# Proposal of a BEPU Methodology for Containment Safety Analysis

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## ABSTRACT

Containment safety analyses are still performed using conservative assumptions due to the difficulties in modeling the phenomena associated, and/or to satisfy the regulatory bodies' requirements. Nevertheless, in order to obtain accurate predictions, realistic analyses have to be performed. In 1989, the U.S. NRC modified the licensing requirements allowing the use of realistic methods if uncertainties are identified and quantified, the so-called BEPU analyses. Therefore, a BEPU methodology specifically developed for containment analysis is proposed. Conservative assumptions are avoided by developing best estimate containment models. Uncertainties are quantified and propagated through the code in order to obtain the results accuracy. The proposed methodology is defined in a hierarchical structure, similar to the U.S. NRC Regulatory Guide 1203. It is divided in two main blocks; the first is related to the best estimate model setting; and the second to the uncertainty treatment.

## 1. INTRODUCTION

Usually, safety analyses are performed using conservative assumptions. These conservatisms are due to the lack of knowledge of physical phenomena, and/or to satisfy the regulatory authority requirements. With these assumptions, the results are unrealistically conservative, assuring a safety margin in the analyzed plant. In order to obtain an optimal nuclear power plant design and reactor operation, conservatism may be avoided from the safety analyses. Consequently, in 1989, the U.S. NRC modified the licensing requirements allowing the use of realistic methods if uncertainties are identified and quantified [1].

BEPU analyses has been historically applied to Reactor Cooling System (RCS) transient analysis [2], but it starts to be also applied to containment analysis, due to the NPP new designs, such as [3], [4]. Nevertheless, the containment building and the in-containment equipment are still licensed based on the pressure and temperature obtained with conservative containment analyses using the Lumped Parameter (LP) approach. The average containment pressure calculated with the LP approach is quite representative of the containment pressure, as the pressurization is quite homogeneous, at least for more common designs, such as a PWR dry containment [5], [6]. On contrary, the containment temperature calculated by the LP approach is an average temperature and does not necessarily represent the heterogeneity of it [5], [6]. Therefore, realistic containment analyses taking into account local conditions are needed.

In addition, some new Nuclear Power Plants (NPPs), such as the EPR and the APR1400, have more core thermal power than actual Generation II plants, and therefore, they probably will produce higher Mass and Energy (M&E) releases in case of Loss of Coolant Accident (LOCA). This means that a larger containment building will be needed, increasing the investment cost. In such cases, the containment size could be decreased by avoiding conservatism during its design phase analyses. It also could be applicable to the Small Modular Reactor (SMR) concept in order to minimize the total volume occupied by the plant, since usually, conservative calculations are performed in order to determine the containment volume necessary to accommodate all the RCS inventory during a LOCA  Applying realistic methods during the design phase, containment volume can be optimized.

Since a single Best-Estimate (BE) calculation brings results with unknown accuracy, an uncertainty analysis is required to estimate the solution accuracy, as is required by the authorities.

In this paper, a BEPU methodology specifically for realistic containment safety analysis, and based on the Regulatory Guide 1203 philosophy, is proposed and depicted in order to reconsider the in-containment equipment qualification process and/or to ensure the safety margins in new generation containment designs when conservatism is avoided.

This methodology does not attempt to develop any new mathematical tool for quantifying uncertainties and/or errors. The goal is to make use of the existing methods and apply them to containment DBA analyses, in a structured manner, differencing between uncertainties types and errors, and applying the correct method for quantifying them.

## 2. METHODOLOGY PHILOSOPHY

The proposed methodology is based on the white-box philosophy, making possible to rank uncertainties sources in relation to its contribution to the total output uncertainty. Until now, the proposed methodology will be referred as Best Estimate Plus Uncertainty methodology for Containment Safety Analysis (**BEPU-CSA**).

In BEPU-CSA, the “Evaluation Model (EM)” concept is adopted. It is defined as the framework for evaluating the behavior of the NPP system during a postulated transient, like in the Regulatory Guide 1.203  [7]. On the other hand, the “model” concept is described as the representation of a particular physical phenomenon.

The **first principle** adopted in BEPU-CSA is that expert judgment should be minimized. Instead of a subjective Parameter Identification and Ranking Table (PIRT), a “coarse” sensitivity analysis is proposed to identify the influencer input parameters. It requires a high understanding of the transient to be analyzed, and therefore, a full description of it becomes mandatory. The code selected has to be able to reproduce precisely enough the key phenomena, thus a code evaluation has also to be performed to assure its adequacy.

Uncertainties and errors are quantified and propagated through the EM in order to obtain the global output uncertainty. The calculation time has also to be accounted in order to select the correct method and assure the methodology pragmatism. Therefore, since it is pretended that this methodology will be used as a licensing tool, the BEPU-CSA **second principle** adopted stablish that the EM should be computationally affordable.

After uncertainty propagation, a sensitivity analysis is then performed in order to rank the input variables relative to its contribution to the total output uncertainty. Therefore, uncertainty ranking becomes a consequence of the result analysis, and not for subjective estimates.

BEPU-CSA methodology is divided into two main sections: Best Estimate thermal-hydraulic model(s), and the uncertainty/error quantification and sensitivity analysis. Each section is organized in phases, being these the Description, Decision, and Modeling phases for the Best

Estimate section; and Identification, Quantification, and Interpretation for the Accuracy Assessment, as can be seen in the BEPU-CSA flowchart at the end of the document (section 7).

## 3. BEST ESTIMATE EVALUATION MODEL

This section describes the steps contained in the first part of the BEPU-CSA methodology, being these the scenario description, code selection, code adequacy and EM building process.

### 3.1 Scenario Description

The description of the transient to be analyzed is essential for choosing the code to be used. Different phenomena could exist during diverse Design Basis Accidents (DBAs). Flashing, for instance, is a key phenomenon in a LOCA, and it is not produced during a Main Steam Line Break (MSLB) accident. Consequently, it is necessary to use a code that can reproduce the key phenomena present during the transient.

In addition, transient phenomena will also influence the modeling strategy chosen. If figures of merit only involve averages values, a LP framework could be enough. However, if local parameters are needed (i.e. local temperature for equipment qualification), a more detailed nodalization, or even a three-dimensional EM should be considered.

Consequently, the scenario should be minutely described, identifying all the phenomena involved in order to decide which code has to be used, and what will be the modeling strategy to be followed.

### 3.2 Code Selection

Once the phenomena associated with the selected transient has been identified, a simulation code is chosen. Historically, containment analyses have been performed using specific purpose codes like CONTAIN [8] or GOTHIC [9]. In these codes, an input with the Mass and Energy (M&E) release data is introduced via boundary conditions. Nevertheless, there are also codes that allow integral analysis, such as MELCOR [10]. With these codes, the RCS and its components can be modelled along with the containment building and the safety systems. This integral codes do not include three-dimensional capabilities (at least for containment modeling), but they are still useful for many studies, depending on the figures of merit needed. For analysis where three-dimensional phenomena are determinant, the code has to be able to reproduce it. Computational Fluid Dynamics (CFD) codes, or at least codes with 3D-capabilities such as GOTHIC [9], becomes indispensable for that purposes.

It has to be accounted that, when an Integral Analysis Code (IAC) is used, a unique uncertainty analysis will be needed, since all the uncertain parameters can be treated during the same "sequence". However, if a Containment-Specific Code (CSC) is used, or the code does not allow modeling the RCS, two codes will be needed for the analysis. Consequently, the BEPU analysis is divided into two steps (double-BEPU analysis). One BEPU analysis for the M&E release calculation and the other for the containment analysis itself. Of course, a conservative M&E release input from a conservative calculation can also be applied, but then, the analysis cannot be considered purely best estimate.

### 3.3 Code Adequacy

The code selected has to be able to reproduce the scenario key phenomena. Since, most of the codes used in the nuclear industry for licensing purposes have been qualified under requirement of the regulatory authorities; we can take advantage of this valuable information to justify the code applicability in our study If the code qualification assessment does not include all the key phenomena, a set of experiments have to be selected in order to evaluate the code capability in reproducing such phenomena.

## 3.4 Evaluation Model

The next phase is the EM build-up. Since the goal is to perform a best estimate analysis, the EM has to be as precise and detailed as possible, and this means that input data has to be equally detailed. Data will probably come from a huge amount of plant schematics, diagrams, and other related documents. Therefore, the EM building process is divided into two or three practical steps (depending on the modeling strategy followed).

### *3.4.1 NPP CAD model(s)*

In order to organize the plant data available, a **detailed three-dimensional Computational Aid Design (CAD) model** is constructed. It will be helpful to join all the information in only one place, which will be used during all the process. The Vertical Snap method [5] is employed for that purpose. As a first step, the plant schematics are digitalized and exported to the CAD environment. After that, the schematics are vectored using the CAD tools. When the NPP main desks have been vectored, they are extruded to add volume supported by the section schemes.

It is well known that the codes used for containment analyses cannot usually represent the plant geometry as detailed as in a CAD environment. For this reason, a **second CAD model**, with a simplified geometry (but maintaining the main parameters), could become useful in some cases. Of course, this will not be the case of an EM that is being modeled using a LP framework, but it is in three-dimensional EMs where the geometry distribution is explicitly represented. Finally, the data needed to feed the thermal-hydraulic code is extracted.

### *3.4.2 Thermal Hydraulic Evaluation Model(s)*

The data obtained from the CAD model(s) is used to set up the Control Volume (CV) parameters and the geometric distribution in case of three-dimensional approach. Model nodalization should be fine enough to capture all the key phenomena and fast enough in calculating to be affordable in order to accomplish the BEPU-CSA second principle. These two characteristics are antagonist, since a finer model will usually require higher computational resources. Once again, it will depend on the objectives of the analysis and the resolution needed. What is proposed is to perform a mesh independence study in order to identify the coarser mesh able to reproduce the key phenomena. The EM nodalization is progressive refined until the key phenomena becomes independent from the mesh size. How well are these phenomena reproduced will be discussed during the accuracy assessment.

Heat structures data, such as the wall thickness, height and surface, is also extracted from the CAD model(s) as well as the flow connections between the containment compartments. Depending on the scenario to be analyzed, the safety systems that are assumed available have to be also modeled. For a more detailed description of the EM building process see [5].

# 4. ACCURACY ASSESSMENT

Does not matter how detailed the best estimate EM is. It never will reproduce real physics in a perfect manner, since many simplifications and approaches had been implemented on it. Consequently, a single best-estimate calculation give results with an unknown accuracy and therefore, an uncertainty analysis has to be performed in order to estimate the EM accuracy. The goal is to assure that results are under the safety margins established by the regulatory authority, being these to be at least with a 95% probability with a 95% confidence level. This is the well-known 95/95 criterion, required for best estimate analyses [1].

## 4.1 Uncertainty and Error Sources

To estimate the parameters contribution to the total EM uncertainty, its sources have to be previously identified and quantified. EM accuracy will be dependent on the combination of different uncertainty and error sources. Experimental data; plant data; model inadequacy; numerical schemes; geometry simplification; and user effect are the main uncertainty and error sources. Nonetheless, all of them can be classified in three main groups:

- **Random uncertainties**, which are produced when in an experiment that is repeated several times under equal (or similar) conditions, shows different results. Increasing the number of observations does not decrease the uncertainty, but it becomes useful to accurate the Probability Density Function (PDF), which describes the parameters of interest. In other word, random uncertainty is a property of the system that defines a parameter variability.
- **Epistemic uncertainties**, which arise with the lack of knowledge. A parameter uncertainty is considered epistemic when it is not random and cannot be measured. In other words, epistemic uncertainty is a property of the analyst and defines our ignorance rather than a parameter variability.
- **Errors** are defined in [11] as deficiencies in any phase of the analysis that is not due to lack of knowledge. When an error is identified, it can be corrected or allowed to remain. It implies at least two error types. Intentional errors are those that are allowed to remain, such as the finite precision arithmetic in a computer, physical approximations, a specified level of iterative convergence of a numerical scheme, conversion of the governing Partial Differential Equations (PDE's) into discrete equations. On contrary, unintentional errors are due to unknown mistakes, such as human errors. There is no manner to estimate or bound the contribution of unintentional errors; therefore, they will not be accounted in the analysis.

Distinction between random and epistemic uncertainties can be traced back to the beginnings of probability theory [12], and its differentiation becomes indispensable in rational analyses of systems [13]. In addition, the distinction between an uncertainty and an error is crucial for the correct representation of results [11].

## 4.2 PIRT Assessment

In order to accomplish the BEPU-CSA first principle, all uncertainty sources should be ideally taken into account. However, due to the lack of knowledge in some fields and the computational requirements needed for that purpose, it becomes difficult to reach. In most of the BEPU methodologies already developed, uncertain parameters accounted are reduced to the most important ones [2,16,17]. The identification and ranking phenomena is usually performed applying what is denominated "expert judgment" [16]. This process has been heavily critiqued, being labeled even as dangerous when scientific information is insufficient, inclusive or uncertain [17]. For that reason, subjective decisions should be minimized.

To accomplish both BEPU-CSA principles, a sensitivity analysis should be performed for identifying the most influential parameters. Since the sensitivity analysis is just for assessing the parameters influence, the use of a simplified EM is justified, making possible the reduction of the computing-time. This simplified EM is referred to the EM with the coarser mesh able to reproduce the key phenomena from the mesh independence study performed during the modeling process can be used for that purpose. Note that when the LP approach is employed, the use of a simplified EM is not necessary.

The ranking procedure adopted is based on the difference in values for target variables between a base case and a posterior perturbed case. A sensitivity coefficient is $C_s$ is defined as the ratio between the variability in the target variable and the variability in the perturbed parameter. If $C_s >$ 1, the parameter is considered relevant and should be included in the accuracy analysis.

As a result, a parameter ranking can be established accounting for the sensitivity results, and not for subjective decisions.

### 4.3 Uncertainties and Errors Characterization

Since multiple sources of uncertainties and errors have to be considered for a robust prediction, both types of uncertainties (aleatory and epistemic) and errors will be present together in our system. Ranges and probability distributions are generally used to characterize parameter uncertainties. These distributions (or ranges) should be taken into account for input parameters instead of one discrete value only. There are different methods to characterize uncertainties, but it seems to be a dark issue in the BEPU collective, since it is quite difficult to find the uncertainty characterization process in released studies.

When characterizing uncertainties, the case of aleatory variables is clear, since the most appropriate mathematical representation for them is the probabilistic framework. Therefore, if the information is complete, uncertainty parameters can be characterized with an adequate probability distribution. However, it is not common to have all information needed available. In these cases, the uncertainty becomes imprecise or incomplete.

Many BEPU methodologies, such as [18] or [3], treat random and epistemic uncertainties in the same manner, that is applying the Classical Probability Theory (CPT). When the information is incomplete or inexistent, inference methods are normally used in order to estimate prior PDFs. Methods such as Bayes' theorem [19]; Maximum Entropy method [19, 20]; or Expert Judgment [16]. It is common to apply the Principle of Insufficient Reason [22] by assigning a uniform distribution (assumed the most conservative) to estimate the parameter shape when there is complete lack of knowledge, or the only information available is an interval. However, could be situations where assuming "conservative" uniform distribution could lead to a serious underestimation in the resulting probability [22–24], since once an assumption is introduced, the resulting probability will be highly influenced by it.

We have to account that uncertain variables cannot be modeled as random variables unless sufficient information can be provided to verify the assumed probability density and/or joint probability density functions. The problem with CPT is that it is not possible to quantify the lack of knowledge. At the end, it only presents a unique value for the probability. Therefore, the assumption of uniformity (or any other assumption) has to be properly justified to avoid a serious underestimation in probabilities when characterizing epistemic uncertainties under the classical probability framework.

Since most of scientific and engineering community have been accepted that CPT has its limitations in handling epistemic uncertainties, alternative theories and methods have been developed. During the 70s decade, the Possibility theory [26], based on the fuzzy sets concept [27], emerged as tool for dealing with uncertainty in terms of lack of knowledge. Almost at the same time, Shafer limited the word "probability" to the objective concept and assumed the word "belief" as a base of a new subjective theory [28]. Inspired by the previous work of Dempster during the 60s decade about the upper and lower probabilities for statistical hypothesis [29], he proposed the Theory of Evidence [30], also known as Dempster-Shafer Theory (DST). Since DST is capable of treating with both aleatory and epistemic uncertainties, it is suitable to characterize imprecise uncertainties.

Summarizing, uncertainties will be treated by applying different methods and theories, which will depend on its nature (random or epistemic), and on the information available.

It is convenient firstly to start quantifying the numerical errors. Once the numerical errors are estimated, it becomes possible to estimate models/correlations adequacy and scalability, avoiding code errors to mask them. Finally, plant data uncertainties will be quantified.

#### *4.3.1 Numerical Errors*

Verification process is performed in order to check the implementation of the numerical scheme and to measure its accuracy. However, our goal is to distinguish errors in mathematical modeling accuracy from other errors. The five major sources of numerical errors are due to spatial and temporal discretization, the iterative procedure, computer round-off, and computer programming errors [11].

The discretization is referred to the conversion of the continuum model into a discrete mathematical problem. There are different methods to reach an approximated solution for the Partial Differential Equations (PDE's). The most common methods used in thermal hydraulics are the Finite Difference Method (FDM) and the Finite Volumes Method (FVM). Since the discretization series have to be finite, the discretization process basically adds <u>truncation errors</u>.

The discretization process produces difficulties in the numerical solution of nonlinear PDE's. Direct methods attempt to solve the problem by a finite sequence of operations. In the absence of rounding errors, direct methods would deliver an exact solution. In contrast, an iterative method is a mathematical procedure that generates a sequence of improving approximate solutions for a class of problems, in which the n-*th* approximation is derived from the previous ones. Iterative methods are required for solving nonlinear equations, but they are also used for linear problems involving a large number of variables, where direct methods would be computationally expensive. Often a scaled iterative-convergence tolerance is specified, and the difference between the solutions of successive iteration steps at each point in the grid is computed. If the magnitude of this difference is less than the specified tolerance, then the numerical scheme is defined to be iteratively converged. Consequently, the iteration errors (residuals) are present in codes that use iterative solvers, where the result must converge to the exact value as the iterations develop.

Computers used to have a limited capability for storage digits, thus it introduces round-off errors to the calculation. In addition, programming errors could be present in the code being used for the analysis, adding additional errors. Since most of the commercial software does not allow accessing the source code, and both, round-off and programing errors, are unintentional, they will not considered in the analysis.

In order to obtain accurate estimates of the different numerical schemes errors, they have to be converted to epistemic uncertainties [31]. The simplest method to do that is using the error estimate to apply uncertainty bands above and below the simulation prediction. The Richardson's method [32] makes possible to estimate numerical errors by using two or three meshes and by knowing the order of the different numerical schemes. Roache's Grid Convergence Index [33] provides a specific example of converting the discretization error estimate from Richardson extrapolation to an uncertainty.

It has to be noted that when treating epistemic uncertainties as intervals, the proper mathematical method for combining uncertainties due to discretization, and incomplete iteration, is simply sum the intervals using interval arithmetic [31].

#### *4.3.2 Experiment Data Uncertainties*

Validation is defined as the process of determining the model adequacy in reproducing the real physics. What is normally done is to simulate experiments and compare the code predictions against measurements. Nevertheless, uncertainties are not usually included in code qualification reports, and therefore, one has to deal with incomplete data to estimate its uncertainty.

The main uncertainty source added by experiments use to be the measure instrument accuracy. These uncertainties are of random nature; thus experiments should be repeated several times to obtain an adequate data set. Unfortunately, this is not a common practice between experimenters. At least for the experiments that concern us, where most of them were performed once. In such cases, methods like possibility theory or DST may be applied.

However, if there is enough information the most appropriate mathematical representation for aleatory uncertainties is the probabilistic framework.

#### *4.3.3 Model & Correlation inadequacy*

As was commented above, models and correlations are based on measured data. Since the use of data obtained from the reference reactor is complicated, simulation of accidents in experiments with scaled test facilities are inevitable. Therefore, the question is if models resulting from reduced-scaled experiments are suitable or not for a full-scaled plant EM.

Physical models in codes use empirical, mechanistic, and/or semi-empirical correlations for the closure laws of balance equations. Constants in these formulas are sometimes determined by curve fitting, and may depend strongly on the geometry and fluid conditions.

A purely empirical correlation is a best fit of experimental data, wherein the quantity to model is expressed as any function of the principal variables. It can be very accurate within the domain of experimental study, but extrapolating beyond it will result in unknown calculation accuracy. Therefore, it is mandatory to determine the correlation application range, and not surpass it.

The mechanistic approach consists in assuming a governing physical mechanism. The correlation then is derived theoretically with no experimental data. This approach properly accounts for the scaling effects, as far as physical assumptions are valid.

Semi-empirical models rely on some governing physical assumption, but retain some free parameters to adjust the experimental data. It is the most frequently used in current codes.

Scale distortions can be classified in two categories:

- Test facility's scale distortions on relevant processes.
- Scale-up capability of model/correlations used in the code.

Experimental data measured cannot be extrapolated to the NPP because of unavoidable distortions in the design and construction of it. Distortions such as heat releases from structures to the coolant, and heat losses to the environment are impossible to avoid, no matter what scaling laws are adopted [34]. To estimate <u>facilities' scale distortions</u>, it is necessary to analyze key parameters on Separate Effect Tests (SETs) and Integral Effect Tests (IETs) with different scale factors. All relevant phenomena at local scale should be predicted correctly when compared against several SETs at different scales. This may demonstrate that it predicts the distorted and non-distorted phenomenon with the same quality. Most of these studies should been performed during the code verification and validation assessment. Therefore, code qualification report could be used to support models/correlations adequacy to NPP scales.

The triad method used by [35], which is related with the Kv-method [36], can be used for determining the model/correlation <u>scale-up capability</u>. It is based in three separate, but related computer models, being these one for the prototype, other for an ideal scaled experiment, and the last for the scaled experiment. It is of interest to estimate scale distortions from a reduced-scaled experiment to plant conditions. Therefore, at least two EMs will be needed, being these the experimental facility and a NPP-scaled EM. Intermediate-scaled EMs may be also necessary in order to estimate scale-up capability at different ranges.

**Firstly**, since the quantification of model uncertainties takes place by comparison with experimental data, an appropriate selection of the adequate experimental matrix is imperative. Choosing an appropriate experimental matrix will considerably reduce the compensating errors, which can mask the uncertainty estimation. The experimental data selected for quantification have to be representative of the considered application, including the scale of the analyzed facility.

**Secondly**, the experiment-scaled EM is compared against SET data to estimate the uncertainty due to model/correlation inadequacy. This comparison makes possible to estimate the model capability in reproducing the experiment phenomena. Measurement uncertainties have to be accounted to avoid masking the model/correlation error. It has to be noted that scale distortions in code predictions are narrowed related with the spatial discretization used. Therefore, the EM nodalization has to be equivalent to as in the model/correlation validation process.

**Thirdly**, a comparison between the NPP-scaled and the experiment EM is performed. NPP-scaled EM is a scaled-up version of the experiment facility. Scaling criteria have to be applied by using the adequate method, see [37], which will be dependent on the phenomenon analyzed and on the experimental matrix being used. At the end, uncertainties due to model/correlation accuracy and scaling distortions can then be “easily” estimated by comparing both EM results.

This procedure should be applied to every model/correlation related to the key phenomena, which were previously identified during the PIRT assessment.

#### *4.3.4 System Uncertainties*

System uncertainties come from two main sources. The incompleteness of technical data when modeling the plant geometry, and the measurements performed during the plant operation.

To develop an input deck NPP of interest, difficulties may be encountered on deciding how to provide some coefficients of models, and correlations used in the system code when they are very dependent on the specific geometrical design, or when they were tested and characterized in conditions far from the operation conditions.

Normally, availability of real plant schematics and documentation is scarce. Hence, the information we have for plant modeling is usually incomplete, and incompleteness of data is by definition an epistemic uncertainty. Even if all schematics and plant data were available, they actually will differ from the real plant, since in a construction site, the precision used to be limited. Furthermore, there may be the case where the plant geometry has to be simplified due to code limitations or analyst decision for improving the computational requirements. These uncertainties may affect to critical parameters in the containment analysis, such as free volume and heat sink areas. This kind of uncertainties are considered epistemic. Since it is quite difficult, if not impossible, to found reference data to compare with, a conservative band should be applied (e.g. applying a coefficient to the estimated free volume as in traditional licensing analysis).

In contrast, plant-operation data, which is introduced in the EM as initial / boundary conditions, are of random nature, as happen with the experimental measurements. Therefore, the procedure for quantify them is similar. When enough information is available, the CPT can be applied to define its PDF. When it is insufficient, or there is total ignorance, DST or equivalent becomes again the best choice.

Simplifications due to code limitations in representing the system geometry are also included in this section. They will be treated as errors and defined as commented in section 4.3.1. That is by applying bands to the affected variable (such as free volume or heat surfaces) based on the error estimation.

### 4.4 Uncertainty Propagation

The EM is considered deterministic in the sense that when all input data is specified, the model only produces one response. However, it could be also considered non-deterministic because it can produce multiple system responses due to the existence of input data uncertainties, or multiple alternative models available. Therefore, to predict the non-deterministic response of the system, the EM has to be executed multiple times to account for additional uncertainties during its execution [23]. These uncertainties are produced during each time step calculated, and accumulates with the progress of the transient, changing the applicability of models and correlations, and therefore affecting the output accuracy and credibility.

The Monte-Carlo method [38] is selected for the uncertainty propagation through the EM. However, since most of EMs require a considerable amount of computational resources (consider the BEPU-CSA first principle), the uncertainty propagation is performed by applying the non-parametric Tolerance Limit Criteria [39] to account for all uncertain parameters with a reduced number of Monte-Carlo iterations.

Since this is a non-parametric method, the number of iterations needed will be dependent only on the tolerance and confidence limits established, being 59 runs to establish the 95th percentile at 95-percent confidence (95/95) for one tolerance limit. A random sample is drawn according to the specified parameter distributions, as well as to any quantified state of knowledge dependences. All uncertain quantities are varied simultaneously for each code run. Finally, from this sample, quantitative uncertainty statements are immediately derived by applying statistical concepts and methods.

### 4.5 Sensitivity Analysis

The application of the Wilks method by itself only ensure that the established limit is not surpassed with a 95% probability and 95% confidence level. However, the influence of each of the input uncertainties in the EM output is still unknown, making necessary a sensitivity analysis. Fortunately, since a “reduced” set of Monte-Carlo iterations has been already performed, uncertainty statements and sensitivity measures are available simultaneously for output quantities of interest from the same variation of input parameters and code calculations.

Sensitivity measures like Standardized Rank Regression Coefficients, Rank Correlation Coefficients and Correlation Ratios permit a ranking of uncertainties in model formulations and input data with respect to their relative contribution to code output uncertainty. It makes possible to rank the input variables relative to its contribution in the total output uncertainty. Like stated in the GRS methodology [15], this ranking become a result of the analysis, and not of prior estimates and expert judgments. The method relies only on actual code calculations without using approximations like fitted response surfaces or goodness-of-fit tests.

## 5. CONCLUSION

A BEPU methodology, based on the Regulatory Guide 1203 philosophy, is proposed specifically for containment accident analysis. It is referred as BEPU-CSA and it is built around two main principles: expert judgment is minimized and it has to be computational affordable.

BEPU-CSA is structured in two main blocks, being these the best estimate evaluation model and the accuracy assessment. These two main blocks are also subdivided in six differenced phases, being these a Description, Decision, and Modeling phases for the best estimate evaluation model block; and the Identification, Quantification, and Interpretation phases for the accuracy assessment

The best estimate containment evaluation model has to be detailed enough in order to evaluate the figures of merit desired. The code used and the mode ling strategy followed will be dependent on the transient of interest, e.g. for local phenomena analysis, a three-dimensional framework is needed, and therefore a code with three-dimensional capabilities. In addition, if the code used does not has the capability of modeling the primary cooling system, a double-BEPU analysis will be required.

In order to estimate the evaluation model accuracy, an uncertainty and error analysis should be performed. A PIRT assessment based on a sensitivity analysis is recommended in order to avoid subjective decisions. Different methods for uncertainty quantification are proposed depending on the nature of the uncertainty and the information available. The Monte-Carlo approach, along with the non-parametric Tolerance Limit Criteria is suggested to reduce the number of iteration needed in the uncertainty propagation process, but maintaining the 95/95 criterion established by the NRC. The sensitivity analysis could be used to rank the uncertainties relative to its contribution to the total output uncertainty. Therefore, ranking becomes a consequence of the result analysis, and not of subjective estimates. It avoids approximations like fitted response surfaces.

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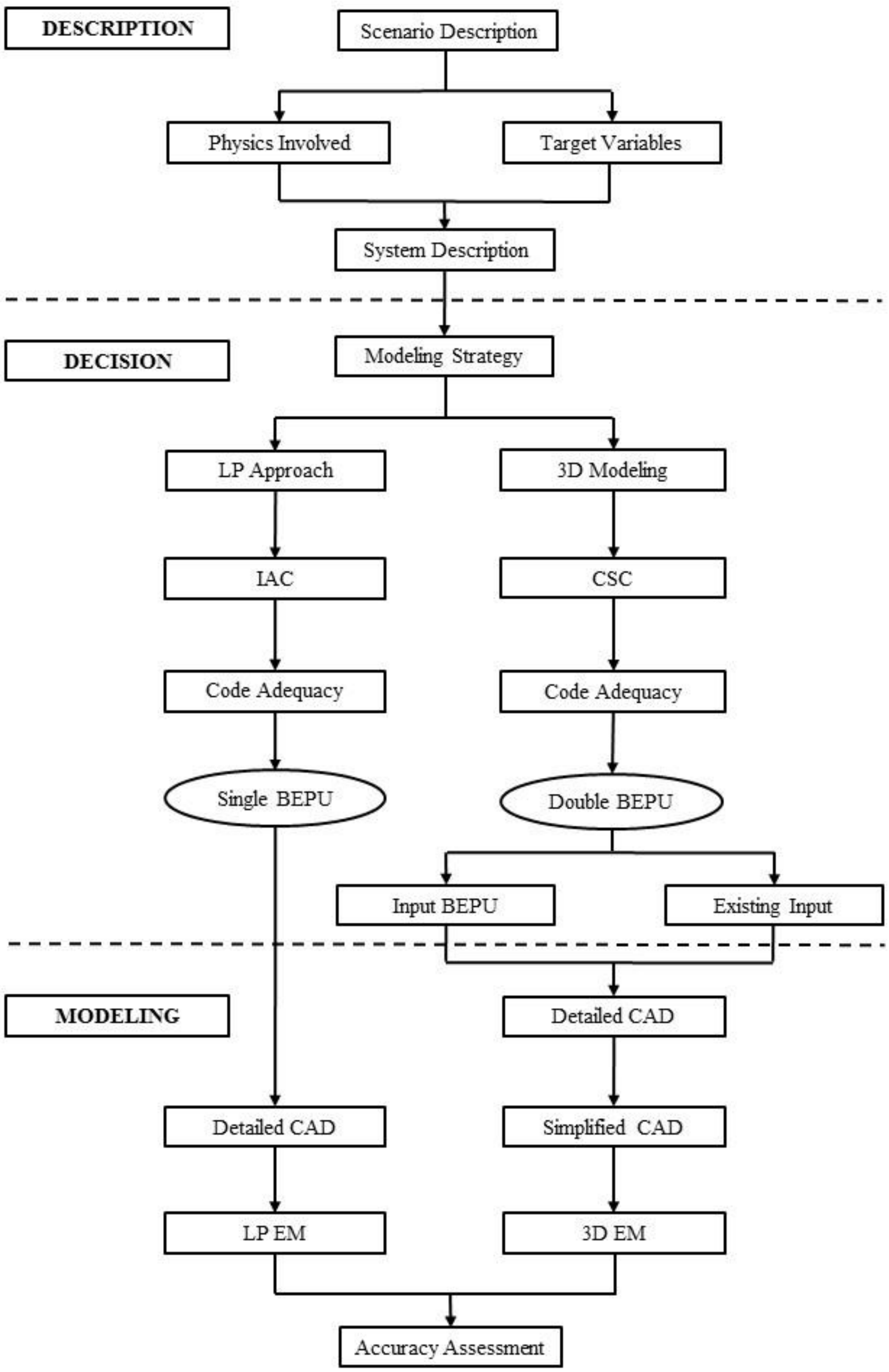
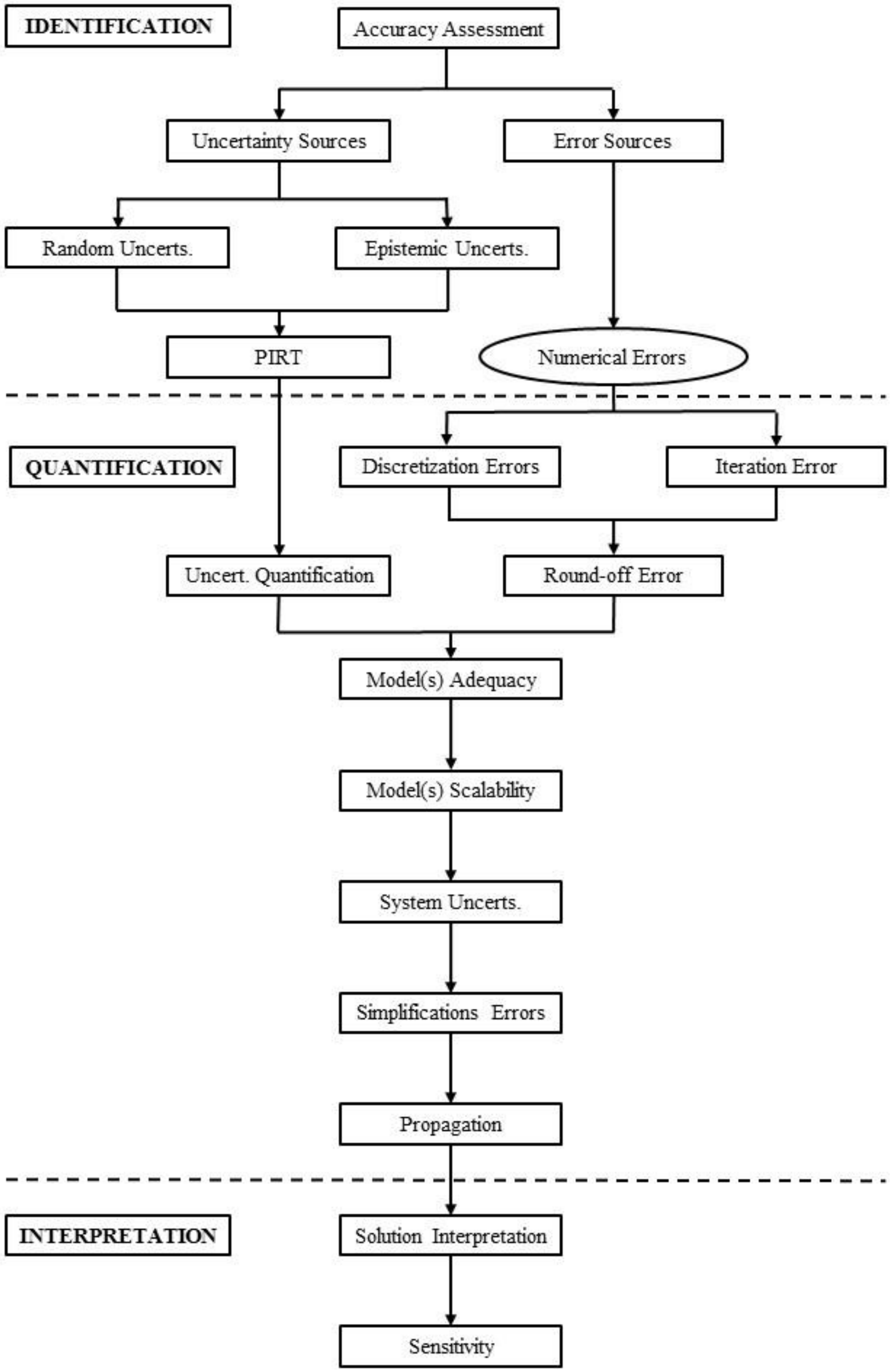
# 7. APPENDIX A: BEPU-CSA FLOWCHART




IDENTIFICATION
Accuracy Assessment
Uncertainty Sources
Error Sources
Random Uncerts.
Epistemic Uncerts.
PIRT
Numerical Errors
QUANTIFICATION
Discretization Errors
Iteration Error
Uncert. Quantification
Round-off Error
Model(s) Adequacy
Model(s) Scalability
System Uncerts.
Simplifications Errors
Propagation
INTERPRETATION
Solution Interpretation
Sensitivity