COMPARISON OF SOME APPROACHES FOR THE ESTIMATION OF TOLERANCE LIMITS IN THE CONTEXT OF LBLOCA UNCERTAINTY ANALYSIS

F. Sánchez-Saez, A.I. Sánchez, J.F. Villanueva,
S. Carlos, S. Martorell
Universitat Politècnica de València
Camí de Vera s/n, 46021, Valencia - Spain
frasansa@etsii.upv.es: aisanche@eio.upv.es; jovillo0@iqn.upv.es; smartore@iqn.upv.es;
scarlos@iqn.upv.es

ABSTRACT

Computer codes are widely used for NPP safety analysis. Deterministic safety analysis is an essential tool for evaluating the safety on nuclear power plants, but nowadays, it is moving towards a more realistic approach in which uncertainty analysis with best estimate codes are essential in the assessment of accidents analysis, called Best Estimate Plus Uncertainties, BEPU.

Most methods for performing uncertainty analyses involve propagating uncertainties in the input parameters through the model in order to quantify the resulting uncertainty in the outputs which are of interest. The outputs are calculated by running the thermohydraulic code. In presence of uncertainty, a large number of runs of the code may be required to adequately represent the full distribution of the safety parameters in the output. Wilks' tolerance interval method is a nonparametric approach based on order statistics widely used in the literature to estimate the maximum parameter output from the limited number of code simulations. However, the use of the Wilks method at the first order statistic leads to a conservative result.

In this context, the paper proposes different alternatives to the Wilks method (conservative approach) for obtaining the upper tolerance limit of the output. The methods proposed, named closeness approaches, are based on empirical quantiles. Additionally, confidence intervals to quantify the uncertainty in tolerance limit estimations are calculated using bootstrap. The bootstrap is a computational intensive, nonparametric technique for assessing the accuracy of a parameter estimator which requires very little assumptions.

An application case focused on uncertainty analysis of a Large-Break Loss of Coolant Accident, LBLOCA, in the cold leg of a Pressurized Water Reactor using the thermal-hydraulic code TRACE is presented. The aim is to estimate the upper tolerance limit of the Peak Cladding Temperature (PCT), using the approaches based on empirical quantiles. The results obtained are compared with the Wilks method for different sample sizes.

KEYWORDS
Tolerance limits, LBLOCA, uncertainty analysis, nonparametric approach

1. INTRODUCTION

Nuclear industry has relied on the concept of defense in depth and safety margins to deal with the uncertainties associated with the design and operation of nuclear facilities. This approach suggests making extensive use of redundancy, diversity and large margins to guarantee plant safety in a conservative way [1]. In this context, both deterministic and probabilistic safety analyses are performed with an aim to achieve regulatory approval of NPP (Nuclear Power Plant) design and operation according to well-established licensing basis.

What concerns Deterministic Safety Analysis (DSA), recently, the International Atomic Energy Agency (IAEA) produced guidance on the use of deterministic safety analysis for the design and licensing of nuclear power plants (NPPs): ''Deterministic Safety Analysis for Nuclear Power Plants Specific Safety Guide,'' Specific Safety Guide No. SSG-2 [2] (hereinafter referred to as SSG-2). SSG- 2 addresses four options for the application of DSA. Options 1 and 2 are conservative and they have been used since the early days of civil nuclear power, and are still widely used today. However, the desire to utilize current understanding of important phenomena and the availability of reliable tools for more realistic safety analysis without compromising plant safety has led many countries to use option 3. Option 3 involves the use of best-estimate codes and data together with an evaluation of the uncertainties, the so called BEPU methodologies.

The IAEA Safety Report series Nº.23 "Accident analysis for Nuclear Power Plants" [3] already recommended sensitivity and uncertainty analysis if best estimate codes are used in licensing analysis. A comprehensive overview about uncertainty methods can be found in the IAEA Safety Report Series Nº.52 "Best Estimate Safety Analysis for Nuclear Power Plants: Uncertainty Evaluation", issued in 2008 [4].

Several BEPU approaches have been developed in a scope that are accepted by the regulatory authorities nowadays to perform deterministic safety analysis. In [5], it is presented the results and the main lessons learnt from Phase V of BEMUSE, an international program promoted by the Working Group on Accident Management and Analysis (GAMA) of OECD to address the issue of the capabilities of best-estimate computational tools and uncertainty analysis. The scope of Phase V is the uncertainty analysis of a Large Break Loss-Of-Coolant-Accident (LBLOCA) in a Pressurized Water Reactor. Fourteen participants from twelve organizations and ten countries participated in the Phase V of BEMUSE.

Best Estimate Plus Uncertainty (BEPU) approaches for the analysis of a particular design-basis accident assumes that the uncertainty in the safety outputs [i.e., the figures of merit (FOMs) involved in the acceptance criteria of the analysis] derives from the uncertainties in the inputs to the calculations (initial and boundary conditions) and those arising from the computational model. These FOMs are usually extreme values (minima, maxima) of safety variables during the transient (PCT, CHF …). Current BEPU methodologies mainly rely on a probabilistic description of the uncertainty and on the use of statistical techniques to estimate it. In this framework, the uncertainty of a FOM can be identified with its probability distribution.

Most of BEPU approaches accepted by the regulatory authorities are based on propagation of input uncertainties and make use of the Wilks' –based methods to determine the number of calculations of the output, i.e. FOMs, needed to verify compliance of acceptance criteria with "standard tolerance levels (STL)", typically 95/95 in accordance with current regulatory practice. Accordingly, the value of the FOM that is compared with the corresponding acceptance criterion is often an upper or lower tolerance limit with level 95/95 instead of the FOM probability distribution. For example, it is often used one-side tolerance interval of FOM based on the use Order Statistics (OS) of first order with STL=95/95, which requires a sample size of N=59 runs

The main advantage of using first order statistics (FOS) based on Wilks' formulae to derive the STL is that it provides always a conservative result with a few runs of the computer code. This way, the computational cost is kept practicable since the simulation of the evolution of the plant transient for each sample of inputs using complex Thermal Hydraulic (TH) models of NPP is very expensive in terms of computational cost. However, FOS linked to BEPU approaches provides often very conservative results. Several authors have explored the advantage of using OS of higher levels, which not only reduce conservatism but also increase the computational cost [6, 7]. Other authors propose the use of sensitivity and uncertainty analysis in an integrated manner within the framework of BEPU approach [3, 5].

This paper focuses on the study of NPP accident scenarios based on the BEPU approach and the use of order statistics according to the current practice for the formulation, propagation and analysis of uncertainties, with the identification of representative parameters and ranges of uncertainty to be considered together with boundary conditions and inputs to the best estimated TH code. In addition, the paper introduce an alternative non-parametric method to the use of the traditional first order statistic. The results of the use of the alternative method are compared against the traditional one. The alternative method should be conservative in nature also but producing not only more realistic and less conservative results but also keeping computational cost practicable.

In particular, the case of application selected for the feasibility study of the proposed methodology considers a Large-Break Loss of Coolant Accident (LBLOCA) in the cold leg. Specifically, the study focuses on the analysis of the uncertainty associated with the PCT as FOM by comparing the use of first order statistics against non-parametric method.

1.1. BEPU Approach

Option 3 requires implementation of a BEPU approach consisting of at least a detailed evaluation of the uncertainties, and therefore, several calculations are performed to estimate the probability distribution of the FOM, or rather some descriptor of this distribution, for instance, a tolerance interval. SSG 2, in accordance with current regulatory practice, recommends that the value that should be compared with the acceptance criterion is an upper tolerance limit with level 95/95. This is a statistic that encompasses the value of the FOM with a probability of at least 0.95 with a 95% confidence level (STL). Thus, changes can be made to the plant provided that the tolerance level does not exceed the licensing acceptance criterion. A typical procedure used in BEPU approaches can be summarized in the following ten steps:

1. Selection of the accident scenario
2. Selection of the safety criteria linked to the accident scenario under study and the FOM involved in the acceptance criteria
3. Identification and ranking of relevant physical phenomena based on the safety criteria
4. Selection of the appropriate TH (Thermal Hydraulic) parameters to represent those phenomena
5. Identification of relevant safety-related systems involved in the accident scenario. Establish conservative assumptions on the availability of such safety systems.
6. Development of the TH computer model of the accident scenario, e.g. develop an input for TRACE integrated into the SNAP platform [8, 9]
7. Association of PDF (Probability Density Functions) for each selected TH parameter
8. Random sampling of the selected TH parameters and plant configurations according to PDF. Sample size (N) will depend on the particular statistical method and the acceptance criteria adopted to verify compliance of safety criteria. Perform N computer runs to obtain FOM for each run.
9. Processing the results of the multiple computer runs (N) to estimate either the probability distribution of the FOM, or rather some descriptor of this distribution, such as for example a percentile of the FOM, or a tolerance level of FOM with STL using OS, etc.

10. Verify compliance of acceptance criteria for each FOM depending on the particular statistical method and acceptance criteria adopted.

Despite of SSG 2 recommends development of uncertainty analysis based on the use of OS (normally first order to produce FOM with STL), several alternatives can be explored integrating not only uncertainty but also sensitivity analyses to produce conservative results in order to provide more realistic and accurate results keeping computational cost practicable.

2. ORDER STATISTICS AND NON PARAMETRICS MODELS

2.1. Order Statistics

Since best-estimate plus uncertainty analysis was approved by Nuclear Regulatory Commission (NRC), several uncertainty approaches have been proposed and applied in nuclear industry in the context of best-estimate code calculations. The Wilks' method [10] is a most popular statistical method used in the thermo-hydraulic codes uncertainty analysis. Wilks' method is based on the idea of determining the minimum number of simulations of the thermohydraulic code in order to infer a certain coverage of a population, with a certain confidence, thus is a nonparametric statistical tolerance limit.

The starting point of the problem setting is that a sample of size n is obtained sampling the input parameters according to their corresponding probability distribution. This sample is used as simulation code inputs and n values of the interest output are obtained. The probability distribution of the output f(y) is an unknown function. Tolerance limits are obtained using the Wilks method as:

$$P\left(\int_L^U f(y)dy > \gamma\right) = \beta \tag{1}$$

Where γ is the coverage, β is confidence level, L and U the lower and upper tolerance limits. In the case of the one sided tolerance interval the lower tolerance limit is selected to be $-\infty$

Next, a set of result parameter values picked from the unknown distribution f(y) are arranged in ascending order. When the minimum value is marked with index r and the maximum value with index s, Equation (1) can be written as

$$\beta \leq 1 - \sum_{j-s-r}^{n} \binom{n}{j} y^j (1-y)^{N-j} \tag{2}$$

In the case of the one sided upper tolerance interval the lower tolerance limit is selected to be $-\infty$ and the upper tolerance limit is the highest value obtained in the random sample if the first order Wilks is used (s=n). Substituting s=n and r=o en Equation (2) the following expression is obtained

$$1 - \gamma^n \geq \beta \tag{3}$$

So, if the output sample is ordered the maximum value of the sample infers the γ percentile of the output population with a β confidence. For example, if according with current regulatory practice, a Standard Tolerance Level (STL) 95/95 is selected a sample of 59 code runs is required,

The experience has determine that the use of the first order statistic leads to a conservative result. The BEMUSE analysis indicated that applying the Wilks formula to the 4th or 5th order usually produced a more realistic tolerance limit of the output code, at the price of some additional code runs. Table I shows the minimum number of code runs from the 1st order to 5th order for a STL 95/95.

Table I: Minimum number of code runs

Order Wilks formula	Minimum number of code runs (n)	Order Wilks formula	Minimum number of code runs (n)
1	59	4	153
2	93	5	181
3	125		

2.2. Non Parametric Models

Other approach to obtain one sided upper tolerance interval requires

$$E[P(-\infty \leq X_i \leq \widehat{w})] \approx \beta \tag{4}$$

The approximation makes it possible to choose the estimator, $\widehat{w}$, from a set of independent observations X_1 to X_n, with minimum variance $V(\widehat{w})$ and small bias $E(\widehat{w}-w)$. In this context, the approach easier to estimate a particular percentile p is the use of empirical percentiles, which are obtained from the statistics of order. A general formula for estimating the percentile w [11] from the order statistics is

$$\widehat{w} = (1-\gamma)X_{(j)} + \gamma X_{(j+1)} \tag{5}$$

where

$$\frac{j-m}{n} \leq w < \frac{j-m+1}{n} \tag{6}$$

and $m \in \Re$ y $0 \leq \gamma \leq 1$. The value of γ is function of $j=\lfloor wn+m \rfloor$ and $g=\lfloor wn+m-j \rfloor$ denoting $\lfloor u \rfloor$ the largest integer not greater than u. Depending on the value of m, [11] show up to 9 different definitions for the estimation of the percentiles. This study concluded that the three best definitions correspond to the values of the parameters m and γ shown in table II:

Table II: Values parameters m and γ for estimation of the percentiles

Method	m	γ
Method 1	*0.5*	$\gamma = \begin{cases} 1 \text{ if } wn+m<1 \\ g \text{ if } 1 \leq wn+m \leq n \\ 0 \text{ if } wn+m>n \end{cases}$
Method 2	*w*	
Method 3	*(w+1)/3*	

The approach based on empirical percentiles can be robust in large samples, but in small samples, these percentiles are inefficient and large variance, recommending in that case the use of bootstrap technique.

The first of the methods complies with the desirable properties for a sample quantile [11] but its definition is not well justified. The second and third method satisfy most of these properties and their definitions are more justified. The third method seems to be the best since gives unbiased estimators for any kind of distribution in comparison with others methods which estimators are not unbiased or are unbiased only for normal distributions.

3. CASE STUDY

3.1. Description of LBLOCA transient

This work is focused on one of the most common Design Basis Accidents (DBA) in Pressurized Water Reactors (PWRs), the Large Break Loss Of Coolant Accident (LBLOCA) located at a cold leg of the reactor.

As consequence of this transient, a fast depressurization of the primary is produced, and consequently the corresponding activation of the SCRAM signal by low pressure, continuing with the accumulators' injection and later injection of the emergency core coolant from Low Pressure Injection System (LPIS), to prevent the core uncovery.

With the SCRAM, a reduction of the thermal power is achieved, and with the injection of water by means of accumulators and LPIS a core temperature reduction is produced. Heat removal through secondary system is not considered by the fast depressurization of the primary system.

The plant selected has been a typical 4-loops PWR-Westinghouse, whose reference is Zion Nuclear Power Plant (NPP), and the thermal-hydraulic system code used is TRACE V5.0 Patch 4.

3.2. Safety and acceptance criteria

For a LOCA accident, several criteria were established by USNRC in 1974 [12] when that accident is produced. These criteria can be resumed mainly in three thermal boundaries that must not be exceeded: the peak cladding temperature, the maximum cladding oxidation of the core, and the maximum of the total amount of hydrogen produced during the transient. The most used criterion from thermo-hydraulic point of view is the PCT that must be ever below than 1477K. This criterion has been chosen as output variable of interest for the study.

3.3. Relevant physical phenomena and thermal hydraulics parameters

Once selected, the accident scenario (LBLOCA) and the safety criterion of interest (PCT) is necessary to identify and rank the important phenomena affecting the progression of the transient. The PIRT process is used as a means for selecting the phenomena of the highest importance.

In [13] is showed a comparison of the completed PIRTs, for LBLOCA in 4 loop PWR NPP, corresponding to three studies performed by CSAU [14], AREVA [15] and Westinghouse/EPRI [16]. In this comparison, common phenomena modelized by the three studies are observed such as heat transfer in different phases, behavior of rods, etc. However, significant differences were also observed between the three studies.

These three PIRTS has been used as references, combined herein, and updated based on qualitative analysis for the specific scenario under consideration. Important phenomena identification were as follow:

- Heat transfer in different phases.
- Physical models of hot rod, stored energy, fuel response, initial distribution power core and fuel behavior after the breakage.
- Flow distribution, Interphase friction and Break Flow.
- Critical heat Flux.
- CCFL.
- Boundary Conditions.

Initially, and in accordance with the relevant phenomena obtained on previous PIRT studies, 68 parameters have been selected, which permit to model the phenomena previously identified with respect to the behavior of the PCT. These parameters include the previous selected as important and other parameters included in latest studies (BEMUSE, PREMIUM, etc.) that incorporate new phenomena such as the reflood, as well as using new capabilities of the code TRACE to simulate them.

Because of the high number of input variables is necessary to develop an initial screening. This screening has been developed using the Placket-Burman method [17] a design of experiments at two levels, which allows assessing the sensitivity of the same in their extreme values within the range of uncertainty, assigned when there is not sufficient information about the process. Based on this preliminary sensitivity study the number of parameters has been reduced to 45 with which finally the case study has been carried out. Tables III shows the selected parameters together with other initial conditions.

Table III: Parameters and Initial conditions primary and secondary systems

Parameter	Units	Ref. Value [5][18]	Uncertainty
K-Factor Axial Loss Coefficient in Downcomer Vessel	(-)	0.54	KDWNC
K-Factor Axial Loss Coefficient in Lower Core Plate	(-)	0.2	KLCPL
K-Factor Axial Loss Coefficient in Break Cold Leg Pipe	(-)	0.68	KBRCL
Subcooled Multiplier for Choked-flow	(-)	1	CHFC1
Two-phase multiplier for Choked-flow	(-)	1	CHFC2
Single Phase Liquid to Wall Heat Transf. Sens. Coef.	(-)	1	CONVL
Single Phase Vapor to Wall Heat Transfer Sens. Coef.	(-)	1	CONVV
Dispersed Flow Film Boiling Heat Transfer Sens. Coef.	(-)	1	FILMB
Film to Transition Boiling Tmin Criterion Temperature	(-)	1	TMIFS
Critical Heat Flux Multiplier	(-)	1	CRIHF
Form Loss Sensitivity Coefficient	(-)	1	FLOSS
Interfacial Drag (Droplet) Sensitivity Coefficient	(-)	1	DRAG4
Interfacial Drag (Dispersed Flow Film) Sens. Coef.	(-)	1	DRAG5
Interfacial Drag (Inverted Annular Flow) Sens. Coef.	(-)	1	DRAG7
Wallis Correl. for the CCFL in the Upper Core Plate	(-)	0.8625	CCFLC
K-Factor Axial Loss Coefficient in Accumulators	(-)	1	ACCKL
K-Factor Axial Loss Coefficient in Surge Line	(-)	1	KSURG
Liquid to Wall Inverted Annular HT sensitivity Coef.	(-)	1	LIQIA
Liquid to Interface Annular-mist HT sensitivity Coef.	(-)	1	LINT2
Liquid to Interface Transition HT sensitivity Coef.	(-)	1	LINT3
Vapor to Interface Transition HT sensitivity Coefficient	(-)	1	VINT3
Vapor to Interface Stratified HT sensitivity Coefficient	(-)	1	VINT4
Subcooled Boiling Heat Transfer sensitivity Coefficient	(-)	1	SBHTC
Departure from Nucleate Boiling/CHF sensitivity Coef.	(-)	1	DNBHC
Fuel Thermal Conductivity before Burst Sens. Coef.	(-)	1	WH001
Cladding Metal-Water Reaction Rate Sensitivity Coef.	(-)	1	WH002
Rod Internal Pressure Sensitivity Coefficient	(-)	1	WH004
Thermal Power	MW	3250.0	INPOW
Primary System total Mass Flow Rate	kg/s	17357	MASFR
Cold Leg Temperature	K	565	CLTEM
Upper Head Vessel Temperature	K	570	UHTEM
Accumulators Liquid Temperature	K	334	ACCLT
Liquid Volume of each Accumulator	m3	10.564	ACCLV
Pressurizer Pressure	MPa	15.5	
Pressurizer Collapsed Water Level	m	8.8	
Average Temperature	K	582	
Pressurizer Temperature	K	617.65	
Pressure Loss in the core	kPa	250	
Steam Generators Pressure	MPa	6.78	

Parameter	Units	Ref. Value [5][18]	Uncertainty
Steam Generators outlet Temperature	K	557.60	
Steam Generators inlet Temperature	K	485.00	
Steam Generators Pressure Loss	kPa	20	
Steam Generators Level (NR)	%	50.60	
Mass Flow Rate by Steam Generator	kg/s	439.00	

Table IV shows main fuel physical data used thermal hydraulic model

Table IV: Fuel physical properties

Parameter	Units	Ref. Value [5] [18]	Uncertainty
Fuel Thermal Conductivity	W/m K	Table[1]	UO2TC
Fuel Specific Heat	J/Kg K	Table[2]	UO2SH
Gas Gap Heat transfer Coefficient	W/m2K	6300	GTHCO
Clad Thermal Conductivity	W/m K	Table[3]	CLCON
Clad Density	kg/m3	6551.4	CLDEN
Hot Rod – Average Peaking Factor	(-)	1.2468	PEAKF
Average Rods Gap Size	m	5.4e-5	HGSAV
Hot Rod Gap Size	m	5.4e-5	HGSHR
Rod Outside Diameter	mm	9.48	

Table V shows relevant operational conditions for the transient and corresponding uncertain parameters.

Table V: Relevant conditions for the transient

Parameter	Units	Ref. Value [5] [18]	Uncertainty
Residual Power Multiplier	-	Table[4]	RPOWM
Containment Maximum Transient Pressure	Pa	3.5e5	CONTP
Accumulators Pressure Setpoint	MPa	4.14	ACCPR
Low Pressure Injection System Mass Flow Rate	kg/s	88	LPISQ

3.4. Description of typical PWR model and relevant safety-related systems.

The safety-related systems involved in the accidental transient are scram system, accumulators and low-pressure injection system

Figure 1 outlines the primary system modeled for TRACE V5.0 Patch 4 using the SNAP suite, which includes a tri-dimensional component type VESSEL, which represents the reactor pressure vessel including the core. It also includes the primary part of the four cooling loops (PIPES, 4 SGs, PRZ and 4

[1] Fuel Thermal Conductivity vs Temperature Table

[2] Fuel Specific Heat vs Temperature Table

[3] Clad Thermal Conductivity vs Temperature Table

[4] Residual Power Multiplier vs Time Table

PUMPS). In addition, safety systems needed in the transient supporting the primary system have been modeled (4 accumulators, 4 low pressure injections, all in cold legs). The large break is simulated as a double guillotine break by three VALVE and two BREAK components, in the cold leg.

Figure 2 outlines the secondary system, which includes steam generators (4 SG) associated each with the corresponding cooling loops in the primary system.

There are heat structures for reactor pressure vessel, core and steam generators. The reactor pressure vessel (RPV) has been simulated with a 3D Vessel component, made of 31 axial, 5 radial and 8 azimuthal nodes.

The conditions imposed for the thermal hydraulic transient simulation related to safety systems can be summarized as follows:

- No actuation of the high pressure injection system (HPIS).
- Accumulator's injection at 4.14 MPa.
- Low pressure injection system (LPIS) initiate at 1.42 MPa. Driven by a flow-pressure table.
- Containment pressure imposed as a function of time after the break.
- Reactor coolant pumps velocity imposed as a function of time after the break.
- Power after scram imposed by means of a reactor power multiplier as a function of time after the break.

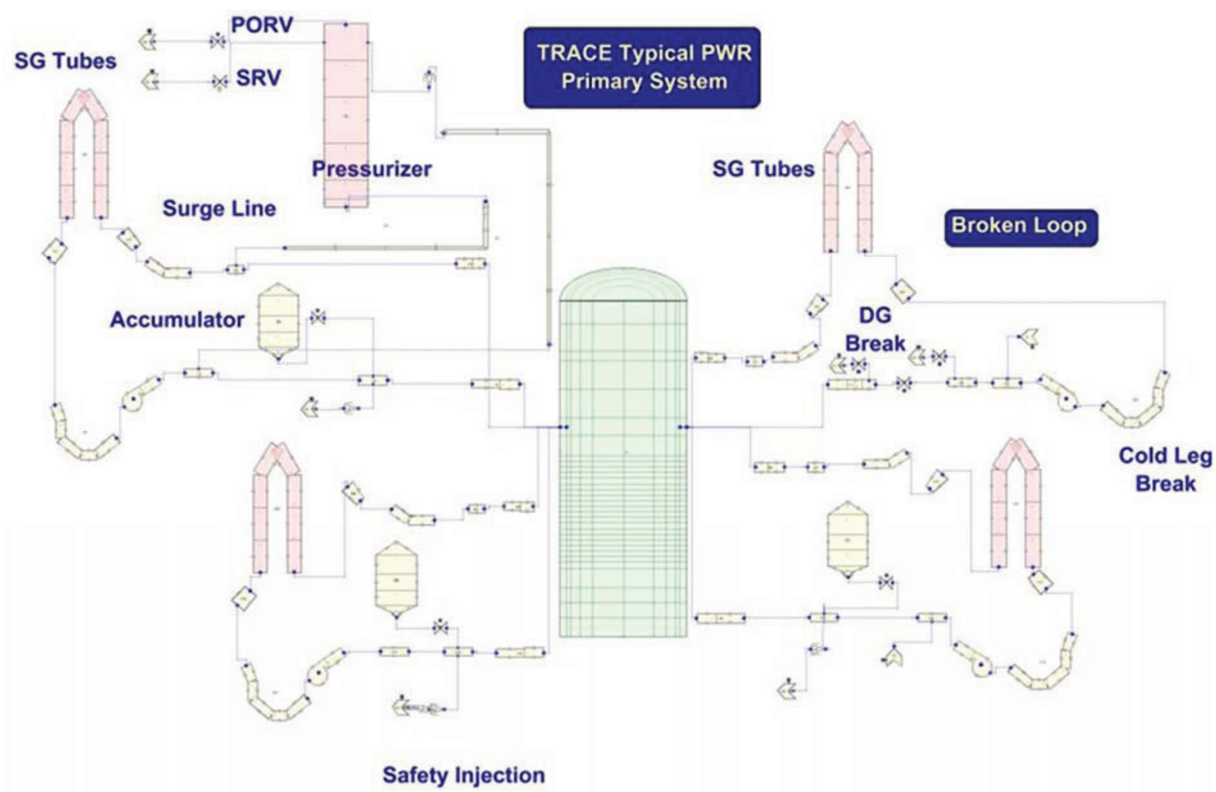

Figure 1: TRACE typical 4-loops PWR. Primary System SNAP view.

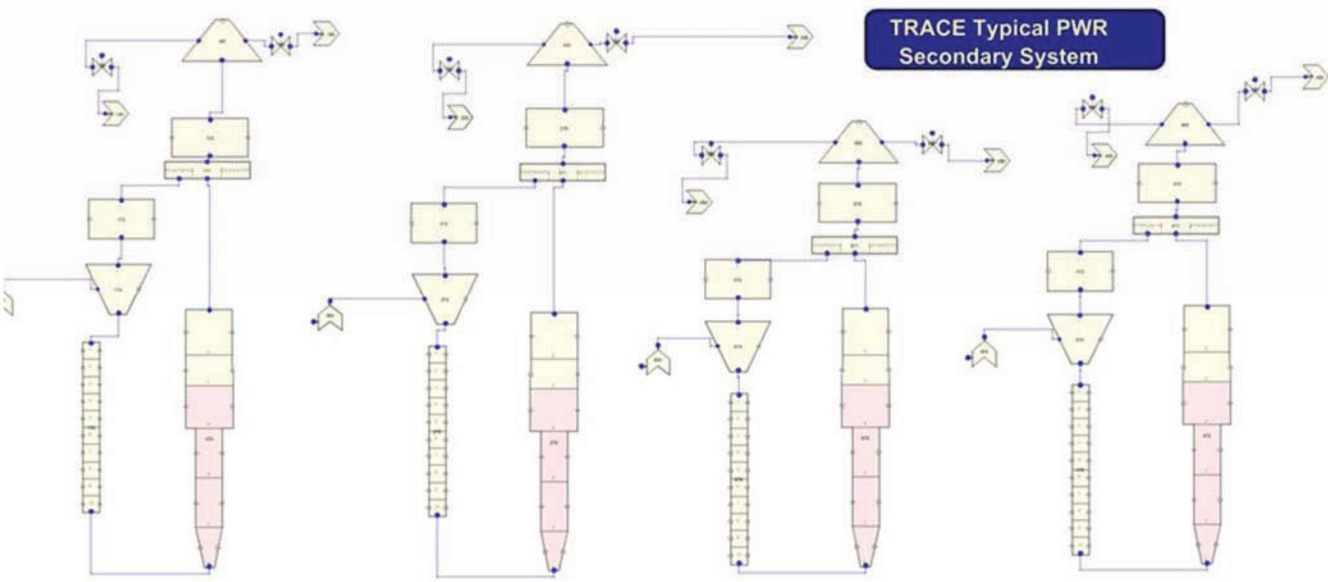

Figure 2: TRACE typical 4-loops PWR. Secondary System SNAP view

3.5. Uncertainty input and data sampling

Table VI shows the description of the uncertain TH parameters considered in this case study. The parameters of Table V are considered as source of uncertainty, introducing the uncertainty through a multiplicative or additive factor with a range of $\mu \pm 2\sigma$, i.e., these uncertainty parameters which can act as multipliers or as additive factors for the reference values of the inputs selected. The probability density functions that characterize these parameters are normal, uniform and lognormal distributions.

Table VI: Description of uncertain TH parameters

Parameter	Parameter type	Distribution type	Min	Max	Parameter	Parameter type	Distribution type	Min	Max
INPOW	Multiplicative	Normal	0.98	1.02	ACCLV	Additive	Uniform	-0.5	0.5
PEAKF	Multiplicative	Normal	0.95	1.05	KSURG	Multiplicative	Lognormal	0.5	2.0
KDWNC	Multiplicative	Uniform	0.95	1.05	LIQIA	Multiplicative	Uniform	0.9	1.1
KLCPL	Multiplicative	Uniform	0.95	1.05	MASFR	Multiplicative	Normal	0.96	1.04
KBRCL	Multiplicative	Uniform	0.95	1.05	CLTEM	Additive	Normal	-2	2
CHFC1	Multiplicative	Uniform	0.95	1.05	UHTEM	Additive	Uniform	0	10
CHFC2	Multiplicative	Uniform	0.95	1.05	LINT2	Multiplicative	Uniform	0.9	1.1
HGSAV	Multiplicative	Normal	0.8	1.2	LINT3	Multiplicative	Uniform	0.9	1.1
HGSHR	Multiplicative	Normal	0.8	1.2	VINT3	Multiplicative	Uniform	0.9	1.1
RPOWM	Multiplicative	Normal	0.92	1.08	VINT4	Multiplicative	Uniform	0.9	1.1
CONTP	Multiplicative	Uniform	0.85	1.15	SBHTC	Multiplicative	Uniform	0.9	1.1
CONVL	Multiplicative	Uniform	0.9	1.1	DNBHC	Multiplicative	Uniform	0.9	1.1
CONVV	Multiplicative	Uniform	0.9	1.1	WH001	Multiplicative	Uniform	0.9	1.1
FILMB	Multiplicative	Uniform	0.9	1.1	WH002	Multiplicative	Uniform	0.9	1.1
TMIFS	Multiplicative	Uniform	0.9	1.1	WH004	Multiplicative	Uniform	0.9	1.1
CRIHF	Multiplicative	Uniform	0.8	1.2	UO2TC	Multiplicative	Normal	0.9	1.1
FLOSS	Multiplicative	Uniform	0.9	1.1	UO2SH	Multiplicative	Normal	0.98	1.02
DRAG4	Multiplicative	Uniform	0.9	1.1	GTHCO	Multiplicative	Uniform	0.9	1.1

Parameter	Parameter type	Distribution type	Min	Max	Parameter	Parameter type	Distribution type	Min	Max
DRAG5	Multiplicative	Uniform	0.9	1.1	CLCON	Multiplicative	Uniform	0.9	1.1
DRAG7	Multiplicative	Uniform	0.9	1.1	CLDEN	Multiplicative	Uniform	0.95	1.05
CCFLC	Multiplicative	Uniform	0.9	1.1	ACCPR	Additive	Normal	-0.2	0.2
ACCKL	Multiplicative	Lognormal	0.5	2.0	LPISQ	Multiplicative	Normal	0.95	1.05
ACCLT	Additive	Normal	-10	10					

4. RESULTS

There are three output variables of interest, however, in order to develop the methodology, this paper will present the results referred to PCT. Thousand simulations of the transient were ran with the TRACE code. These simulations have been used with the purpose of estimate the empiric distribution function of the PCT. This distribution has been taken as reference for the comparison of the results obtained with the different methods chosen to characterize the behavior of the PCT: an order statistic method, as Wilk's method, comparing it with a non parametric method for estimation of the95% percentile.

In **¡Error! No se encuentra el origen de la referencia.**Figure 3, the empirical function distribution of the 1000 executions is shown. The value of 95% percentile (1259.5 K) has been taken as reference value.

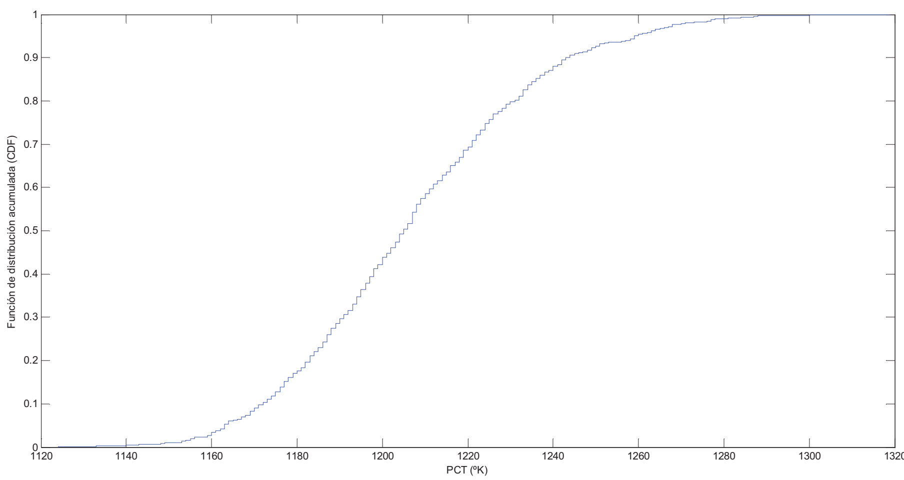

Figure 3: PCT cumulative distribution function

4.1. Tolerance intervals

From a sample size of 59, tolerance intervals corresponding to Wilks, first-order statistical method, and the rest of non-parametric approaches have been obtained. Tolerance/confidence in all cases is 95/95. Table VII shows the upper limit of the tolerance interval obtained from the different methods seen in section 2.2.

Table VII. Upper tolerance interval limit for the PCT (K)

Sample Size	Wilks	Method 1	Method 2	Method 3
59	1287.7	1255.55	1263.4	1258.24

If we compare the values obtained with different methods with reference value obtained with the simulation of 1000 transient (1259.5 K) is observed that, in the case of the selected sample, Wilks method and method 2 overestimate the value of the PCT being the overestimation much greater in the case of the method of Wilks (28.2 K). In the case of the other two methods, the retrieved value is close to the reference value but underestimating it.

To analyze the behavior of the PCT of the different approaches, 1000 samples of the same size (n=59) have been simulated and distributions corresponding to the distribution of the estimates of the 95th percentile for the conservative approach (Wilks) and the rest of non-parametric approaches have been obtained. Figure 4 shows the corresponding distributions of *w* with a confidence/tolerance limit of 95/95 for the different approaches. This figure shows one of the main differences, between the distribution of the approach by Wilks and the other models, that lies mainly in that distribution is asymmetrical positive as a result of the confidence criterion, however, more accurate approximations for the distribution of the estimator are less biased. The same figure shows the value corresponding to the percentile of 95% from 1000 simulations of the thermo-hydraulic code (1259.5 K is shown as a vertical line). In the simulations performed with the conservative approach only 5% of the time underestimated the value of the 95th percentile as a result of the criterion $\gamma \geq 0.95$. Using the rest of estimators, approximately 45% of the time, the reference of the 95th percentile value is underestimated.

5. DISCUSSION

The presented study has focused on the analysis of uncertainty of the behavior of the PCT. The scenario under analysis is a LBLOCA. This analysis of uncertainty has been addressed by obtaining a tolerance/confidence interval the 95/95 using the method of Wilks and first-order statistics and, therefore, a sample size of 59 simulations of transient. It has compared the results obtained with the implementation of other non-parametric methods, which allow the estimation of the 95th percentile using the same sample, and a reference value obtained with the simulation of 1000 transient (1259.5 K).

Three non-parametric methods to obtain the 95th percentile have been proposed based in their consistency and accuracy. It is shown as the Wilks method and method 2, which was not unbiased, overestimate the value of the 95th percentile, while 1 and 3 non-parametric approaches, first more robust in terms of properties and second more robust in terms of unbiased regardless of the distribution type, underestimate the percentile but with values much closer to the reference value.

As a result of the foregoing, when a small number of simulations and a large number of inputs, the option which looks more suitable for analyzing variables of interest in transient simulations is the Wilks method given its conservative character, while to obtain an accurate value of the variable, the non-parametric approach presents better results.

It would be interesting to study the influence of sample size which for Wilks method is known to increase the precision or decreases the conservatism, but unknown for the rest of the methods that are best values although underestimated.

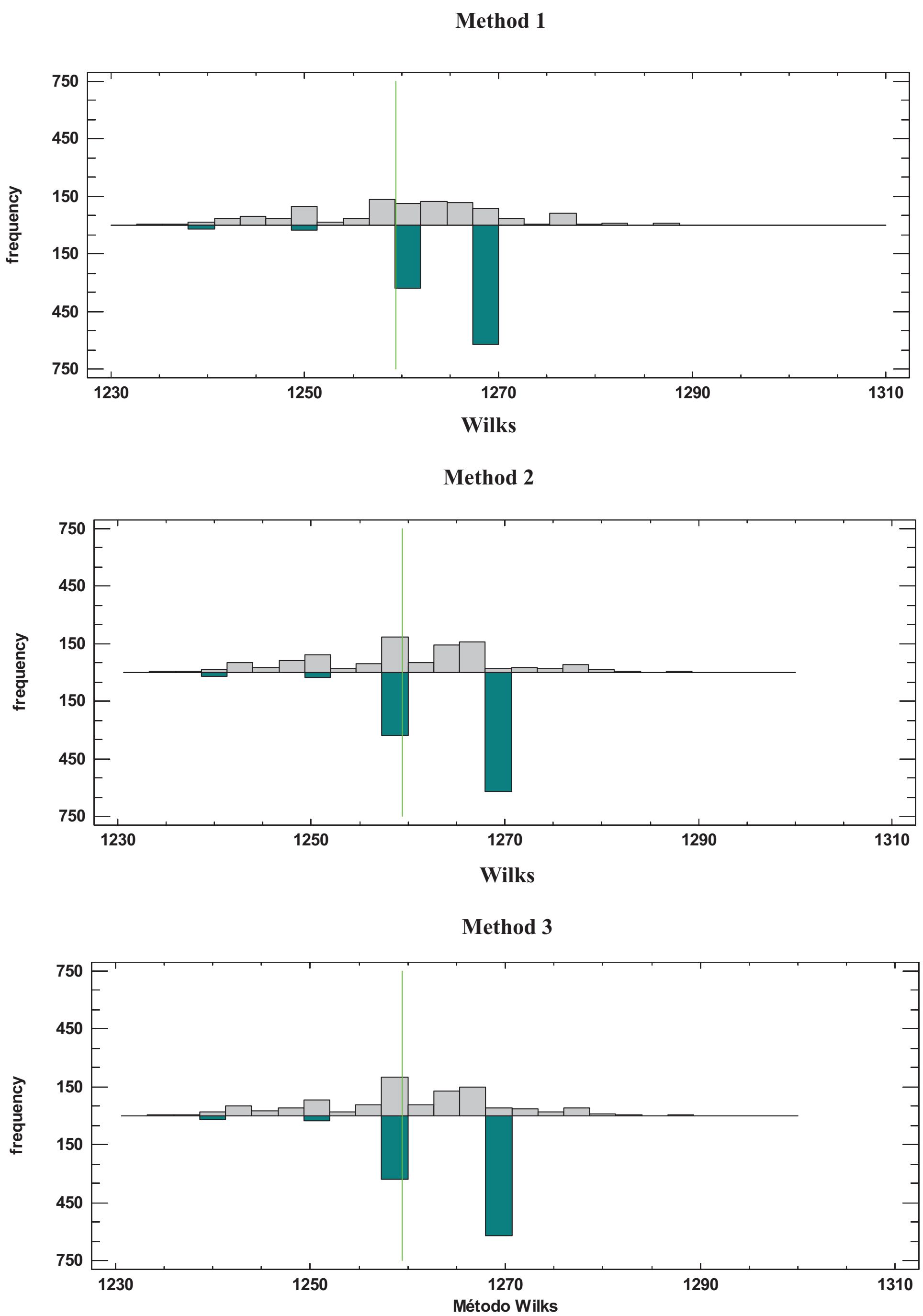

Figure 4: Comparison of the distribution of the non-parametric estimation of *w* (95%) by the method of Wilks and the rest of analyzed approaches

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