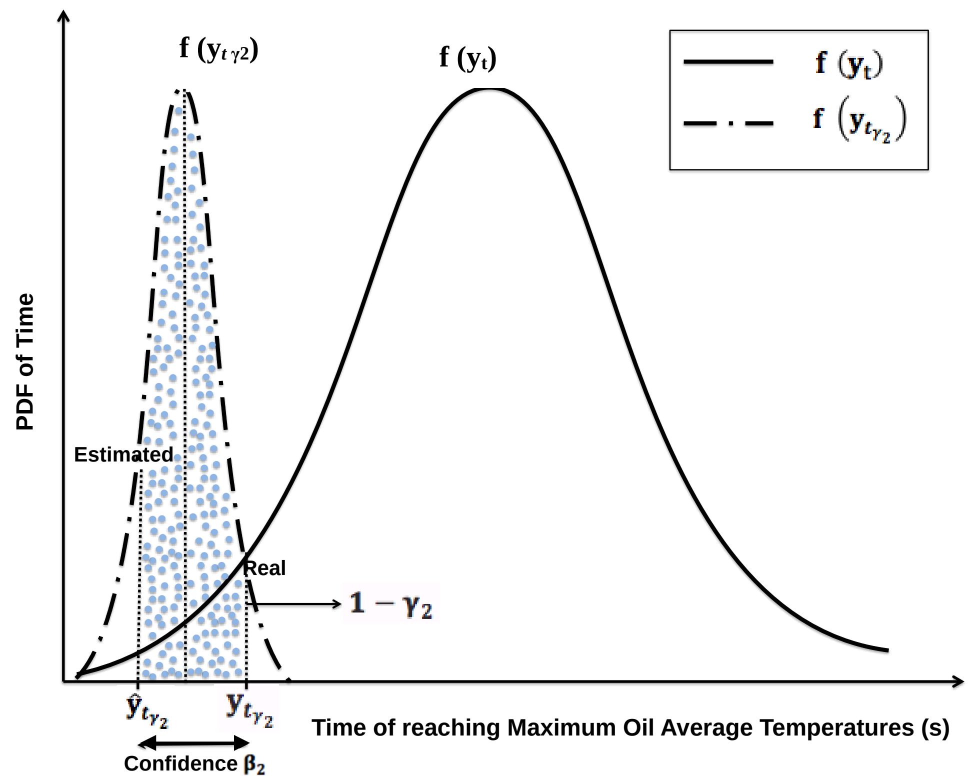

Figure 2 Sketch of the probability distribution of the values of time t, the real $y_{t_{\gamma_2}}$ and estimated $\hat{y}_{t_{\gamma_2}}$, values of a given percentile (e.g., 5th)

3. ORDER STATISTICS FOR PERCENTILES ESTIMATION

Order Statistics (OS) and Finite Mixture Models (FMMs) [Carlos et al., 2013; Di Maio et al., 2014[b]] can be used for the quantification of the uncertainties of the outputs. FMM provides a natural "clustering" of the TH code outputs, by reproducing them providing information pertaining to the most important input variables which affect the output uncertainty, whereas OS focuses on characterizing the PDFs of certain percentiles and providing approximate estimation of safety limits. This latter can also be integrated with Artificial Neural Network (ANNs) for speeding up the computation by substituting the TH code with a simpler and faster surrogate [Di Maio et al., 2014[b]; Zio et al., 2008[b]; Mclachlan et al., 2000]. In this study, the estimates $\hat{y}_{\gamma_1}$ and $\hat{y}_{t_{\gamma 2}}$ are quantified using Order Statistics [Nutt et al., 2004] methodology to get the optimal number of samples N of the TH code simulations to be run to guarantee confidences β_1 and β_2 in the estimation of $\hat{y}_{\gamma_1}$ and $\hat{y}_{t_{\gamma_2}}$, respectively. This is done to avoid the computational costs for running complex TH models for obtaining the full distributions of y and y_t. [Zio et al., 2008[a]; Nutt et al., 2004].
Let us assume we have a collection of two output vectors $\bar{y} = \{y_1, y_2, \dots\dots, y_N\}$ and $\bar{y}_t = \left\{y_{t_1}, y_{t_2}, \dots\dots, y_{t_N}\right\}$ that are obtained from N runs of the TH code, each one with a different input deck $\bar{x}$. Let $\bar{y}^* = \left\{y^{(1)}, y^{(2)}, \dots, y^{(N)}\right\}$ and $\bar{y}_t{}^* = \left\{y_t^{(1)}, y_t^{(2)}, \dots, y_t^{(N)}\right\}$ be the ordered set of values of the two outputs. Without loss of generality, with reference to only the safety parameter y (or the time y_t) to be limited from above by U, the approach aims at showing

that the m^{th} member y_m ($y_{t,m}$) of the N sorted output $\bar{y}^*$ ($\bar{y}_t{}^*$) has a certain probability β_1 (β_2) of exceeding (undershooting) the unknown true $\gamma_1 - th$ ($\gamma_2 - th$) percentile $y_{\gamma_1}(y_{t_{\gamma_2}})$. Then, one has a level of confidence β_1 (β_2) that the actual value of y_{γ_1} ($y_{t_{\gamma_2}}$) is less (more) than the value obtained for y_m ($y_{t,m}$): if y_m ($y_{t,m}$) meets the criterion of being less than the safety threshold U, then the unknown y_{γ_1} ($y_{t_{\gamma_2}}$) will do so, too [Nutt et al., 2004; Wald, 1943; Zio et al.,2008[a,b]]. It is worth noticing that the m^{th} member $y_{t,m}$ of the N sorted outputs y_t is required to guarantee a confidence (β_2) of not exceeding (i.e., being smaller than) the unknown true γ_2^{th} percentile $y_{t_{\gamma_2}}$.

Two approaches (namely Bracketing and Coverage) can be embraced to calculate N and to deal with a multi-dimensional output $\bar{y}$ and $\bar{y}_t$ and their uncertainties (The interested reader should refer to [Nutt et al., 2004; Wald, 1943; Di Maio et al., 2016] for further details).

4. Case Study of ZION NPP

The methodology of Sections 2 and 3 is pplied to a dataset of $N = 96$ accidental scenarios consisting in a cold leg Large Break Loss Of Coolant Accident (LBLOCA) occurring in one of the four loops of the ZION 4-loop Primary Water Reactor (PWR) plant [NEA 2011; Perez et al., 2008] and simulated by a TRACE BE-TH code (whose nodalization scheme is shown in Figure 3).

The Zion 1 NPP is a four-loop pressurized water reactor (PWR) located in Zion (Illinois, USA). The system parameters values and their distribustions at steady-state conditions are summarized in Table 1.

After the emergency shut-down of the reactor (SCRAM), a LBLOCA scenario entails three phases: i) blowdown, that begins with the break of size S_{23} (Table 1) and ends when the Emergency Core Cooling System (ECCS) starts injecting water in the remaining intact loops; ii) refill, that begins when the water injections starts and ends when the mixture level in the lower plenum reaches the core inlet; iii) reflood, that begins when the liquid level in the core increases and ends when the core is totally quenched. In the PWR here considered two Emegency Core Cooling Systems (ECCS) are installed: one is a passive safety system consisting of one large accumulator per loop, containing borated water under a blanket of nitrogen at mean pressure S_{10} = 4.16 [MPa] (Table 1), that is poured into the cold legs of the vessel; the other system is an electrically driven low-pressure coolant injection system (LPIS) that discharges water into the hot legs of the primary loops after it has passed through the heat exchangers. In particular, the accidental scenario here analyzed consists in:

1. mean blowdown period of 13 [s], when the accumulators start injecting water;
2. mean delay for the activation of the LPIS equal to S_{16} = 15 [s] (Table 1) (High Pressure Injection System (HPIS) is not modeled);
3. LPIS injection with a pressure set point of 1.42 [MPa];
4. mean refill phase (started about 13 [s] after the break) period of 26 [s], when the core is filled again with liquid;
5. core quenching at about 460 [s] after the break.

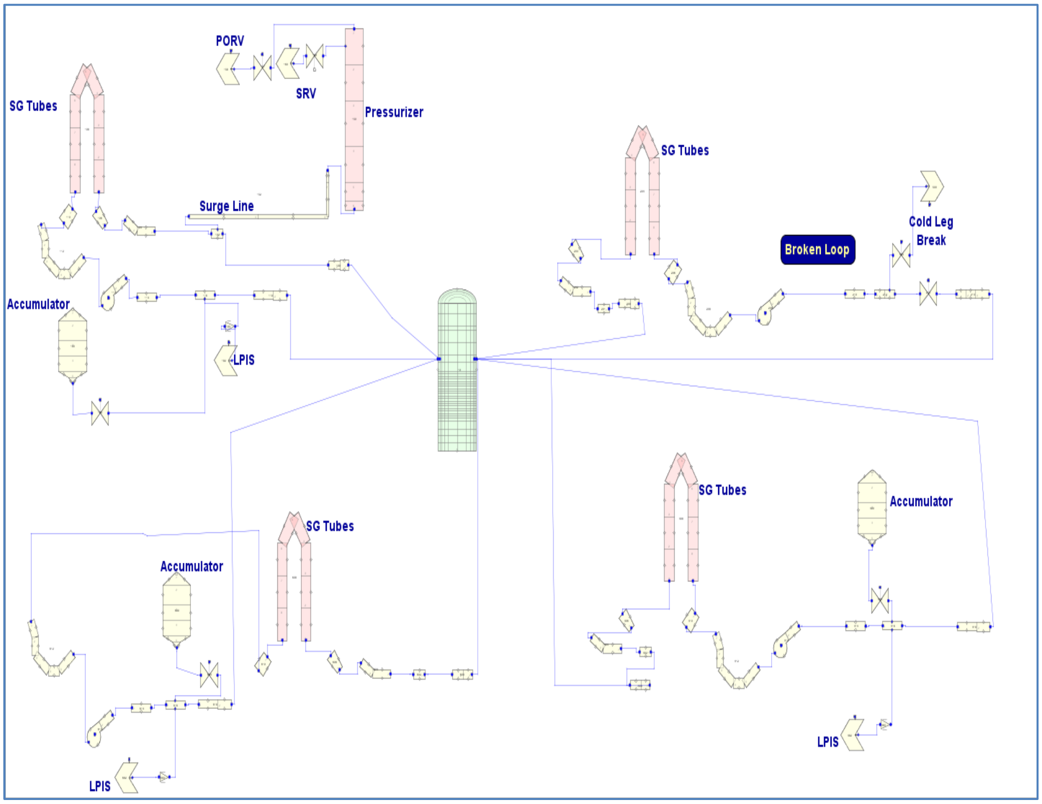

Figure 3 TRACE model of the ZION 4-loop PWR with LOCA accidental events

The first Peak Cladding Temperature (PCT) reached during bolwdown has a value of about 1000 [K], whereas the second larger PCT is reached during the reflood phase, about 170 [s] after the initiation of the transient. The threshold of the PCT not to be reached during the LBLOCA is set equal to 1477 [K].

For each simulation, a batch of values of the 23 input variables listed in Table 1 is sampled and the maximum PCT (i.e., PCT_{max}) reached during the transient is collected.

A pre-analysis of the available data has shown that an anti-correlation between the two outputs of PCT and time at which PCT_{max} (with a Pearson's Coefficient $R^2 = 0.86$) is to be considered. As in [Nutt et al., 2004], we have, thus, calculated the maximum allowed confidence β when $N = 96$ and $\gamma = 0.95$ with $\beta = 1 - 2\gamma^N + (2\gamma - 1)^N$ (for bracketing approach), resulting in 0.985 [Nutt et al., 2004]. Whereas (for the coverage approach), the confidence β is calculated with $\beta = 1 - \gamma^N - N(1-\gamma)\gamma^{N-1}$, resulting in 0.956 [Nutt et al., 2004] for two anti-correlated outputs.

As expected, with fixed N runs of a TH code, the Bracketing approach provides the percentile estimates with a larger confidence than compared to the Coverage approach. The point estimates of the percentiles obtained from Bracketing and Coverage approaches are given in Table 2. The safety threshold for the PCT is considered as 1204.45 [°C] (1477.6 [K]) [Kim et al., 2012] and the reference value of the PCT at nominal conditions has been taken as 760 [°C] (1033.15 [K]). The probabilistic safety margin is obtained using equation (8).

Input variables	*Description*	*Unit*	*Mean*	*Std. deviation*	*Dist. type*
S_1	Reactor core initial power	MW	3.250E+03	2.167E+01	*Normal*
S_2	UO_2 specific heat capacity	$\frac{J}{kgK}$	3.073E+02	2.049E+00	*Normal*
S_3	UO_2 thermal conductivity	$\frac{W}{mK}$	3.502E+00	1.167E-01	*Normal*
S_4	Reactor core power peaking factor	–	1.247E+00	2.078E-02	*Normal*
S_5	Hot gap size of the hot fuel rods	mm	5.400E-02	3.600E-03	*Normal*
S_6	Hot gap size of the reactor core	mm	5.400E-02	3.600E-03	*Normal*
S_7	Pressurizer water initial level	m	8.800E+00	3.333E-02	*Normal*
S_8	Surge line coefficient of friction	–	1.000E+00	1.000E+00	*Lognormal*
S_9	Pressurizer initial pressure	Pa	1.550E+07	3.333E+04	*Normal*
S_{10}	Accumulator initial pressure	Pa	4.160E+06	6.667E+04	*Normal*
S_{11}	Accumulator liquid initial temperature	K	3.251E+02	3.333E+00	*Normal*
S_{12}	Accumulator volume	m^3	3.890E+01	3.175E-01	*Uniform*
S_{13}	LPIS water mass flow rate	$\frac{kg}{s}$	8.800E+01	1.467E+00	*Normal*
S_{14}	LPIS water temperature	K	3.026E+02	4.792E+00	*Uniform*
S_{15}	Reactor vessel pressure	Pa	1.344E+07	2.327E+05	*Uniform*
S_{16}	LPIS delay	s	1.500E+01	8.660E+00	*Uniform*
S_{17}	Feed-water initial mass flow rate	$\frac{kg}{s}$	1.736E+04	2.314E+02	*Normal*
S_{18}	Cold leg initial temperature	K	5.650E+02	6.667E-01	*Normal*
S_{19}	Water initial mean temperature in the reactor upper header	K	5.680E+02	1.667E+00	*Normal*
S_{20}	Intact loops primary pumps rotational speed after LOCA	$\frac{rad}{s}$	7.684E+01	5.123E-01	*Normal*
S_{21}	Broken loop primary pump rotational speed after LOCA	$\frac{rad}{s}$	1.851E+02	6.171E+00	*Normal*
S_{22}	Reactor core power after SCRAM multiplier	–	1.000E+00	2.667E-02	*Normal*
S_{23}	Break section equivalent diameter	in	3.000E+01	5.774E+00	*Uniform*

Table 1: model input variables list with their associated distributions.

These results have been benchmarked with the results of the Best Estimate Methods - Uncertainty and Sensitivity Evaluation (BEMUSE) programme - phase VI [NEA 2011]] promoted by the Working Group on Accident Management and Analysis (GAMA) of OECD, on the same case study as the one considered in this Section. It can be concluded that the here estimated percentile of the PCT_{max} agrees with those given by the different participants of the BEMUSE consortium, although they have resorted to a much larger number of simulations (up to N=3000); also we add the information on the grace time before the estimated percentile of PCT_{max} is reached.
We have further compared these results with those presented in [Perez et al., 2008] and we can conclude that we improve them because in [Perez et al., 2008] only a point-estimate of the time at which the PCT_{max} is reached is given (equal to 252 [s]), whereas we provide the 5^{th} percentile of the distribution of the earliest time required to the safety parameter to reach the given percentile value (equal to 50.04 [s]): on one hand, by so doing we avoid to estimate a grace time as in [Perez et al., 2008], and, on the other hand, we keep under control the confidence on our grace time estimation, we gauge conservativism in the estimation of the available grace time and the risk associated to this.

	Bracketing approach		Coverage approach		Safety Threshold	Probabilistic safety margin
	Estimated Value	Real Value	Estimated Value	Real Value	-	-
95th percentile of PCT (in °C)	1190.91	1181.90	1190.91	1181.90	1204.45	0.030
5th percentile of time (s)	50.04	50.07	50.04	50.07	-	-
Confidence	98.55%		95.60%		-	

Table2 Point estimates of percentiles of PCT and time to reach PCT_{max} obtained using Bracketing and Coverage approaches

5. CONCLUSION

In this work, we address the problem of the estimation of dynamic probabilistic safety margin for taking into account the aleatory and epistemic uncertainties affecting the physical behavior of dynamic systems. We adopt using Order Statistics to jointly estimate percentiles of the distributions of the safety parameter and of the time required for the safety parameter to reach these percentiles values. This information, here originally provided within the framework of safety margin, is quite important in practice.

The computational framework has been applied to the ZION pilot case study considered in BEMUSE showing its practical applicability with a fixed (limited) number of TH code simulations: the Bracketing and Coverage approaches differ in achieving the same confidence level due to a larger computational burden of the coverage approach. It can be concluded that, using an optimal number of samples N as proposed by the OS theory, the point estimates of the percentiles of the distributions of a safety parameter and of the earliest time required for the safety parameter to reach this percentile can be computed for estimating the dynamic safety margins with a given confidence.

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