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Uncertainty and sensitivity analysis of a PWR LOCA sequence using parametric and non-parametric methods

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ABSTRACT

The Best Estimate Plus Uncertainty (BEPU) approach is being used worldwide for nuclear power plants licensing. This method relies on the use of best estimate models to simulate sequences, evaluating the uncertainties involved. To assess these uncertainties, several methodologies have been developed such as the non-parametric Wilks/Wald method, parametric methods that reconstruct a distribution from the data, or the binomial approach. Additionally, sensitivity analyses can be performed to obtain the correlation of the output-inputs. Finally, a variability analysis of the most influential parameters made to find a combination of parameters that can lead to damage is also useful. In this paper, all previous techniques are described, studied and applied by performing a large Monte Carlo set of simulations of a loss of coolant accident in a pressurized water reactor assessing two figures of merit. The comparison of the different methods show that the most conservative is the Wilks/Wald method; the least conservative is the parametric approach, and in between, the binomial one. The impact of the sample size is also studied for all methods, showing different behaviors for the different approaches.

1. Introduction

The analysis of transient and accidental sequences is a core aspect of nuclear safety. In order to evaluate a Nuclear Power Plant (NPP) behavior during an event, conservative approaches have been used worldwide since the 60s. These approaches involve conservative hypotheses and codes to obtain the plant response during an accidental sequence. The values obtained with this method are then compared against the acceptance criteria to assess the NPP response, e.g. the Standard Review Plan [1].

During the 80s, a Best Estimate (BE) approach to accident analysis and safety limits assessment was proposed, it was developed in an effort to create a licensing method that bring some benefits to the plants as it would be less demanding, see Fig. 1. This approach reduces the use of conservatisms, and provides more realistic values. However, to accept this approach for licensing, it is required that the uncertainties involving the accident simulation are identified and assessed so the uncertainty of the calculated results can be estimated. In the US, this was established according to the regulatory guide RG 1.157 [2] and later RG 1.1203 [3]. This approach was named Best Estimate Plus Uncertainty (BEPU) approach.

The BEPU development started in the US with the Code Scaling, Applicability and Uncertainty methodology, [4]. After the first successful application of this approach, other methods appeared such as GRS method [5], ASTRUM [6], TRACG-AOO [7] or UMAE [8]. Along time, it has been used in more than 75% of the PWR fleet in the US. A common element between all BEPU methods, is that they follow two main steps. The first is the identification and quantification of the input uncertainty, and secondly the quantification of the inputs uncertainty propagation on selected key output Figures of Merit (FoM).

The output parameters or FoMs assessed in BEPU and uncertainty analyses are normally selected because they are limited by the acceptance criteria for licensing. In this aspect, the most common FoMs are Peak Cladding Temperature (PCT), Local Maximum Oxidation (LMO), core wide oxidation, primary system pressure, fuel enthalpy, minimal critical power ratio and suppression pool temperature.

In order to assess the uncertainty of the calculations, the different methodologies have different approaches. One of the most successful in terms of usage and reliability is the consideration of non-parametric tolerance limits for the FoMs, based on the works of Wilks and Wald [9]. The first nuclear safety analysis methodology that established this basis was the GRS method, [10], which was later followed by other countries and institutions [11]. This approach is based on non-parametric statistics and relies on the simulation of dozens or hundreds of simulations of the same event to obtain a confidence interval for the desired FoM. Several recent examples of non-parametric analysis can be found in the literature [12,13]. Besides non-parametric techniques, there are methodologies that use parametric methods such as TRACG-

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Nomenclature

BEPU	Best Estimate Plus Uncertainty
BE	Best Estimate
CDF	Cumulative Distribution Function
DEGB	Double Ended Guillotine Break
FoM	Figure Of Merit
GoF	Goodness Of Fit
LBLOCA	Large Break Loss of Coolant Accident
LMO	Local Maximum Oxidation
NPP	Nuclear Power Plants
PWR	Pressurized Water Reactor
PDF	Probability Density Function
PRCC	Partial Ranked Correlation Coefficient
PSA	Probabilistic Safety Assessment
PCT	Peak Cladding Temperature
RCS	Reactor Cooling System
SI	Safety Injection

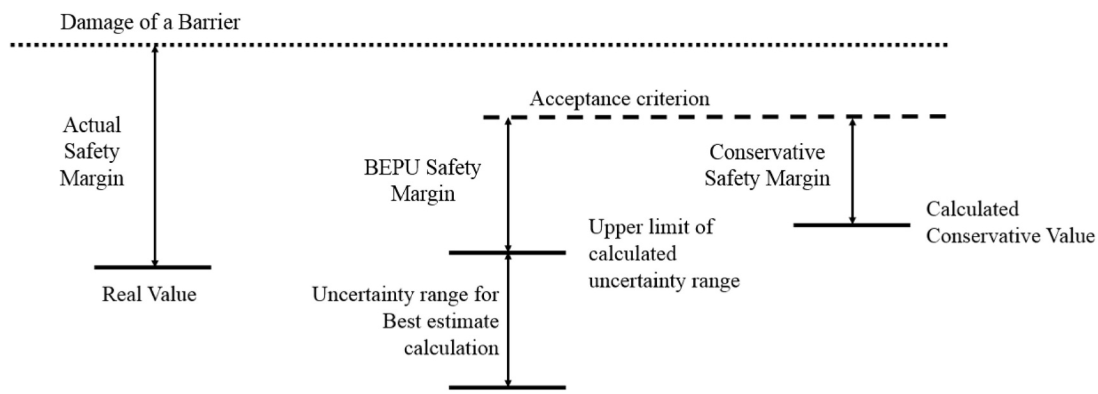

Fig. 1. Safety Margins and calculated values.

AOO, TRACG-ATWS or TRACG-LOCA [7,14]. In these approaches, the FoM are tested for normality through Goodness of Fit (GoF) tests and, if succeed, the data is analyzed extracting information from the reconstructed normal distribution. If the data does not fit a normal distribution, non-parametric methods are used instead. Examples of these methods can be found in the recent literature, [15–17].

The uncertainty analysis have been applied in many areas of nuclear safety. For Deterministic Safety Analyses (DSA) in NPP licensing, BEPU methodology has been applied for many reactor power uprating, see [18]. Additionally, this kind of methodologies has also been applied to uncertainty estimation of computational simulations relative to experimental results, [5,19–21]. Moreover, it has been used in order to obtain the safety margin in Probabilistic Safety Assessment (PSA) applications e.g. SM2A exercise, [22].

In addition to uncertainty analysis, a sensitivity analysis is a valuable tool to study the sequence [23]. These analyses allow to study how the uncertainty in an output of a model can be apportioned to different sources of uncertainty in the model input, i.e. the derivative of the FoM (output) with respect to the input [24], as studied in recent references, [25,26].

The present paper presents an uncertainty analysis of an accidental sequence in a Pressurized Water Reactor Westinghouse design (PWR-W) with the TRACE code. The sequence is a Large Break Loss of Coolant Accident (LBLOCA), and the analyzed FoMs are PCT and LMO. These variables are relevant as they limited by the acceptance criteria. Additionally, the present research has focused on both parametric and non-parametric studies of the data obtained. The non-parametric Wald method is used, but the FoM results are also interpreted as a binomial distribution, and Probability Density Functions (PDFs). The present paper compares these three approaches, and is able to present how the parametric and non-parametric results vary with the sample size of the Monte Carlo. Finally, a sensitivity analysis is also performed to complete the analysis including a damage domain search. This is, varying the most influential input parameters in order to find the combinations of those that lead to damage, identifying that region and then calculate the probability.

The present paper is divided into six sections. The second section contains a description of the TRACE code and model. The third section analyzes the Base Case for the LBLOCA in a PWR. The fourth section contains all the simulation results, the parametric and non-parametric uncertainty analyses of the results, and a discussion on the sample size. The fifth section is dedicated to the sensitivity analysis and the parameter influence assessment including a damage domain development. Finally some conclusions are drawn at the end of the article.

2. TRACE PWR-W model

The NPP model corresponds to a PWR-W with 3 loops, with a nominal power of 2900 MWt. The main characteristics of the TRACE model are shown in Table 1 and the Reactor Cooling System (RCS) nodalization is shown in Fig. 2. The core data corresponds to the beginning of the cycle, Xenon equilibrium, with all the control rods out, operating at full power and with a burn-up of 1000 MWd/tU. The version of the code used for the present study is TRACE5 Patch 4, [27].

The present model has been validated against steady state, load rejections and several SCRAM transients performed with TRACE5 Patch 4. It has been used in many analyses, see, [28–30]. It is important to mention that the model validation process is a significant requirement

Table 1
PWR-W TRACE model Components.

Vessel components	Pipes	TEEs	Valves	Pumps	Fills
2	67	41	58	3	12
Breaks	Heat Structures	Power Components	Signal Variables	Control Blocks	Trips
35	56	3	762	1671	69

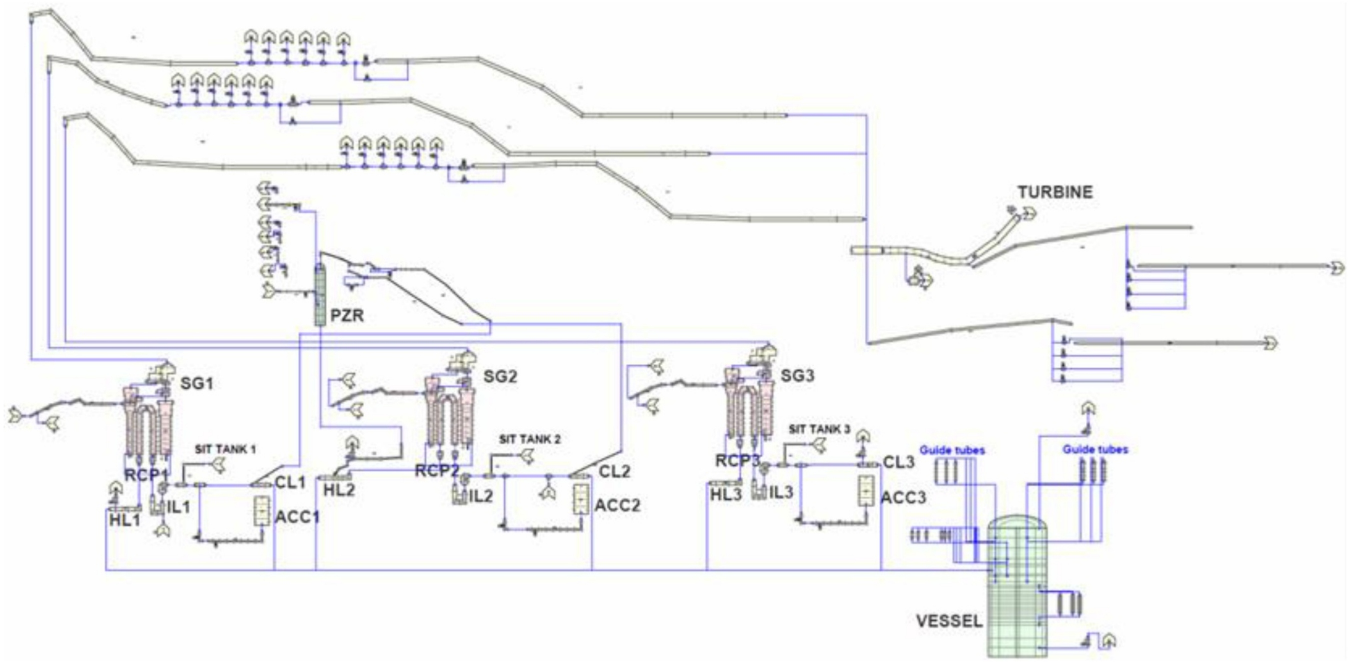

Fig. 2. Full-plant TRACE model visualized with SNAP mask.

for any uncertainty analysis in order to not misinterpret variations in the output corresponding to model errors instead of input variations.

3. Base case LBLOCA

The selected Base Case corresponds to a Double Ended Guillotine Break (DEGB) LBLOCA with loss of offsite power but without another system failure. At the beginning of the sequence, the DEGB LBLOCA induces a fast depressurization of the Reactor Coolant System (RCS), leading to the reactor trip and the Safety Injection (SI) signal. Then, the PCT increases rapidly as the cooling capability in the core is partially lost, Fig. 3. The first temperature peak occurs 6 s after the break during this blowdown phase. After this phase and during the refill and reflood phases, the upper regions of the core are still uncovered, so its temperature rises again leading to the second maximum. The cladding oxidation occurs mainly during this period, 40–60 s after the break, see Fig. 3 (right). Later, during the reflood phase, the temperatures decrease steadily until the quenching has been completed and long term cooling is achieved.

As commented above, with regards to the regulatory requirements under LOCA conditions; the PCT shall not exceed 1477 K and the LMO shall nowhere exceed the 17% of the total cladding thickness before oxidation. In this case, the PCT corresponds to 1169.03 K, lower than 1477 K and a final LMO of 1.689%, see Fig. 3.Therefore, the acceptance criteria are satisfied with a large margin on both limits. However, a confidence interval (95/95) for these values is necessary to comply with the common regulatory requirements; this is studied in the next section.

4. Monte Carlo sampling and uncertainty analysis of a LBLOCA

In this section, the Monte Carlo sampling of the uncertain parameters for the DEGB LOCA is depicted. The list of the input parameters subject to uncertainty is presented in addition to the different analysis of the results obtained. The present uncertainty analysis follows the regular steps: determination of input uncertainties, selection of the sample size, Monte Carlo random sampling of the input parameters, run the simulations, set the confidence level, and finally determination of the tolerance limits from the results obtained; these last two aspects are covered in Sections 4.1–4.5. The uncertainty analysis has been performed by means of parametric and non-parametric approaches stemming from a Monte Carlo random sampling of the uncertain input parameters. These two approaches are explained and applied later in the following sections.

For the first step, a large set of parameters were identified from

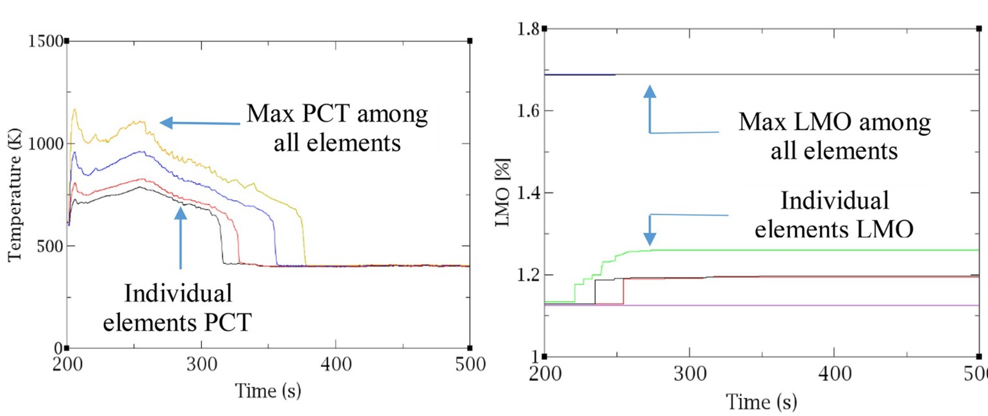

Fig. 3. PCT (left) and LMO (right) of the Base Case.

previous LBLOCA studies, including their associated state of knowledge and its quantification in the PDFs [19,21,26,31–37]. Moreover, the phenomena related to the sequence were identified through the LBLOCA PIRT, see [38,39]. Afterwards, and by means of the literature sensitivity analyses see [10,40–42] the parameters and phenomena with a significant relevance were also selected.

Finally, 25 uncertain parameters complete the set employed in the analyses. The parameters chosen cover different uncertainties: Initial and boundary conditions (BC), thermal-hydraulic (TH), thermo-mechanical (TM) and geometrical uncertainties (GU); they are shown along with its range in Table 2.

The Monte Carlo sampling of the uncertain parameters has been accomplished by using DAKOTA software [43] with TRACE5 Patch4 code within the SNAP platform. The total number of simulations run is 1020, and the FoM assessed are the PCT and the LMO.

The evolution of the PCT and the LMO for the 1020 code runs is shown in Figs. 4 and 5. Comparing the simulation with the acceptance criteria, none of the cases surpasses 1477 K and only one exceeds the LMO limit of 17%. It is remarkable that the maximum PCT and maximum LMO correspond to different cases. Despite their direct and strong correlation, the maximum PCT and maximum LMO values do not necessarily need to belong to the same case, as seen in [32,44]. The highest PCT obtained is 1432 K which develops a LMO of 4.42%, meanwhile the highest LMO exceeds the regulatory limit and reaches 17.74% with a PCT value of 1259 K. The primary system pressure is very similar for all simulations; only small differences during the pressure decrease can be observed, see Fig. 6.

4.1. Non-parametric approach: Wilks/Wald method

Among the exisiting uncertainty analysis methodologies, the first method applied is the Wilks non-parametric, as it is one of the most widespread of the nuclear analyses, [10]. Based on Wilks and Wald statistical works, [9], this statistic method can be interpreted as the following: *"Given a set of measurements (N) of a sample, those are ordered from lowest to highest with the highest value being L. If this set of N measurements is repeated ad infinitum, on β% of the times this set of measurements is done (confidence level, β), the γ% of the set measurements (percentile content, γ) will be lower than the initial highest value obtained (L)."*

Moreover, this restriction can be provided not only for the highest value, but also for the second, third and subsequent highest values (order *p*). Loosely speaking, if all *N - p + 1* simulations are below the regulatory limit, one can be β% confident that at least γ% of the combined influence of all the characterized uncertainties are below the regulatory limits.

A fundamental advantage of using Wilks method is that it has no limit on the number of uncertain parameters considered in the analysis, and the number of code runs required in the analysis only depends on the statistical features of the tolerance limits imposed (amount of percentile contained, confidence level and order) and not in the amount of the uncertain parameters.

When the number of FoMs (*R*) is greater than one, as it is the case of this analysis, (PCT and LMO), the multi-variable approach of the Wilks formula obtained by Wald can be used, [45,46]. The relationship between these parameters, *N*, β, γ, *R* and *p* is established in the previously mentioned works, and is shown in Eqs. (1) and (2), where d_i is the number of bounds of the FoMs (upper and/or lower).

$$\beta = \sum_{j=0}^{N-R^*} \binom{N}{j} \gamma^j \cdot (1-\gamma)^{N-j} \tag{1}$$

$$R^* = p \cdot \left(\sum_{i=1}^{R} d_i \right) \tag{2}$$

Numerically, the one sided confidence interval 95/95 criteria for two FoMs is limited by the highest value of a sample of 93 code simulations for first order, see Table 3. From the 1020 simulations performed in the present analysis, and setting β and γ to 95/95, the Wald criterion corresponds to $p = 20$ order, which means that the 20th highest value would be higher than the 95% percentile with at least 95% confidence level. As these values of LMO and PCT are both below the acceptance criteria, the 95/95 regulatory requirement would be fulfilled.

Alternatively, the data can be used in the formula with a lower order; then a higher probability content and confidence level can be obtained. Given that only one sample exceeded the acceptance criteria, a value of $p = 2$ is acceptable. Given the 95% confidence required by the regulatory bodies and second order, a 99.23% of the probability content can be achieved so the probability of exceedance the acceptance criteria will be less than 0.77%.

4.2. Binomial distribution approach

The Wald criterion applied to PCT and LMO is not the only possible non-parametric interpretation of the results. Following the discussions in [45–47], the authors have continued the analysis by evaluating the data as a binomial distribution with two states (acceptance criteria meet/not meet). On each case, the resulting PCT and LMO are compared against the associated acceptance criteria limit, and only two possible outcomes are obtained: failure or success.

As shown in Fig. 7, a PCT-LMO region is defined, where the cases succeeding the acceptance criteria (the ones below LMO and PCT limits) are easily identified. As stated above, in this analysis only one case has exceeded the 17% LMO.

Along with the failure mean value (1 case out of 1020), a confidence interval can be obtained for this approach. Amongst the existent confidence intervals, the Clopper–Pearson interval has been selected. This method is not only a derivation from the binomial distribution, but also guarantees that the coverage probability is always equal to or above the nominal confidence level. In this regard, following the 95% one-sided confidence limit results in 0.464% exceedance probability. The values of the Clopper–Pearson confidence interval would be the same than the

Table 2
Uncertain parameters and range.

Number	Parameter	Normalized range	Distribution	Group
1	Break discharge coefficient	(0.86, 1.14)	Normal	TH
2	Initial Core Power	(0.98, 1.02)	Normal	BC
3	Decay Heat	(0.92, 1.08)	Normal	BC
4	Power peaking factors	(0.95, 1.05)	Normal	BC
5	Forced Convection HTC	(0.746, 1.254)	Normal	TH
6	Film Boiling HTC	(0.6272, 1.3728)	Normal	TH
7	Transition Boiling HTC	(0.702, 1.298)	Normal	TH
8	Critical Heat Flux	(0.644, 1.356)	Normal	TH
9	Accumulator Pressure	(0.955, 1.045)	Normal	TH/BC
10	LPSI mass flow factor	(0.95, 1.05)	Normal	TH
11	RCP broken loop speed	(0.9, 1.1)	Normal	TH
12	RCP intact loop speed	(0.98, 1.02)	Normal	TH
13	Gap conductance	(0.8, 1.2)	Normal	TM
14	Cladding inner radius	(0.995,1.005)	Normal	GU
15	Cladding thickness	(0.93, 1.07)	Normal	GU
16	Pellet radius	(0.998, 1.002)	Normal	GU
17	Fuel density	(0.99, 1.01)	Normal	TM
18	Fuel thermal conductivity	(0.85, 1.15)	Normal	TM/TH
19	Burst temperature coefficient	(0.908, 1.092)	Normal	TM
20	Metal-water reaction coefficient	(0.94, 1.06)	Normal	TM
21	Containment pressure	(0.85, 1.15)	Uniform	BC
22	Accumulator Temperature	(0.97, 1.03)	Uniform	BC
23	Gap pressure	(0.9, 1.1)	Uniform	TM/BC
24	Burst Strain	(0.2, 1.6)	Uniform	TM
25	Oxide layer	(0.6, 1.4)	Uniform	BC/TM

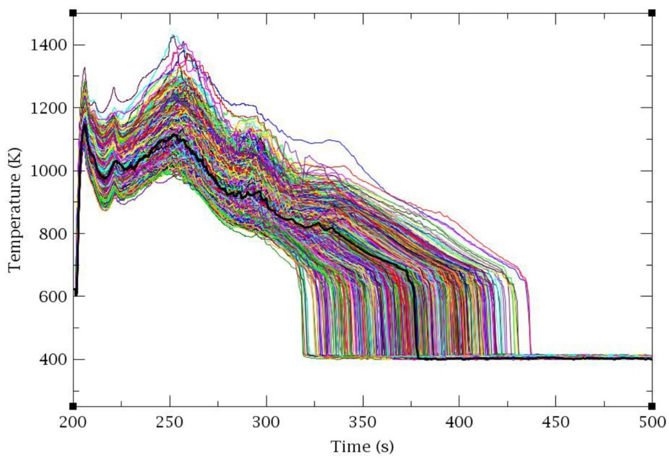

Fig. 4. PCT of the 1020 Monte Carlo simulations.

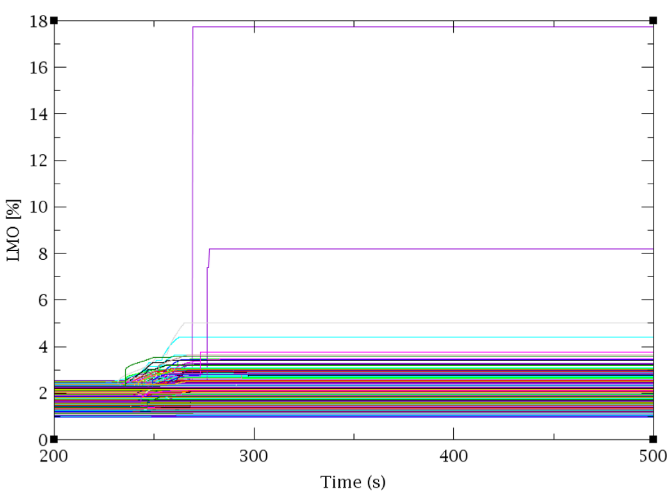

Fig. 5. LMO of the 1020 Monte Carlo simulations.

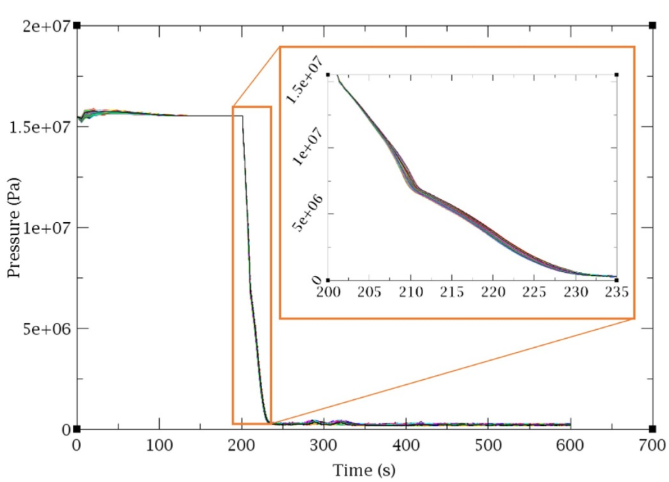

Fig. 6. Primary System Pressure of the 1020 Monte Carlo Simulations.

ones obtained by Wilks method of a single variable, as in fact they are equivalent methods.

4.3. Parametric approach: distribution fit

Part of the robustness of the non-parametric methods is that they assume that the function they are analyzing can have any shape, it only requires the hypothesis of continuity. However, after performing a large set of measurements, a PDF of the observed value can be reconstructed with certain degree of goodness, and it is possible to analyze the data by analyzing the reconstructed function. For example, BEPU TRACG methodologies apply this approach to verify certain acceptance criteria (e.g. Pressure, CPR) by testing the results against normality, and if succeed, the confidence intervals are obtained using properties of the normal distribution, [7,14].

Table 3
Example values of the minimum samples for FoMs and one sided tolerance limit.

β	γ values 0.95	0.99	p
0.95	93	473	1
	153	773	2
	208	1049	3
	…	…	…
	1013	5088	20
0.99	130	662	1
	198	1001	2
	259	1307	3

As part of the analysis, two different PDFs, one for the PCT and other for LMO have been determined. The PDFs are determined independently for each FoM due to the complexity of obtaining a reliable joint PDF for PCT and LMO. In the present study, the results have been tested through Anderson-Darling GoF test, against 60 different distributions. The GoF test and PDF reconstruction have been performed using the statistical tool EasyFit [48].

For the PCT, the best fit corresponds to the Johnson SU distribution. The exceedance probability of the acceptance criteria can be obtained by means of the integration of the PDF curve beyond the 1477 K limit, see Fig. 8. The calculated value for PCT exceedance is 2.67E-04. However, this value lacks of a confidence interval necessary to fulfill the regulatory requirement, so further work is needed.

Following the same procedure, a function has been reconstructed for the LMO. In this case, the best fit is the 4-Parameter Dagum distribution. Despite the single case beyond the LMO limit, the calculated probability for acceptance criteria exceedance is as low as 1.5E − 07, see Fig. 9. The reason can be deduced from the LMO histogram, as almost the complete set of LMO values fall into the 1%–4% range, far from the 17% acceptance criterion.

In order to test the accomplishment with the 95/95 criterion, it is necessary to determine a tolerance interval from the PDFs: Johnson SU and Dagum 4P. To do so, there are methods based on the probability-box concept [49], which is based on the calculation of statistical limits for the real and unknown Cumulative Distribution Function (CDF). In this method, the selected model CDF is evaluated on the all possible combinations of the confidence intervals of the model parameters which can be obtained more precisely by means of the Log-Likelihood Ratio statistic test, the Wald method or the Lagrange Multiplier test [9,50]. These methods rely on the analytic formulation of the profile likelihood from the Maximum Likelihood function or its normal approximation.

The likelihood formulation become complex because of the analytic expression of the Johnson SU and Dagum 4P PDFs as a large number of dependences appear. For this reason, the Bootstrap method, even though it is more computationally demanding, is found the most appropriate to calculate the confidence intervals for the present research. The bootstrap method is able to provide approximate confidence intervals for the 95% probability region limit using re-sampling techniques of the data. The key idea is to perform computations on the data itself to estimate the variation of statistics that are themselves computed from the same data, [51]. The upper limit obtained will limit the 95/95 tolerance interval.

Fig. 7. Acceptance Region of PCT and LMO relative to all simulations.

In the present research, the nonparametric bootstrap resampling with the simple percentile method has been used, [9,52]. In this method, $B = 1000$ bootstrap samples have been extracted for both PCT and LMO. Each bootstrap sample contains 1020 values taken from the original sample with replacement. Then, all those samples have been adjusted to the correspondent Johnson or Dagum distribution and the probability of exceeding the acceptance criteria has been retained. The probabilities obtained range from 7.0E − 06 to 9.0E − 03 for PCT and 1.0E − 09 to 8.0E − 06 for the LMO, see Fig. 10. Then, the 95th higher percentile of the 1000 different values is used, and it corresponds to the limit of the 95% one-sided empirical approximated confidence interval of exceeding the acceptance criteria. Then, the obtained probability of exceeding 1477 K with a 95% confidence is 6.00E − 04, the probability of exceeding the 17% of LMO is 1.02E − 06, and therefore, the joint probability is 6.01E − 04.

As commented above, to obtain the confidence interval for the probability of exceeding the acceptance criteria, the Maximum likelihood estimate-ratio test method can also be used to estimate the PDFs parameters. Then, to remark differences between methods, the Maximum Likelihood Estimate ratio has been applied using Burr distribution for the PCT. The Burr distribution is not the best adjustment to the PCT, but it passes the GoF tests and the likelihood-ratio method can be applied. The probability of exceeding 1477 K by the Burr distribution is 3.36E − 04. This value is very similar to the one obtained with the Johnson SU distribution. However, the probability for the Burr whose parameters are equal to the upper 95% confidence interval limits is 3.1E − 03, higher than the Johnson SU, but also lower than the non-parametric Wald and binomial approaches.

It is necessary to comment, that in this parametric analysis, there is little or no data of values next to the acceptance criteria; then the distribution is reconstructed based mainly from data separated from the 95th percentile, but then the PDFs are used to extract information of the region we had initially scarce information about. This provokes that some results are very dependent on the distribution selected.

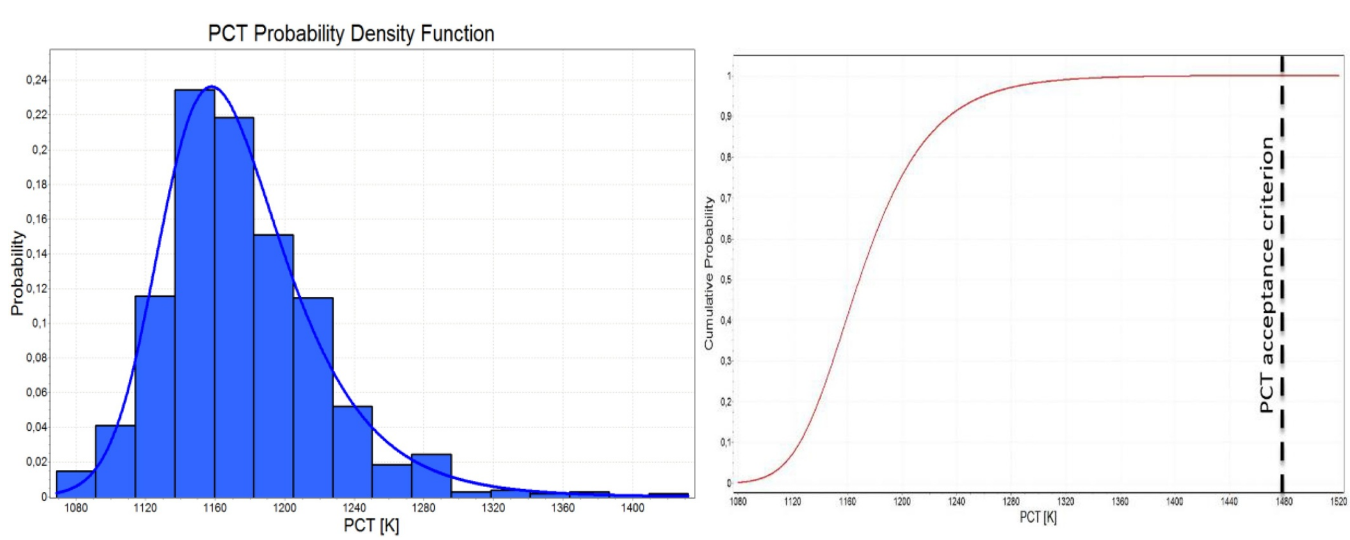

Fig. 8. PCT Johnson SU probability distribution, density (left), and accumulated (right).

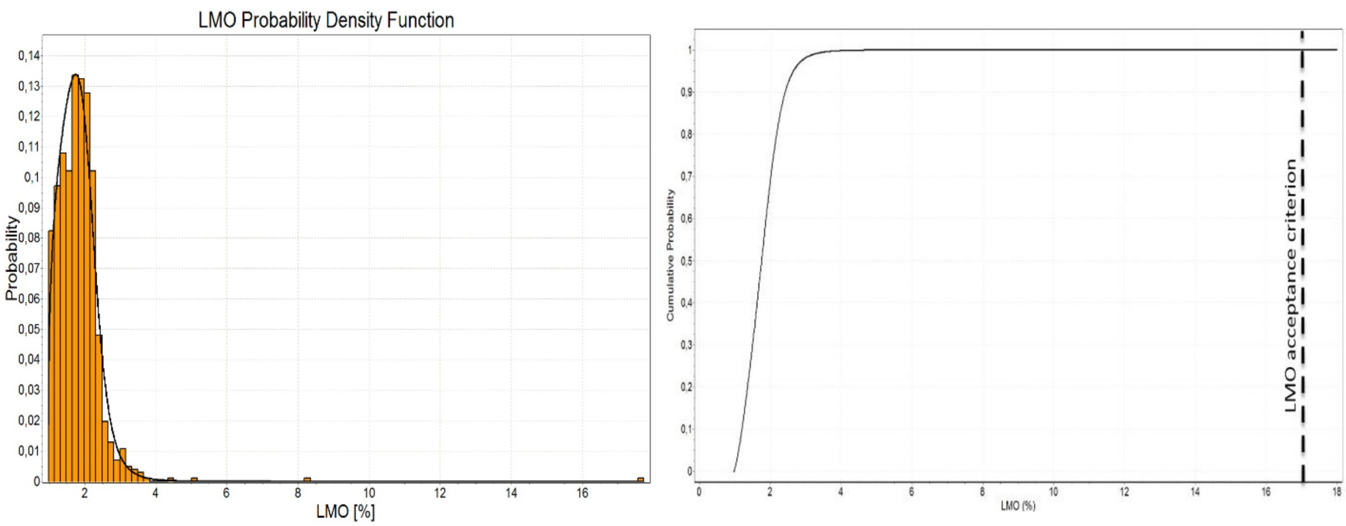

Fig. 9. LMO Dagum 4P probability distribution density (left), and accumulated (right).

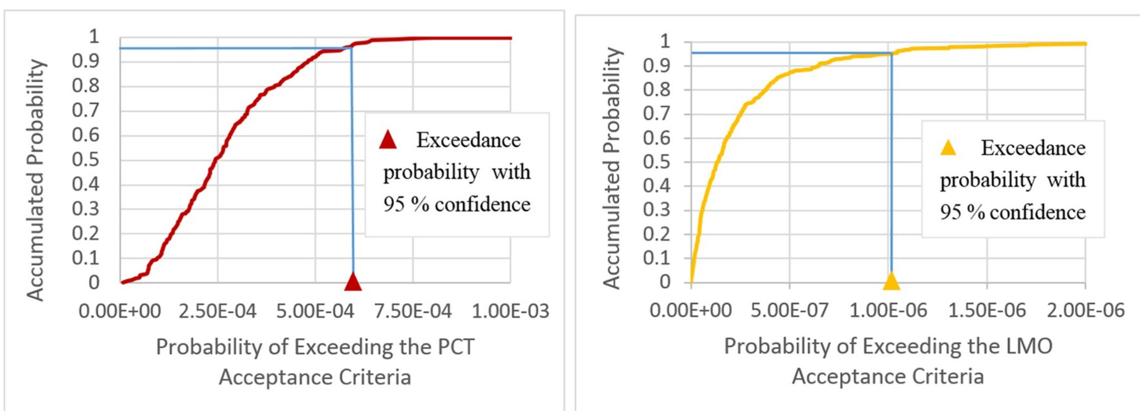

Fig. 10. CDF of the exceedance of the 1000 Bootstrap samples for PCT (left) and LMO (right) acceptance criteria.

4.4. Results discussion: comparison of non-parametric and parametric statistics

Once the non-parametric and parametric analysis have been applied to the results, a comparison between these approaches can be presented, see Table 4. Comparing the three methods, the most conservative approach for these results is the non-parametric approach, and the least conservative would be using the distribution fit approach, proving the Wald method conservative for the regulatory limits.

The safety margins of the different methods are also obtained, comparing the 95% confidence upper limit of the 95th percentile against the acceptance criteria, see Table 5. It is remarkable that the safety margin obtained with the Maximum Likelihood Estimate-ratio method is lower than the non-parametric or the parametric adjustment with Bootstrap confidence interval. This reinforces the comment made in the previous section, which highlights the variability induced by the distribution in the parametric analysis.

4.5. Sample discussion: parameters convergence

In this section, the properties of the sampling are studied along the number of simulations obtained. This approach is interesting from the industry/regulator point of view, as it is possible to observe which limit would have been obtained if instead of 1020, the number of simulations would have been considered sufficient at a lower number.

Observing Figs. 11 and 12, it is seen that the mean, the highest 95th, and the lowest 5th percentile of PCT/LMO converge in a rapid manner to a stable value after 100 simulations. Besides, the 95th percentile is always lower than the bounding value obtained by Wilks/Wald formula increasing the order as more results are obtained. It is also remarkable that both PCT and LMO bounding values found through Wilks/Wald do not behave monotonically. Even though this is statistically probable, it is notable that even at high statistic orders some bounds increase with the number of simulations.

The previous results depend on the order on which the results have appeared in the Monte Carlo sampling. To erase this dependency, 500 different sets of the 1020 runs have been created with a random order and analyzed under Wald criterion see Figs. 13 and 14. When the statistical fluctuation of a single sampling order is erased, the mean of the Wald tolerance interval decreases monotonically for PCT and LMO with an increasing order. Additionally, there is a large difference between low and mid-high statistical orders. This reinforces the idea that it is better to approach higher statistical orders, than increase the

Table 4
Summary of probability of exceedance and confidence level.

Method	Confidence Level	Probability of Exceedance
Non-parametric Wald	95%	0.77%
Binomial with Clopper Pearson	95%	0.46%
Distribution Fit to Johnson SU and Dagum 4P with Bootstrap Confidence interval	95%	0.06%

Table 5
Summary of the Safety Margins of the 95th percentile and 95 confidence for different approaches.

Method	Safety margin PCT	Safety margin LMO
Non-parametric Wald	185 K	13.93%
Distribution Fit to Johnson SU and Dagum 4P with Bootstrap Confidence interval	208 K	13.98%
PCT Distribution fit to Burr with MLE for Confidence Interval	165 K	N/A
Empirical 95th Percentile	219 K	14.42%

confidence level [12,53]. In the study of [54], it was concluded than using the full Monte Carlo (or the highest order) was beneficial as the chance of underpredicting the true 95th percentile is reduced. Observing the 95th percentile, it is seen that it has a quicker convergence, and narrower width than the Wald bounding value. In the case of LMO, this is exacerbated as the majority of the simulations fit in a narrow range of values.

Taking into account the regulator point of view, it is interesting to compare the three methods probability of exceeding the damage for 95% confidence along the 1020 simulations. This evolution is likely to be useful in balancing the efforts to augment the safety margins with a BEPU approach. For this reason, the behavior of the probability of exceedance with 95% confidence of the Wald, binomial and parametric approaches are shown in Fig. 15. As expected, the binomial method with a Clopper–Pearson confidence interval is lower than the one obtained by Wald, before and after finding the case of damage.

In order to obtain the values of the parametric analysis, 1000 bootstrap samples are created using the first 93, 210, 350 and 515 values. The parametric approach provides exceedance values even lower, but they also have a drawback. For less than 515 cases, this method is not adequate because the distribution fitting cannot be always achieved, as it is rejected by the GoF tests. In this particular case, the Dagum 4P distribution is able to fit all the bootstrap samples neglecting the rejection hypothesis, but the Johnson SU distribution cannot fit the majority of the bootstrap samples from $N = 93$ to $N = 515$ and therefore its probability is undetermined and not shown in Fig. 15. For a low number of samples, the Dagum 4P distribution provides values for exceeding the acceptance criteria of 0.1%, which is much higher than the value obtained with 1020 simulations.

5. Sensitivity analyses

This section describes the sensitivity analyses of the input parameters. As already mentioned, once the uncertainty analysis has been performed, a sensitivity analysis has been carried out as recommended by IAEA [55]. This analysis is conducted in order to observe the influence of the uncertainty in certain individual input parameters to the uncertainty results, as well as their correlation. A great variety of techniques and approaches are found in the literature involving increasing levels of complexity and number of code runs associated [56]. In this work a global analysis that allows to observe correlations between inputs and outputs has been performed. Then, the most influential parameters will be deeply studied in a local sensitivity analysis, searching for a damage domain.

5.1. Global sensitivity analysis

In this work, a global sensitivity analysis has been performed in order to consider all input parameters simultaneously. The ranked or Spearman correlation coefficient is initially calculated, and then the Partial Rank Correlation Coefficient (PRCC), [24] is used to assess the correlation of the inputs and FoMs.

Correlation coefficients range from -1 to 1; the closer to these values, the higher the correlation between the input and outputs. A negative value in the correlation coefficients indicates that the input parameter and the output response are inversely proportional.

In order to identify the most influential parameters using the PRCC values another criterion is needed. As stated by NEA, [57], a significance threshold corresponding to a desired confidence level can be

Fig. 11. Convergence of PCT percentiles, Wilks and Wald bounding Values.

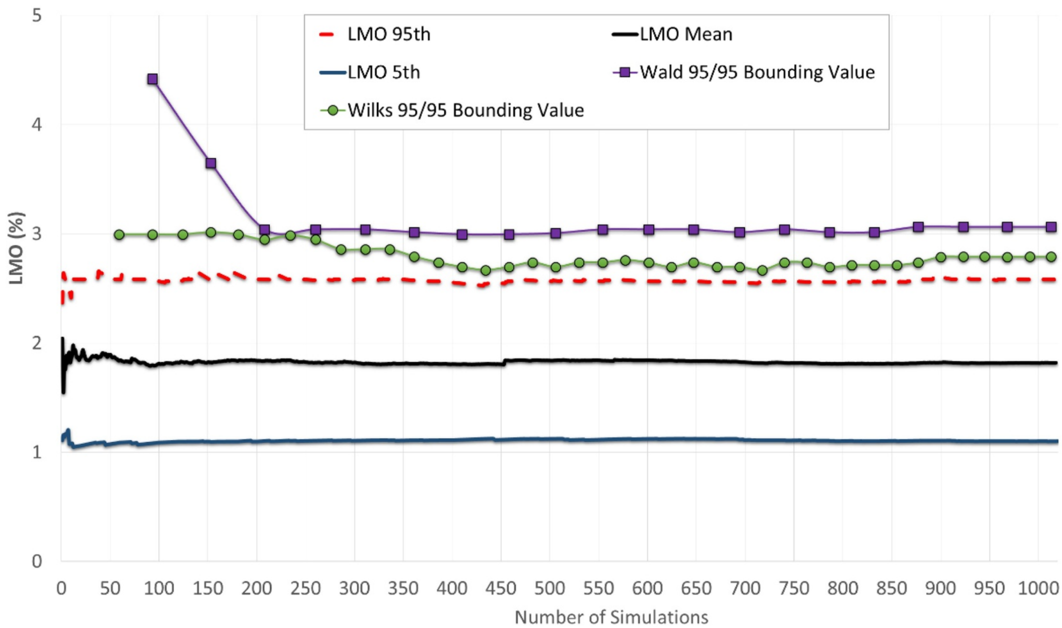

Fig. 12. Convergence of LMO percentiles, Wilks and Wald bounding values.

set and a parameter is considered influential as soon as its PRCC in absolute value is larger than the significance threshold. The threshold decreases with the number of samples and increases with the confidence level requirement, see Table 6.

A confidence level threshold of 95% have been chosen, which relative to 1020 code runs corresponds to a values 0.051 for PRCC as shown in Table 6. The parameters meeting this threshold requirement for the PCT are related to the cladding-coolant heat transfer coefficients, fuel thermal behavior, the break discharge coefficient together with the cladding inner radius and fuel density. Amongst this group the most influential ones are the Fuel Conductivity (−0.77), forced convection HTC (−0.73), break discharge coefficient (0.70), Critical Heat Flux (−0.65), Power Peaking Factors (0.65) and film boiling HTC (−0.56), see Table 7. Due to the inherent relation between the PCT and the LMO, the group of influential parameters are alike. Instead of the cladding inner radius and fuel density, the cladding thickness (−0.29), rod burst temperature coefficient (−0.25) and especially the initial oxide layer, are the most influential parameters (0.91). Again, forced convection HTC (−0.36), break discharge coefficient (0.25) and film boiling HTC (−0.45) stand out due to its influence, see Table 7.

In order to assess the accuracy of the sensitivity analysis, the sum of the squared ranked correlation coefficients ($\sum RCC_i^2$) has been calculated. Each RCC_i^2 gives an estimate of the contribution of the input to the outputs variance, and a value of $\sum RCC_i^2 = 1$ would mean that the variance is totally explained. In non-monotonic or non-additive

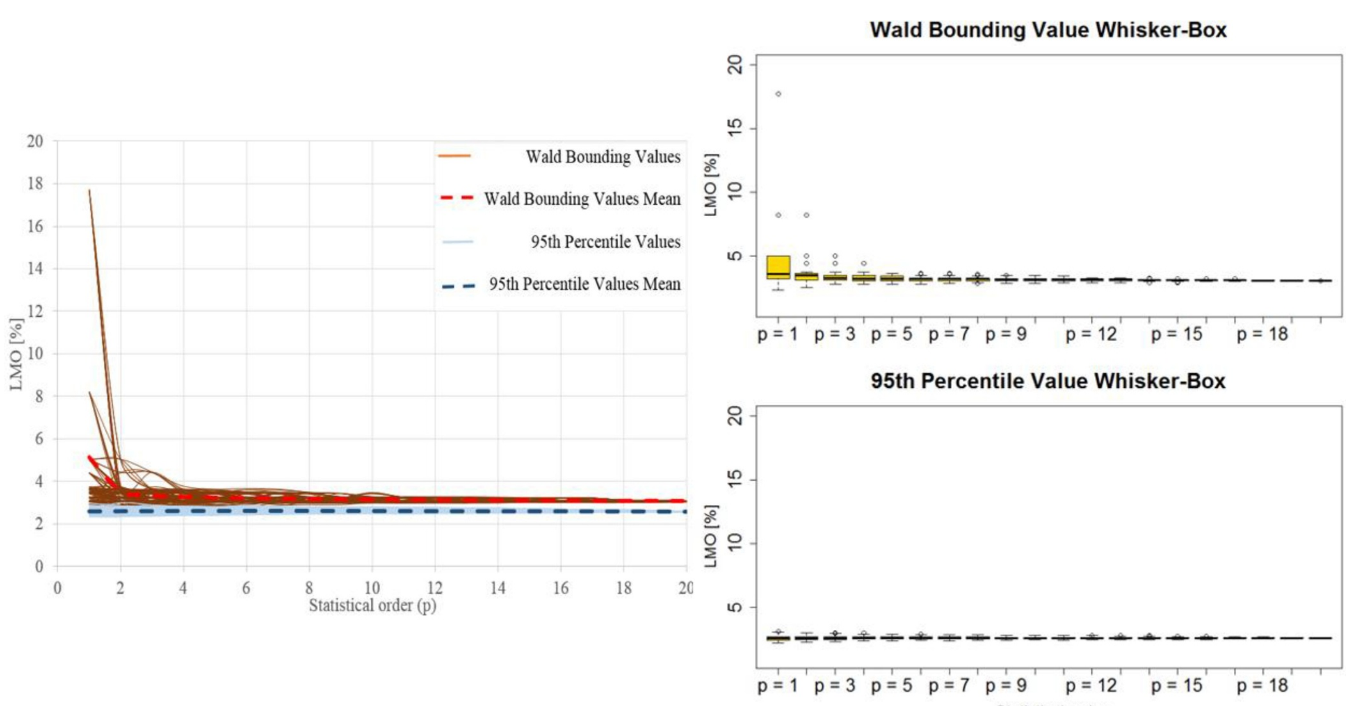

Fig. 13. PCT Wald bounding value and 95th percentile values for different statistical orders.

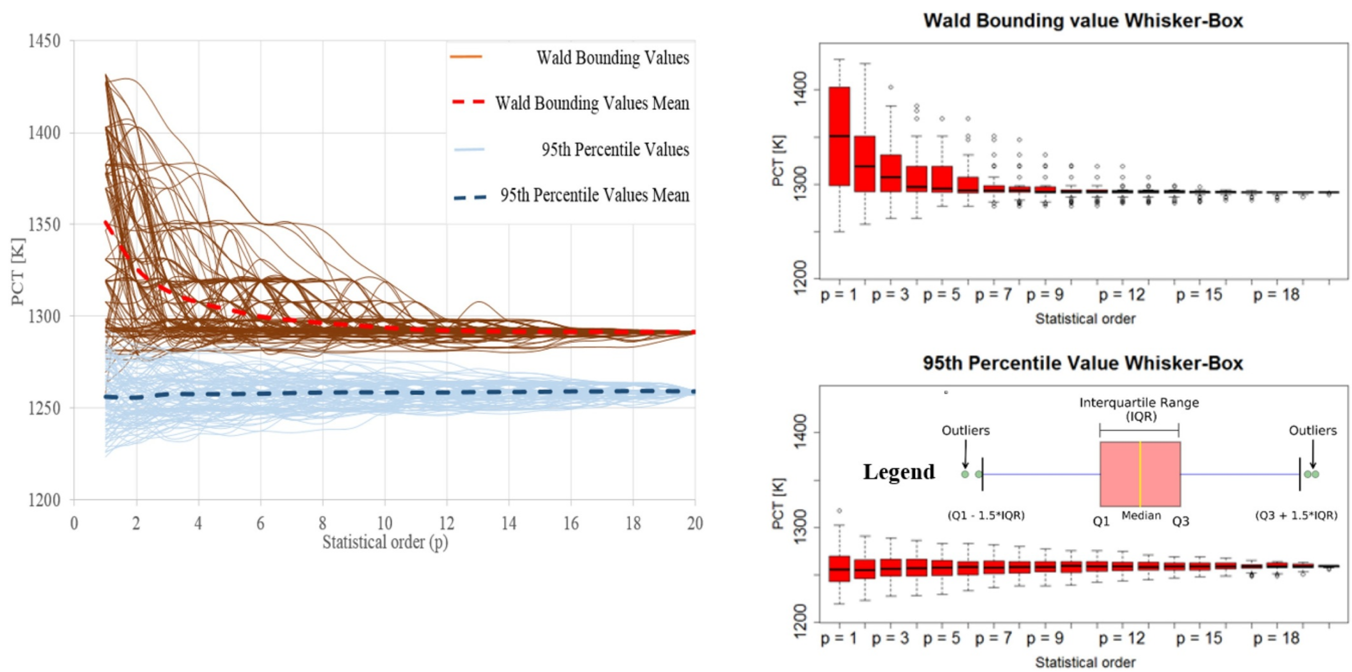

Fig. 14. LMO Wald bounding value and 95th Percentile values for different statistical orders.

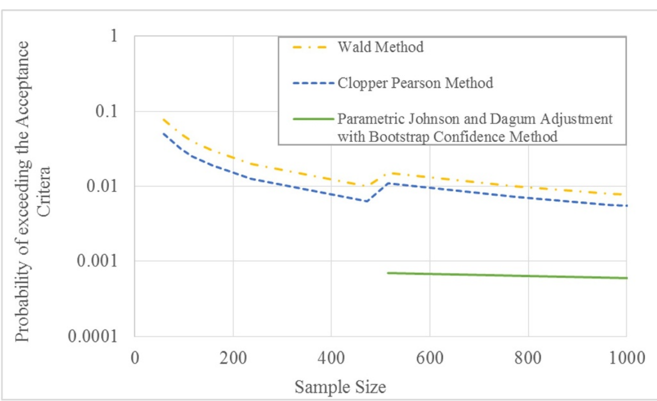

Fig. 15. Evolution of the probability of exceedance with an increasing sample size.

Table 6
Confidence level for 1020 samples threshold for PRCC values.

Confidence level (%)	PRCC limit (abs)
99.98	0.109
99.9	0.097
99	0.072
95	0.051

Table 7
PRCC for PCT and LMO sorted from.

Parameter	PCT PRCC	LMO PRCC	Parameter
Break Discharge Coefficient	0.700	0.907	Initial Oxide Layer
Power Peaking Factor	0.652	0.248	Break DC
Initial Core Power	0.343	0.116	Power Peaking Factors
Decay Heat	0.185	0.104	Decay Heat
Cladding Inner Radius	0.148	0.060	Gap Pressure
RCP Broken Speed	0.052	0.049	Cladding Inner Radius
Transition Boiling HTC	0.034	0.046	Metal Water Reaction
Initial Oxide Layer	0.011	0.037	RCP Broken Speed
ACC Pressure	0.002	0.024	Initial Core Power
Containment Pressure	−0.010	0.009	Gap conductance
Metal Water Reaction	−0.011	0.006	Pellet Radius
Gap Pressure	−0.012	0.002	Burst Strain
Burst Strain	−0.024	−0.012	Fuel Density
RCP Intact Speed	−0.036	−0.019	Transition Boiling HTC
LPSI Mass Flow Factor	−0.040	−0.023	LPSI mass flow Factor
Pellet Radius	−0.042	−0.030	ACC Temperature
ACC Temperature	−0.050	−0.042	Containment Pressure
Gap Conductance	−0.071	−0.062	ACC Pressure
Burst Temperature	−0.080	−0.075	RCP Intact Speed
Cladding Thickness	−0.096	−0.082	Critical Heat Flux
Fuel Density	−0.222	−0.225	Fuel conductivity
Film Boiling HTC	−0.557	−0.250	Burst Temperature
Critical Heat Flux	−0.647	−0.290	Cladding Thickness
Forced Convection HTC	−0.730	−0.360	Forced Convection HTC
Fuel Conductivity	−0.771	−0.448	Film Boiling HTC

systems, this value can be less than one, meaning that the model variance is not fully explained. The values obtained, are 84.2% for PCT and 85.3% for LMO, which explain adequately the variance, indicating certain degree of non-monotonic and non-additive behavior, but a higher order sensitivity measure is not found necessary.

5.2. Local sensitivity analysis: damage domain search

As a final step of the sensitivity analysis, a bi-dimensional damage domain search for PCT and LMO has been developed. The damage domain corresponds to the region of the input space where the PCT or LMO acceptance criteria are exceeded. The damage domain is searched by simulating the transient varying two different input variables along their ranges, and simulating all possible combinations. In this study, an equally-spaced sampling of the inputs has been used.

The analysis covers the specific variability of two parameters that are selected based on the sensitivity analyses obtained in Section 5.2; so attending at PRCC of Table 7, two of the most influential parameters for both LMO and PCT are the Forced convection HTC and the Film Boiling HTC. So, as an example, these two parameters are varied in the range 0.746–1.254 for Forced convection and 0.627–1.3728 for Film Boiling. It must be said that the parameters selection could have been extended to other combination of variables, but the computational effort would have been excessive.

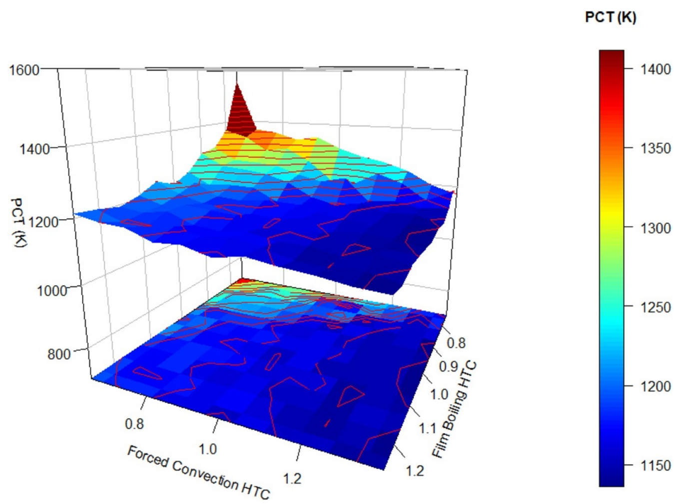

Fig. 16. PCT distribution against Film Boiling and Forced Convection HTC.

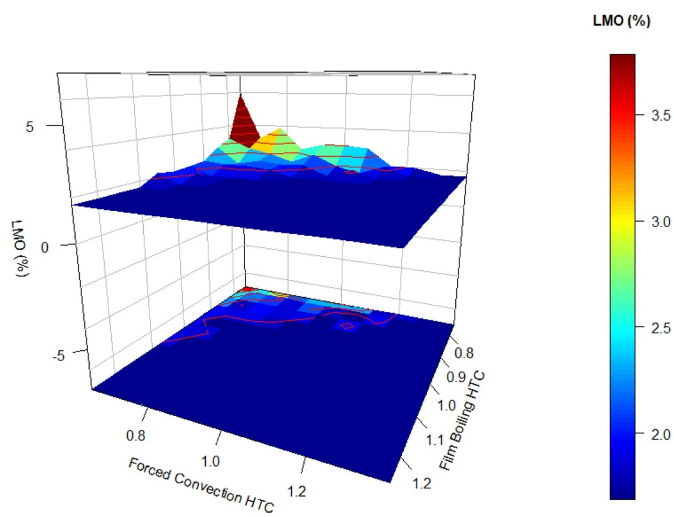

Fig. 17. LMO distribution against Film Boiling and Forced Convection HTC.

The results can be seen in Figs. 16 and 17. It is remarkable that even in the 1020 simulations made for the previous analysis, no simulation showed damage based on PCT exceedance and only one case surpassed the LMO limit; but, in this analysis, the results are the opposite. A damage domain region is found for the PCT with specific values of forced convection HTC and film boiling HTC. It is also found that the shape of the full domain was correctly predicted by the negative PRCC values, see Table 7.

The probability of obtaining the input values that create the damage domain are used to calculate the probability of having the combination of parameters that exceeds the acceptance criteria. In this sense, the quantification of damage probability for the PCT is 3.03E-04 and zero for LMO. This probability is lower than the calculated with the previous methods as it only includes the uncertainty of two input parameters.

Moreover, Figs. 16 and 17, allow to remark the importance of the uncertainty ranges of the input parameters. Regardless of the PDFs selected, a damage domain can remain undetected if this range is not properly chosen.

6. Conclusions

As mentioned in this paper, the BEPU analysis as an evaluation and licensing tool has been strongly developed in the last decades. The present paper has described an uncertainty analysis of a LBLOCA in a 3 loop PWR-W simulated with the TRACE code performing parametric, non-parametric methods, a sensitivity analysis and a damage domain search. The results have been analyzed in three different manners, and therefore, it can be interpreted distinctively:

1 Non-Parametric, Wald Method: This method relies on the order-statistics method of Wilks and Wald that establishes the probability of exceeding an obtained value with certain degree of confidence. In this approach, the acceptance criteria would be exceeded with a probability less than 0.77% and 95% confidence.
2 Binomial Distribution: This approach analyzes the data in terms of a binomial distribution (Failure/Success) that correspond to the exceedance or not of the acceptance criteria. In this approach the mean probability of exceeding the regulatory limits is less than 0.46%, with a Clopper–Pearson confidence level of 95%.
3 Distribution fit: In this approach the obtained data are considered a PDF that can be reconstructed. The curves that best fit the PCT and LMO under the Anderson–Darling GoF test have been selected. Then, the confidence intervals for 95% are obtained thanks to the percentile Bootstrap method, and they are used to calculate the probability of exceeding the acceptance criteria. With this method, the probability of exceeding the acceptance criteria is less than 0.06% with a 95% confidence level.

Comparing the three methods, the most conservative approach to the data is using the Wald method, and the least conservative is using binomial and parametric methods. A sampling study complements this analysis on which a comparison of the three methods relative to the 1020 simulations in order of appearance. The trends on surpassing the acceptance criteria are similar for the three methods, being Wald the one which obtains the most conservative value for any number of simulations and the parametric adjustment the least conservative.

Next, a sensitivity analysis of the data has been performed to study the influence of each input parameters. To observe the influence of each parameter altogether with the others, Spearman partial correlation coefficients have been calculated. It is found that the most influential parameters for PCT and LMO are similar, and that PCT and LMO have certain degree of non-monotonic and non-additive behavior in the input space.

Finally, two of the most influential parameters obtained in the sensitivity analysis were selected to search for a damage domain. This study showed that for certain values of the Film Boiling HTC and the Forced Convection HTC a damage domain appears for PCT, but is inexistent for LMO, which was not detected in the Monte Carlo analysis, reinforcing the importance of sensitivity analyses.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ress.2019.106607.

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