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UNCERTAINTIES IN PREDICTIONS BY THERMAL-HYDRAULIC CODES: APPROACHES AND RESULTS

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ABSTRACT

The present paper deals with the description of the salient features of three independent approaches for estimating uncertainties associated with predictions of complex system codes. The 1st approach is the "standard" one and the most used at the industrial level: it is based upon the selection of input uncertain parameters, on assigning related ranges of variations and, possibly, PDF (Probability Density Functions) and on performing a suitable number of code runs to get the combined effect of variation on the results. In the 2nd approach the uncertainty derives from the comparison between relevant measured data and results of corresponding code calculations. The 3rd approach is based upon a sensitivity analysis procedure and uses the experimental data to characterize the ranges of variation of 'all' input parameters. Selected results from the application of the 2nd approach are outlined.

INTRODUCTION

Uncertainty analysis aims at characterizing the errors associated with experiments and predictions of computer codes, in contradistinction with sensitivity analysis, which aims at determining the rate of change (i.e., derivative) in the predictions of codes when one or more (typically uncertain) input parameters varies within its range of interest.

The first approach, reviewed as the prototype for propagation of code input uncertainties includes the "CSAU method" (Code Scaling, Applicability and Uncertainty) and the majority of methods adopted by the nuclear industry such as the so-called "GRS method". Although the entire set of the actual number of input parameters for a typical NPP (Nuclear Power Plant) input deck, ranging up to about 105 input parameters, could theoretically be considered as uncertainty sources by these methods, only a 'manageable' number (of the order of several tens) is actually taken into account in practice. Ranges of variations, together with suitable PDF (Probability Density Function) are then assigned for each of the uncertain input parameter actually considered in the analysis. The number of computations using the code under investigation needed for obtaining the desired confidence in the results can be determined theoretically (it is of the order of 100). Subsequently, an additional number of computations (ca. 100) with the code are performed to propagate the uncertainties inside the code, from inputs to outputs (results).

The second approach reviewed in this paper is the propagation of code output errors, as representatively illustrated by the UMAE-CIAU (Uncertainty Method based upon Accuracy Extrapolation 'embedded' into the Code with capability of Internal Assessment of Uncertainty). Note that this class of methods includes only a few applications from industry. The use of this method depends on the availability of 'relevant' experimental data, here, the word 'relevant' is connected with the specific NPP transient scenario under investigation for uncertainty evaluation. Assuming such availability of relevant data, which are typically Integral Test Facility (ITF) data, and assuming the code correctly simulates the experiments, it follows that the differences between code computations and the selected experimental data are due to errors. If these errors comply with a number of acceptability conditions, then the resulting (error) database is processed and the 'extrapolation' of the error takes place. Conditions for the extrapolation are:

- building up the NPP nodalization with the same criteria as was adopted for the ITF nodalizations;
- performing a similarity analysis and demonstrating that NPP calculated data are "consistent" with the data measured in a qualified ITF experiment.

The third approach described in this paper is based on ASAP (Adjoint Sensitivity Analysis Procedure) and GASAP

(Global Adjoint Sensitivity Analysis Procedure) methods extended to performing uncertainty evaluation in conjunction with concepts from Data Adjustment and Assimilation (DAA). The ASAP is the most efficient deterministic method for computing local sensitivities of large-scale systems, when the number of parameters and/or parameter variations exceeds the number of responses of interest. The GASAP has been originally designed as a global sensitivity analysis and optimization method by which system's critical points (i.e. bifurcations, turning points, saddle points, response extrema) can be determined in the combined phase-space formed by the parameters, forward state variables, and adjoint variables and then subsequently analyzed by the efficient ASAP. The DAA is the technique by which experimental observations are combined with code predictions and their respective errors to provide an improved estimate of the system state; in other words, DAA uses dynamic models to extract information from observations in order to reconstruct the structure of the system and reduce uncertainties in both the system parameters and responses. The reason for considering this approach derives from its potential to open an independent way (i.e. different from propagation of code input errors or from propagation of code output errors) for performing global uncertainty analysis.

Results from four applications of the second approach to cases of industrial interest are outlined.

- The first discussed case was conducted as an independent analysis within the framework of the licensing of the Angra-2 four-loops PWR (Pressurized Water Reactor) to validate the uncertainty results obtained by the utility.
- The second discussed case, is related to IBLOCA (Intermediate Break Loss of Coolant Accident) in a VVER-440 (Water-cooled, Water-moderated Energy Reactor, type 440) was conducted to demonstrate the similarity of results obtained by two different computer codes (e.g. Relap5 and Cathare).
- The third discussed case, is related to the Double Ended Guillotine Break LBLOCA (Large Break LOCA) in a VVER-440 aimed at demonstrating the differences between the results from conservative and BEPU (Best Estimate Plus Uncertainty) approaches.
- The fourth discussed case is the result of a validation study including the comparison other n uncertainty methods.

Background and Objectives

Let's consider three relevant definitions, i.e., in alphabetic order, accuracy, sensitivity and uncertainty, as they are commonly accepted in the sector of deterministic accident analysis within the more general framework of nuclear reactor safety technology.

Accuracy is defined, [1], as "the known bias between a code prediction and the actual transient performance of a real facility". Therefore, the evaluation of accuracy implies the availability of a calculation result and of a measured value. Point values and continuous time trends shall be included in the definition. The experimental error is not part of the definition. However, in the majority of cases of practical interest in the area of accident analysis of nuclear power plants, the error that characterizes the measurement is much lower of the error (i.e. the accuracy) that characterizes the comparison between measured and predicted values.

The sensitivity is, according to [2], "… the study of how the variation in the output of a model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variation, and of how the given model depends upon the information fed into it.". Furthermore, "Sensitivity analysis studies the relationships between information flowing in and out of the model.". These definitions imply that the parameter values that characterize both (and only) the boundary and initial conditions, e.g. representative of a system, and the numerical structure of a correlation embedded into the model (or code) constitute the typical objective of a Sensitivity Analysis (SA).

The uncertainty is the unknown error that characterizes the prediction of any code or model. The uncertainty analysis is, according to [1] and related to system thermal-hydraulic code predictions, "an analysis to estimate the uncertainties and error bounds of the quantities involved in, and the results from, the solution of a problem. Estimation of individual modeling or overall code uncertainties, representation (i.e. nodalization related) uncertainties, numerical inadequacies, user effects, computer compiler effects and plant data uncertainties for the analysis of an individual event". Furthermore, to conclude with a citation from [2], "… uncertainty is not an accident of the scientific method but its substance.". Within the present context, the uncertainty is the necessary supplement for a best-estimate thermal-hydraulic code prediction; see also [3].

The reason why an accuracy analysis (AA) is performed is mainly connected in the sector under investigation here (i.e. the deterministic accident analysis) with the demonstration of qualification for computer codes. The accuracy analysis implies the availability of relevant experimental data and of tools to characterize the resulting discrepancies from qualitative and quantitative viewpoints, e.g. [4] and [5].

The reasons why a sensitivity analysis (SA) is performed are strongly affected by the type and the objectives of the model and may range from verification purposes, to finding singular points (e.g. maximum and minimum) of an assigned output quantity, or the factors that mostly contribute to that output, or the correlation among input variables. It can be premised that needs for SA come from the fundamental principles of quality assurance.

The reasons why an uncertainty analysis (UA) is performed come from nuclear safety principles and primarily from concepts like defense-in-depth. It must be ensured that the nominal result of a code prediction, 'best-estimate' in the present case, is supplemented by the uncertainty statement, that can be simplified as 'uncertainty bands', in such a way that connected safety margins are properly estimated.

The key result from AA is the demonstration of the qualification level of a code and the characterization of the

range of parameters over which the code should be considered as qualified and applicable to situation of interest to nuclear reactor safety. The AA should also provide an answer to the scaling issue, [6].

The key result from SA is the influence of input parameters upon selected output quantities and the evaluation of the relative influence of input parameters, according to the definition given above.

The key results from UA are error bands that bound the best-estimate predictions. Point value error bands can be distinguished from continuous error bands that bound one or several curves, as well as from three-dimensional graphic representations where instantaneous values for quantity-error (e.g. pressure) are reported together with time-error as a function of time, [7].

Therefore AA, SA and UA are closely linked, but important differences can be identified. All that is needed for a meaningful SA is the model and the input values, while UA attempts to estimate the actual error band value for an output; as a consequence, it needs a reference value typically not available (thus the definition of 'unknown' error). AA, on the other hand needs relevant experimental data. As an example, the check that an assigned model satisfies the first or the second principle of thermodynamics may not be the objective of SA, but it is the objective for UA and can be confirmed following AA. Furthermore, when performing SA, the values of the concerned input parameters are varied arbitrarily around the initial (or nominal) value to a 'small' or to a 'large' extent depending upon the scope of the analysis; when performing the UA, whatever is the method adopted, a range of variation for the concerned input parameters must be assigned or available. SA may be a way to perform UA if input parameters are properly selected with proper ranges of variation.

Specific aspects of thermal-hydraulic computer codes should be considered when performing either AA or SA or UA. One example is the impact of the nodalization upon the results: there are phenomena like Critical Heat Flux or Two-Phase Critical Flow characterized by explicit or implicit equations implemented in the codes and phenomena like Natural Circulation that depend upon both the equations implemented into the code and upon the structure and the parameters related to the nodalization. In this last case a significant (AA, or SA or UA) analysis must account for nodalization parameters like individual node length, equivalent diameters, node density (i.e. average node length) and relative position of nodes (i.e. thermal-hydraulic centers of nodes).

The present paper focuses on UA. The historical triggering for UA in the area of nuclear reactor thermal-hydraulics may be traced as the Regulatory Guides (e.g. RG 1-157 and, more recently 1-203, [3]) issued by US NRC to streamline the application of codes when demonstrating the compliance of reactor accident scenario calculation with the criteria in Appendix K of 10 CFR 50-46. However, an international code assessment project conducted within OECD/NEA/CSNI since the beginning of eighties also showed the exigency for UA.

The first framework for calculating the uncertainty was proposed by US NRC and denominated Code Scaling, Applicability, and Uncertainty (CSAU [8]). The application of the CSAU methodology resulted in the calculation of the Peak Cladding Temperature during a LBLOCA Design Basis Accident event for a Westinghouse 4-loop pressurized water reactor with the uncertainty to a 95% confidence level. The peak temperature was calculated using the TRAC thermal-hydraulic analysis code and was given as a single-valued number with uncertainty bands.

In the meantime, a number of uncertainty methodologies were proposed in other countries, including the GRS, the UMAE and the AEA Technology methods, as summarized in [9] and [10]. These methods, although sharing a common goal with CSAU, use different techniques and procedures to obtain the uncertainties on key calculated quantities. More importantly, these methods have progressed far beyond the capabilities of the early CSAU analysis. Presently, uncertainty bands can be derived (both upper and lower) for any desired quantity throughout the transient of interest, not only point values like peak cladding temperature. For one case, the uncertainty method is coupled with the thermal-hydraulic code and is denominated CIAU (Code with capability of Internal Assessment of Uncertainty, [11]) and discussed below in more detail. All these methods are described into detail in [12], including examples of applications to cases of industrial interest.

The purpose of the present paper is twofold: a) to identify the roadmaps for uncertainty evaluation adopted by the methods currently applied to the cases of industrial interest, making reference to the classification proposed in [12]; b) to propose an innovative method that might not suffer of the drawbacks identified for the current methods.

Namely the propagation of code input error and the propagation of the calculation output error constitute the key-words for identifying the methods of current interest for industrial applications; while the Adjoint Sensitivity Analysis Procedure and the Global Adjoint Sensitivity Analysis Procedure methods extended to performing uncertainty evaluation in conjunction with concepts from Data Adjustment and Assimilation constitute the innovative method, whose fundaments are provided in [13] to [15].

APPROACHES FOR UNCERTAINTY

The features of independent approaches for estimating uncertainties are reviewed below.

The propagation of code input errors (Fig. 1): this can be evaluated as being the most adopted procedure nowadays, endorsed by industry and regulators. It adopts the statistical combination of values from selected input uncertainty parameters (even though, in principle an unlimited number of input parameters can be used) to calculate the propagation of the errors throughout the code.

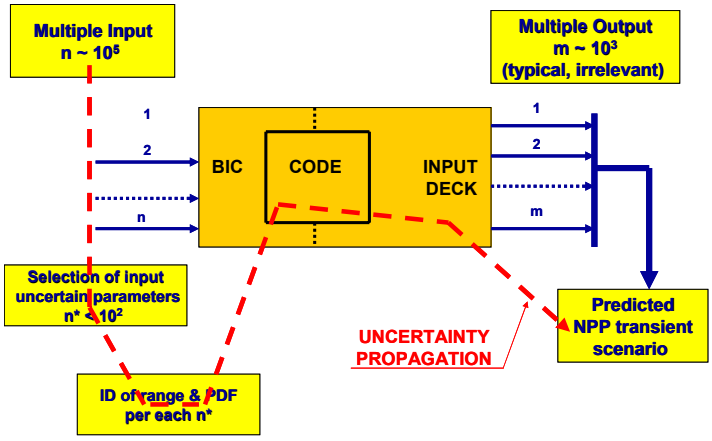

Figure 1 - Uncertainty methods based upon propagation of input uncertainties (GRS method).

The propagation of code output errors (Fig. 2): this is the only demonstrated independent working alternative to the previous one and has also been used for industrial applications. It makes full and direct reference to the experimental data and to the results from the assessment process to derive uncertainty. In this case the uncertainty prediction is not propagated throughout the code.

The 'third' approach, (Fig. 3): this is an independent way, i.e. different from propagation of code input errors or from propagation of code output errors is based on Adjoint Sensitivity Analysis Procedure (ASAP), Global Adjoint Sensitivity Analysis Procedure (GASAP), [13] and [14] and Data Adjustment/Assimilation (DAA) methodology [15] by which experimental and calculated data, including the computation of sensitivities (derived from ASAP), are mathematically combined for the prediction of the uncertainty scenarios. The approach is reviewed hereafter as a deterministic method.

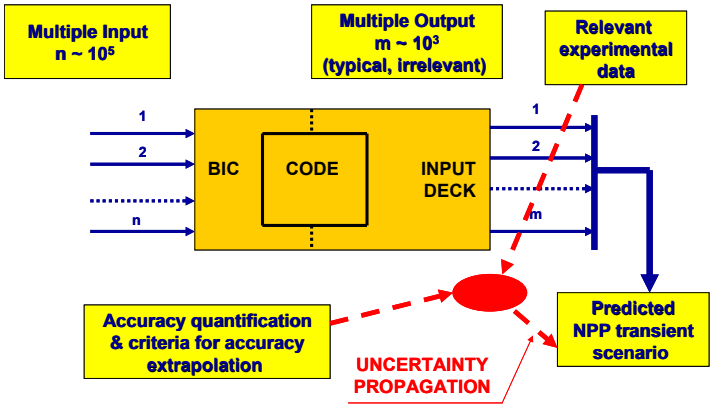

Figure 2 - Uncertainty methods based upon propagation of output uncertainties (CIUA method).

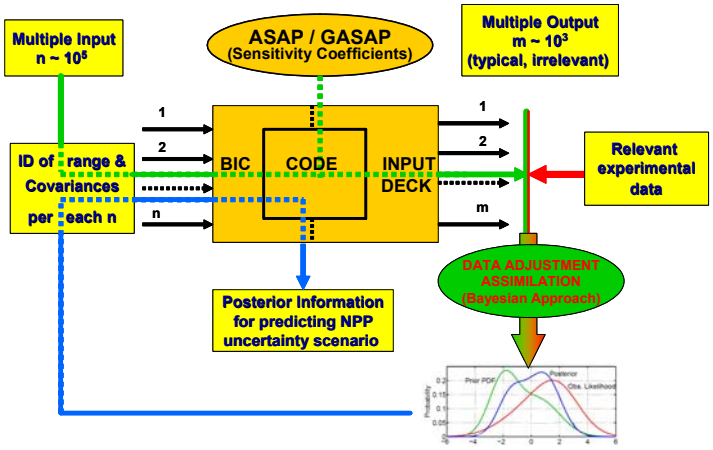

Figure 3 – Uncertainty methodology based on Adjoint Sensitivity Analysis Procedure and Data Adjustment/Assimilation.

The first approach, reviewed as the prototype for propagation of code input errors, is the so-called "GRS method" [16], which includes the so-called "CSAU method" (Code Scaling, Applicability and Uncertainty) [8] and the majority of methods adopted by the nuclear industry. Although the entire set of the actual number of input parameters for a typical NPP (Nuclear Power Plant) input deck, ranging up to about 105 input parameters, could theoretically be considered as uncertainty sources by these methods, only a 'manageable' number (of the order of several tens) is actually taken into account in practice. Ranges of variations, together with suitable PDF (Probability Density Function) are then assigned for each of the uncertain input parameter actually considered in the analysis.

The number of computations needed for obtaining the desired confidence in the results can be determined theoretically by the Wilks formula [17]. Subsequently, the identified computations (ca. 100) are performed using the code under investigation to propagate the uncertainties inside the code, from inputs to outputs (results). The logical steps of the approach are depicted in Fig. 1.

The main drawbacks of such methods are connected with: a) the need of engineering judgment for limiting (in any case) the number of the input uncertain parameters; b) the need of engineering judgment for fixing the range of variation and the PDF for each input uncertain parameter; c) the use of the code-nodalization for propagating the uncertainties: if the code-nodalization is wrong, not only the reference results are wrong but also the results of the uncertainty calculations; d) the process of selecting the (about) 100 code runs is demonstrably not convergent, and the investigation of results from two or more different sets of 100 calculations shows different values for uncertainty. A study performed by KAERI in the framework of the Phase III of BEMUSE project [18] is summarized in Fig. 4. A direct Monte-Carlo simulation consisting of 3500 runs was

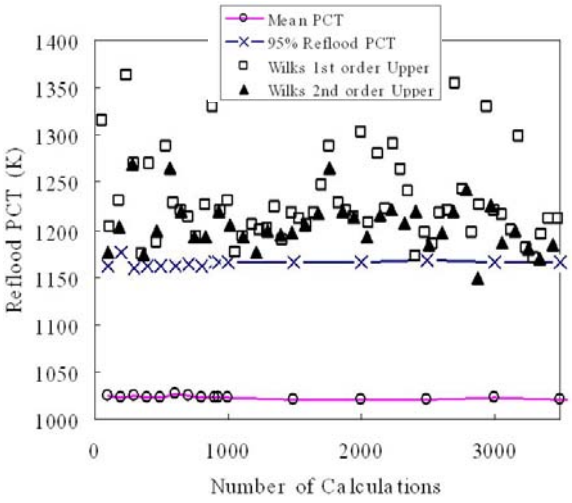

Fig. 4: KAERI direct Monte-Carlo analysis (Phase III of BEMUSE): spread of the upper limit of PCT using Wilks formula at first and second order.

performed for simulating the Large Break Loss Of Coolant Accident (LBLOCA) L2-5 in the LOFT facility and several samples of n = 59 and n = 93 calculations were considered. The following considerations apply:

- From about 1000 runs, the mean value (equal to 1034 K) and the 95% empirical quantile (equal to 1173 K) of the first PCT (Peak Cladding Temperature) are almost stabilized;
- The 95% quantile value of 1173 K has to be compared with the value of 1219 K obtained with the sample of 93 calculations used for evaluating the upper tolerance limit of the first PCT in the BEMUSE project. A difference of 46 K has been attained;
- The dispersion of the upper limit obtained by using Wilks' formula at the first (i.e. the maximum value is retained) and second order (i.e. the second maximum value is retained), with a probability of 95% and a confidence level of 95%, was studied. The following aspects have to be outlined:
  - The spread of the results predicted for the upper limit of the first PCT is equal to roughly 200 K at the first order and 120 K at the second order;
  - At first order, among the 58 calculations, ranging from 1170 K to 1360 K, no-one was found significantly lower than the 95% quantile of the 3500 code runs, notwithstanding statistically 3 cases (i.e. 5% of 58) are expected;
  - At the second order, among 37 calculations, ranging from 1150 K to 1270 K, 1 case was found below 1173 K.

The second approach, reviewed as the propagation of code output errors, is representatively illustrated by the UMAE-CIAU (Uncertainty Method based upon Accuracy Extrapolation [19] 'embedded' into the Code with capability of Internal Assessment of Uncertainty [11, 7]). Note that this class of methods includes only a few applications from industry. The use of this method depends on the availability of 'relevant' experimental data, where here the word 'relevant' is connected with the specific NPP transient scenario under investigation for uncertainty evaluation. Assuming such availability of relevant data, which are typically Integral Test Facility (ITF) data, and assuming the code correctly simulates the experiments, it follows that the differences between code computations and the selected experimental data are due to errors. If these errors comply with a number of acceptability conditions [19], then the resulting (error) database is processed and the 'extrapolation' of the error takes place. Relevant conditions for the extrapolation are:

- Building up the NPP nodalization with the same criteria as was adopted for the ITF nodalizations;
- Performing a similarity analysis and demonstrating that NPP calculated data are "consistent" with the data measured in a qualified ITF experiment.

The main drawbacks of this method are as follows: (i) the method is not applicable in the absence of relevant experimental information; (ii) a considerable amount of resources is needed to establish a suitable error database, but this is a one-time effort, independent of subsequent applications of this method; (iii) the process of combining errors originating from different sources (e. g, stemming from different ITF or SETF (Separate Effect Test Facility), different but consistent nodalizations, different types of transient scenarios) is not based upon fundamental principles and requires detailed validation.

The third approach, depicted in Fig. 3, is based upon the powerful mathematical tools of ASAP, GASAP and DAA by which all parameters $\boldsymbol{\alpha}$ that affect any prediction, being part of either the code models or the input deck can be considered. The Adjoint Sensitivity Analysis Procedure (ASAP) [13, 14] is the most efficient deterministic method for computing local sensitivities $\mathbf{S}$ of large-scale systems, when the number of parameters and/or parameter variations exceeds the number of responses R of interest (that is the case of most problems of practical interest). In addition, also system's critical points $\mathbf{y}$ (i.e. bifurcations, turning points, saddle points, response extrema) can be considered and determined by the Global Adjoint Sensitivity Analysis Procedure (GASAP) [13, 14] in the combined phase-space formed by the parameters, forward state variables, and adjoint variables. Subsequently the local sensitivities of the responses R located at critical points $\mathbf{y}$ are analyzed by the ASAP.

Once the sensitivity matrix S of the responses R respect to the parameters $\boldsymbol{\alpha}$ is available, the moment propagation equation is adopted to obtain the computed covariance matrix $\mathbf{C_R}$ of the responses starting from the covariance matrix $\mathbf{C_\alpha}$ of the system parameters. The elements of the matrix $\mathbf{C_\alpha}$ reflect the state of knowledge about the input (uncertainty) parameters that can be characterized by ranges and PDF. It is very well known that in system thermal-hydraulics only few elements of $\mathbf{C_\alpha}$ are obtained from experimental observations (mainly from SETF),

whereas for the major part of them engineering judgment is adopted for deriving ('first') guess values of ranges and PDF. The imperfect knowledge of the input uncertainty parameter obviously affects the computed responses R and the relative covariance $\mathbf{C_R}$ and constitutes the main reason for which proper experimental data (i.e. connected with the specific NPP transient scenario under investigation for uncertainty evaluation) are needed. The technique by which experimental observations are combined with code predictions and their respective errors to provide an improved estimate of the system state is known as Data Adjustment and Assimilation (DAA) and it is based on a Bayesian inference process.

The idea at the basis of DAA can be made more specific as follows: the computed results R and the respective statistical errors $\mathbf{C_R}$ predicted by mathematical models and based on 'prior' or 'first' guess PDF for the input parameters (i.e. $\mathbf{C}_{\boldsymbol{\alpha}}$) are combined with proper experimental observations M of the states of a system to generate 'adjusted' values for the system parameters ($\boldsymbol{\alpha}^{IE}$, where the suffix IE stays for improved estimate values) and the respective input covariance matrix ($\mathbf{C}_{\boldsymbol{\alpha}}^{\mathbf{IE}}$, or 'posterior' PDF). From this process, which can be considered as improved estimate analysis of the system's states, the responses $\mathbf{R}^{IE}$ and the respective covariance matrix ($\mathbf{C_R}^{\mathbf{IE}}$) are finally derived.

In conclusion, to reduce uncertainties in both the system parameters and responses, the Bayesian inference procedure is used to consistently assimilate computational and experimental information. There are several approaches possible when performing a DAA process in conjunction with time dependent nonlinear systems, but the "on-line data adjustment/assimilation," is the best suited for uncertainty analysis of large-scale highly nonlinear time-dependent problems. It can be performed on-line (i.e., sequentially in time and interactively with the code that calculates the system's dependent variables and responses), by decomposing the original system into simpler but interacting subsystems. In the present case, the assimilation process involves, at every time node, the minimization of a quadratic objective function subject to constraints.

Once a suitable database of improved estimates for the input parameters ($\boldsymbol{\alpha}^{IE}$) and for the respective input covariance matrix ($\mathbf{C}_{\boldsymbol{\alpha}}^{\mathbf{IE}}$) is available, the application of the method to a NPP scenario is straightforward and requires: a) the calculation of the reference responses $\mathbf{R}^{NPP}$, where here the word reference' is connected with the reference NPP boundary and initial conditions supplemented by improved estimates of the input parameters ($\boldsymbol{\alpha}^{IE}$) when other information is not available; b) the computation of the sensitivity coefficients S, c) the application of the moment propagation equation to obtain the computed covariance matrix $\mathbf{C_R}^{\mathbf{NPP}}$ of the responses starting from the covariance matrix $\mathbf{C}_{\boldsymbol{\alpha}}^{\mathbf{NPP}}$ of the system parameters supplemented by improved estimates of the input covariance matrix ($\mathbf{C}_{\boldsymbol{\alpha}}^{\mathbf{IE}}$) when other information is not available.

The main drawbacks of this approach are as follows: (i) the method is not applicable in the absence of relevant experimental information; (ii) the adjoint model, needed for computing the sensitivity S, requires relatively modest additional resources to develop and implement if this is done simultaneously with the development of the original code; however if the adjoint model is constructed a posteriori, considerable skills may be required for its successful development and implementation; (iii) a considerable amount of resources is needed to establish a suitable database of improved estimates for the input parameters ($\boldsymbol{\alpha}^{IE}$) and for the respective input covariance matrix ($\mathbf{C}_{\boldsymbol{\alpha}}^{\mathbf{IE}}$), but this is a one-time effort, independent of subsequent applications of the method.

The maturity of the methods at the first two bullets may be considered as proved also based upon applications completed within the framework of initiatives of international institutions (OECD/NEA [9, 18] and IAEA [1]). The reason for the consideration of the approach at the third bullet derives from its potential to open an independent way (i.e. different from propagation of code input errors or from propagation of code output errors) for performing global uncertainty analysis. In this case, the method itself, as an uncertainty procedure, is not an established technology, but it constitutes an established idea and framework to pursue a mathematically based road to evaluate the uncertainty in system code predictions. In the following sections, short descriptions of the most known methods belonging to the first two discussed approaches are given.

PROPAGATION OF INPUT ERRORS

The CSAU Method

The pioneering work in the area of the BEPU (Best Estimate Plus Uncertainty) methods was done by US NRC and its contractors and consultants while revising the acceptance rules on ECCS (Emergency Core Cooling System, [20]). The revised rule, stating an alternate ECCS performance analysis based on best-estimate methods, may be used to provide more realistic estimates of the plant safety margins if the licensee quantifies the uncertainty of the estimates and includes that uncertainty when comparing the calculated results with prescribed acceptance limits. To support the revised ECCS rule a method called the Code Scaling, Applicability and Uncertainty (CSAU) was developed. A simplified flow sheet of CSAU method is given in Fig. 5.

The method is intended to investigate the uncertainty of safety-related output single-valued parameters (e.g. PCT). A procedure is proposed to evaluate the code applicability to a selected plant scenario and experts shall identify and rank phenomena, examining experimental data and code predictions of the studied scenario. In the resulting Phenomena Identification and Ranking Table (PIRT), ranking is accomplished by expert judgment. The PIRT and code documentation is compared, and it is decided if the code is applicable to the plant scenario.

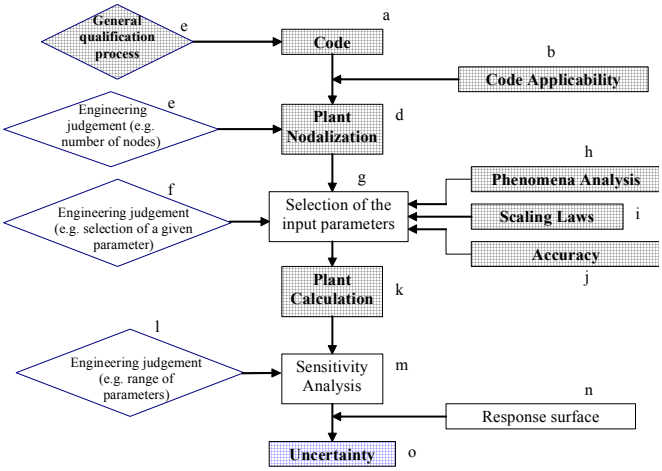

Fig. 5: Simplified flow sheet of CSAU.

All the sensitivity calculations are performed by using an optimized nodalization. This represents a compromise between accuracy and cost, based on experience obtained by analyzing separate effects tests and integral experiments. No particular method or criteria are applied to accomplish this task. Only those parameters modeling the high ranked phenomena are selected to be considered as uncertain input parameters. The selection is based on the judgment about their influence on the output parameters. Additional output biases are introduced to consider the uncertainty of other phenomena not included in the sensitivity calculations.

Information from experiments, manufacturing, and prior calculations performed have been utilized when defining the mean value and the standard deviation of uncertain parameters, for both the Large Break (LB) and the Small Break (SB) LOCA analyses. Uncertainty ranges are defined by intervals of plus/minus two standard deviations from the mean value. Additional biases can be introduced to the input uncertainties.

Uniform and normal distributions were utilized in the two applications performed up to date. Output uncertainty is the result of the propagation of input uncertainties through a number of code calculations. Input parameter uncertainty can be either due to stochastic nature (i.e. code-independent) or due to un-precise knowledge of the parameter values. No statistical method is formally proposed in the CSAU definition. A response surface approach has been used in the applications performed up to date. The response surface fits the code predictions obtained for selected parameters, and is further used instead of the original computer code. Such an approach then implies the use of a limited number of uncertain parameters, in order to reduce the number of code runs and the cost of analysis. However, within the CSAU frame the response surface approach is not required, and other methods may be applied.

Scaling is considered by CSAU, identifying several issues based on test facilities and on code assessment. The effect of scale distortions on main processes, the applicability of the existing database to the NPP range, the scale-up capability of closure relationships and their applicability to the NPP range is evaluated at a qualitative level. Biases are introduced if the scaling capability is not provided, by including either before or after the probabilistic analysis.

The GRS Method

The GRS method [16] is a probabilistic method based on the concept of propagating the input uncertainties. All relevant uncertain parameters including the code, representation and plant uncertainties are identified, any dependencies between uncertain parameters are quantified and ranges and/or PDF for each uncertain parameter are determined. Expert judgment and experience from code applications to separate and integral test and full plant application are principal sources of information for uncertain parameters identification and quantification. Peculiarities of the GRS method are:

- The uncertainty space of input parameters (defined by their uncertainty ranges) is sampled at random according to the combined "subjective" probability distribution of the uncertain parameters and code calculations are performed by sampled sets of parameters.
- The number of code calculations is determined by the requirement to estimate a tolerance/confidence interval for the quantity of interest (such as peak clad temperature). The Wilks formula [17] is used to determine the number of calculations needed for deriving the uncertainty bands.
- Statistical evaluations are performed to determine the sensitivities of input parameter uncertainties on the uncertainties of key results (parameter importance analysis).
- There are no limits for the number of uncertain parameters to be considered in the analysis and the calculated uncertainty has a well-established statistical basis.
- The method relies only on actual code calculations without using approximations like fitted response surfaces.

For the selected plant transient, the method is applied to an integral effects test simulating the same scenario prior to the plant analysis. If experimental data are not bounded, the set of uncertain input parameters has to be modified. Experts identify significant uncertainties to be considered in the analysis, including the modelling uncertainties, and the related parameters, and identify and quantify dependencies between uncertain parameters. Subjective Probability Density Functions are used to quantify the state of knowledge of uncertain parameters for the specific scenario. The term "subjective" is used here to distinguish uncertainty due to imprecise knowledge from uncertainty due to stochastic or random variability.

Uncertainties of code model parameters are derived based on validation experience. The scaling effect has to be quantified as model uncertainty. Additional uncertain model parameters can be included or PDF can be modified, accounting for results from the analysis of Separate Effects Tests. Input parameter values are simultaneously varied by

random sampling according to the subjective PDF and dependencies. A set of parameters is provided to perform the required number n of code runs. For example, the 95% fractile and 95% confidence limit of the resulting subjective distribution of the selected output quantities is directly obtained from the n code results, without assuming any specific distribution. No response surface is used or needed.

Sensitivity measures by using regression or correlation techniques from the sets of input parameters and from the corresponding output values allow the ranking of the uncertain input parameters in relation to their contribution to output uncertainty. Therefore, the ranking of parameters is a result of the analysis, not of prior expert judgment. The 95% fractile, 95% confidence limit and sensitivity measures for continuous-valued output parameters are provided.

Upper statistical tolerance limits are the upper β confidence for the chosen α fractile. The fractile indicates the probability content of the probability distributions of the code results (e.g. α = 95% means that PCT is below the tolerance limit with at least α = 95% probability). One can be β % confident that at least α % of the combined influence of all the characterized uncertainties are below the tolerance limit. The confidence level is specified because the probability is not analytically determined. It accounts for the possible influence of the sampling error due to the fact that the statements are obtained from a random sample of limited size. The smallest number n of code runs is determined by the Wilks formula:

$$(1-\alpha)^n \geq \beta \tag{1}$$

and is representing the size of a random sample (a number of calculations) such that the maximum calculated value in the sample is an upper statistical tolerance limit. For two-sided statistical tolerance intervals (investigating the output parameter distribution within an interval) the formula is:

$$1-\alpha^n - n\cdot(1-\alpha)\cdot\alpha^{n-1} \geq \beta \tag{2}$$

The minimum number n of calculations for both one-sided and two-sided can be found in Table 1. As a consequence, the number n of code runs is independent of the number of selected input uncertain parameters, only depending on the percentage of the fractile and on the desired confidence level percentage. The number of code runs for deriving sensitivity measures is also independent of the number of parameters. As an example, a total number of 100 runs is typical for the application of the GRS method. For regulatory purposes where the margin to licensing criteria is of primary interest, the one-sided tolerance limit may be applied, i.e. for a 95th/95th percentile 59 calculations should be performed.

Table 1: GRS method: number of required calculations.

	One-sided Statistical Tolerance Limit			One-sided Statistical Tolerance Limit		
β / α	**0.90**	**0.95**	**0.99**	**0.90**	**0.95**	**0.99**
0.90	22	45	230	38	77	388
0.95	29	***59***	299	46	***93***	473

PROPAGATION OF OUTPUT ERRORS

The UMAE Method

The UMAE [19], whose flow diagram is given in Fig. 6, is the prototype method for the description of "the propagation of code output errors" approach. The method focuses not on the evaluation of individual parameter uncertainties but on the propagation of errors from a suitable database calculating the final uncertainty by extrapolating the accuracy from relevant integral experiments to full scale NPP.

Considering ITF of reference water cooled reactor, and qualified computer codes based on advanced models, the method relies on code capability, qualified by application to facilities of increasing scale. Direct data extrapolation from small scale experiments to reactor scale is difficult due to the imperfect scaling criteria adopted in the design of each scaled down facility. So, only the accuracy (i.e. the difference between measured and calculated quantities) is extrapolated.

Experimental and calculated data in differently scaled facilities are used to demonstrate that physical phenomena and code predictive capabilities of important phenomena do not change when increasing the dimensions of the facilities (see right loop FG in Fig. 6).

Other basic assumptions are that phenomena and transient scenarios in larger scale facilities are close enough to plant conditions. The influence of user and nodalizations upon the output uncertainty is minimized in the methodology. However, user and nodalization inadequacies affect the comparison between measured and calculated trends; the error due to this is considered in the extrapolation process and gives a contribution to the overall uncertainty.

The method utilizes a database from similar tests and counterpart tests performed in ITF, that are representative of plant conditions. The quantification of code accuracy (step 'f' in Fig. 6) is carried out by using a procedure based on the Fast Fourier Transform Based Method (FFTBM, [21]) characterizing the discrepancies between code calculations and experimental data in the frequency domain, and defining figures of merit for the accuracy of each calculation. Different requirements have to be fulfilled in order to extrapolate the accuracy.

Calculations of both ITF experiments and NPP transients are used to attain uncertainty from accuracy. Nodalizations are set up and qualified against experimental data by an iterative procedure, requiring that a reasonable level of accuracy is satisfied. Similar criteria are adopted in developing plant nodalization and in performing plant transient calculations (see left loop FG in Fig. 6). The demonstration of the similarity of

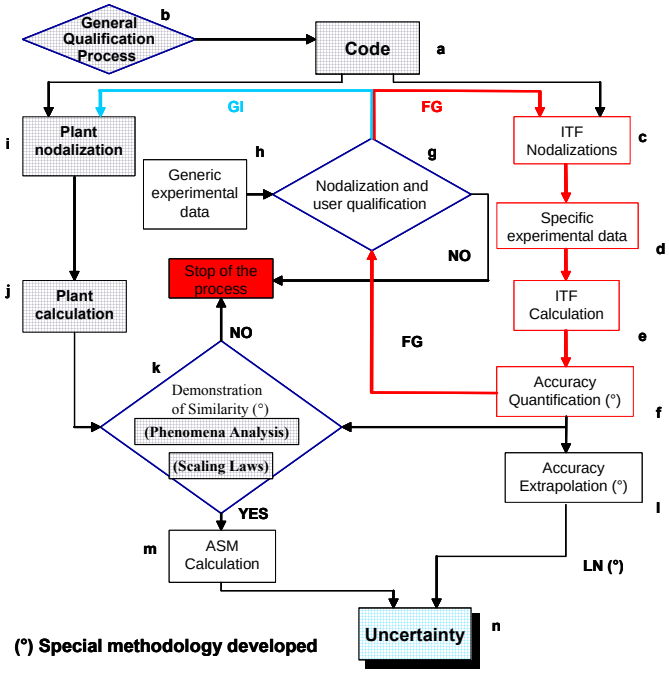

Fig. 6: UMAE flow diagram (also adopted within the process of application of CIAU).

the phenomena exhibited in test facilities and in plant calculations, accounting for scaling laws considerations (step 'k' in Fig. 6), leads to the Analytical Simulation Model, i.e. a qualified nodalisation of the NPP.

The following three main differences between UMAE and CSAU can be outlined:

1. Only expert (or engineering) judgment can stop the process of getting uncertainty in the case of CSAU (blocks "e", "f" and 1 in Fig. 5), while a detailed comparison between measured and calculated trends may give the same results for UMAE (path FG in Fig. 6).
2. Several sensitivity calculations using a plant nodalization approved by expert judgments are necessary in the CSAU to get uncertainty; one plant calculation through a qualified nodalization is necessary in the UMAE.
3. To get uncertainty from UMAE, experimental data in ITF must be available and related to the assigned transient; this is not the case in CSAU. Furthermore, the code must be able to predict the measured scenario.

Minor differences between UMAE and CSAU are related to the following:

a. User qualification: unqualified users presumably will not get acceptable results from the block "f" in Fig.6, while they can perform sensitivity calculations in the CSAU.
b. Errors that may be present in the plant nodalizations of both CSAU and UMAE. The probability that this happens in the UMAE is minimized because of the analysis at block "k" in Fig. 6.
c. The use of the response surface methodology is included in CSAU and not in the UMAE.
d. The assumption in the UMAE that YE/YC is a statistical quantity.

Although the above considerations some steps between CSAU and UMAE are common and have been outlined by dashed blocks in Figs. 5 and 6 (e.g. the code applicability, block "b" in Fig. 5, can be found in block "b" and partly in block h in Fig. 6).

The CIAU Method

All uncertainty evaluation methods are mainly affected by the following limitations:

- The resources needed for their application may be very demanding, ranging up to several man-years;
- The achieved results may be strongly method/user dependent.

The last item should be considered together with the code-user effect, widely studied in the past, and may threaten the usefulness or the practical applicability of the results achieved by an uncertainty method. Therefore, the internal assessment of uncertainty (IAU) was requested as the follow-up of an international conference [10]. The approach CIAU, Code with capability of IAU, has been developed with the objective of reducing the limitations discussed above. CIAU is extensively described in archival technical literature (e.g. ref. [11, 7]) and therefore, only 'spot-information' is given below.

The basic idea of the CIAU can be summarized in two parts:

- Consideration of plant status: each status is characterized by the value of six "driving" quantities (their combination is the "hypercube") and by the time instant when those values are reached during the transient;
- Association of uncertainty (quantity and time) to each plant status.

A key feature of CIAU is the full reference to the experimental data. Accuracy from the comparison between experimental and calculated data is extrapolated to obtain uncertainty. A solution to the issues constituted by the "scaling" and "the qualification" of the computational tools is embedded into the method [6, 4] through the UMAE methodology that constitutes the engine for the development of CIAU and for the creation of the error database.

Assigned a point in the time domain, the accuracy in predicting the time of occurrence of any point is distinguished from the accuracy that characterizes the quantity value at that point. Thus, the time-domain and the phase-space are distinguished: the time-domain is needed to characterize the system evolution (or the NPP accident scenario) and the phase-space domain is used to identify the hypercubes. The safety relevance and the consistency with the technological achievements have been considered when selecting the driving quantities in Tab. 2. The upper and the lower boundaries have been fixed together with a minimum-optimal number of intervals determined considering: a) design of primary system

Table 2: CIAU method: Subdivision of driving quantities into intervals.

PWR -DRIVING QUANTITIES		(1) Upper Plenum Pressure (MPa)	(2) Primary Circuit Mass Inventory (%)[a]	(3) Steam Generator Pressure (MPa)	(4) Cladding Temperature (K)	(5) Core Power (%)[a]	(6) Steam Generator Level (%)[a]
Hypercube Intervals	1	0.09 – 0.5	10 – 40	0.1 – 3.0	298 – 473	0.5 – 1.0	0 – 50
	2	0.5 – 2.0	40 – 80	3.0 – 7.0	473 – 573	1.0 – 6.0	50 – 100
	3	2.0 – 4.0	80 – 100	7.0 – 9.0	573 – 643	6.0 – 50	100 – 150
	4	4.0 – 5.0	100 – 120	-	643 – 973	50 – 100	-
	5	5.0 – 7.0	-	-	973 – 1473	100 – 130	-
	6	7.0 - 9.0	-	-	-	-	-
	7	9.0 – 10.0	-	-			-
	8	10.0 – 15.0	-	-	[a]: Percent of the Initial (nominal) Value		-
	9	15.0 – 18.0	-	-	-	-	-

plant; b) design and licensing of ECCS; c) design and optimization of emergency operational procedures; d) benchmarking of simplified models; e) training purpose; f) code limitations.

Quantity and time accuracies are associated to errors-in-code-models and uncertainties-in-boundary-and-initial-conditions including the time sequence of events and the geometric model of the problem. Thus,

a) The 'transient-time-dependent' calculation by a code resembles a succession of steady-state values at each time step and is supported by the consideration that the code is based on a number and a variety of empirical correlations qualified at steady-state with assigned geometric discretization. Therefore, quantity accuracy can be associated primarily with errors-in-code-models.
b) Error associated with the opening of a valve (e.g. time when the equivalent full flow area for the flow passage is attained) or inadequate nodalization induce time errors that cannot be associated to code model deficiencies. Therefore, time accuracy can be associated primarily with uncertainties-in-boundary-and-initial-conditions.

Once the Time Accuracy (Uncertainty) Vector, TAV (TUV), and the Quantity Accuracy (Uncertainty) Matrix, QAM (QUM) are derived, the overall accuracy (and uncertainty) is obtained by the geometric combination of the two accuracies (and uncertainties) values, i.e. time and quantity, in the two-dimensional space-time plane.

An idea of the architecture of the CIAU methodology can be derived from Fig. 7. Two processes can be distinguished: the "Error Filling Process" by which the NPP statuses are filled with the values of the error database, and the "Error Extraction Process" by which the uncertainty values (derived from the extrapolation process of accuracy) are picked up from the NPP statuses. Two qualification steps are foreseen in the case of CIAU: the Internal Qualification Process and the Independent (External) Qualification Process [22]. Those aspects are of fundamental importance in system thermal-hydraulics to assess, and possibly to show the quality level, of any tool using databases independent from those utilized in the development of the tool itself.

Summarizing, six dimensions constitute the phase-space domain and each combination of intervals of the driving quantities identifies one hypercube in that domain. Therefore, a hypercube and a time interval characterize a unique plant status in the frame of uncertainty evaluation and all plant statuses are characterized by a matrix of hypercubes and by a vector of time intervals. Each point of the curve (generic thermal-hydraulic code output plotted versus time) is affected by a quantity uncertainty and by a time uncertainty. Owing to the uncertainty, each point may take any value within the rectangle identified by the quantity and the time uncertainty. The value of uncertainty, corresponding to each edge of the rectangle, can be defined in probabilistic terms. This satisfies the requirement of a 95% probability level to be acceptable to the USNRC staff for comparison of Best-Estimate (BE) predictions of postulated transients to the licensing limits in 10 CFR Part 50.

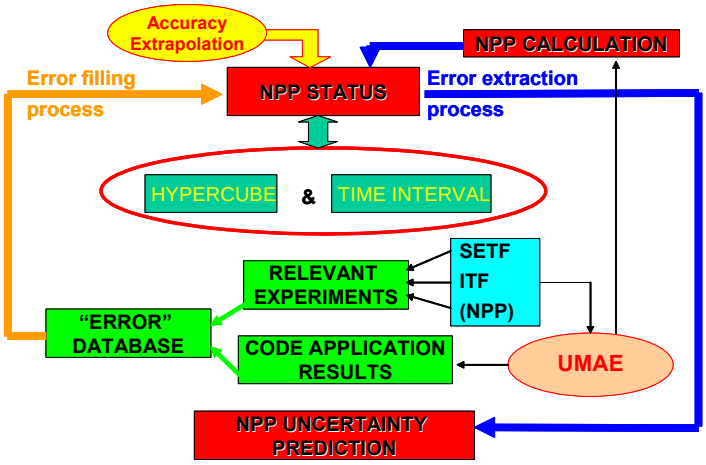

Figure 7 - CIAU Method: "Error Filling Process" and "Error Extraction Process".

Another difference between UMAE and CIAU has to be emphasized: in the UMAE methodology the uncertainty of a given quantity is an average of the values obtained in different simulations of the same class of transients and in the same facility or in similar tests performed in different facilities; in the case of CIAU the results of any kind of transient can be combined to derive the accuracy and then the uncertainty inside the same plant status (i.e. hypercube and time).

SELECTED CIAU APPLICATIONS

Following the CIAU proposal [11], a dozen applications to problems of industrial interest or relevant to the qualification of the method have been completed. Results from the four cases outlined in section 1 are outlined here.

In the first case the CIAU application was requested by the regulatory authority (or 'licensor') in Brazil, [23], within the context of the licensing of the four loop PWR NPP of Angra-2. The results, [24], are given in Fig. 8. Three BEPU (Best Estimate Plus Uncertainty) results are documented, one proposed by the 'applicant' (or the 'licensee') and two derived by the CIAU. Each result includes one center point (the BE PCT) and upper and lower uncertainty bands. The CIAU results allowed the approval by the licensor of the applicant data: the error bands calculated by CIAU are close (difference less than 20 K) to the error bands calculated by a method (the applicant one) based on the combination of input and output error propagation. The BE PCT proposed by the applicant was not the result of a best estimate calculation, but an average of a number of code runs.

In the second case, [25], the CIAU application was requested by the electrical utility in Bulgaria. The problem consisted in the demonstration that results of two different thermal-hydraulic codes, Cathare and Relap5, coincide as far the computation of a safety relevant parameter was concerned. The reference reactor was the VVER-440 unit 3 of Kozloduy and the concerned transient was a "200 mm break" in cold leg. In order to address the question, Fig. 9, a reference calculation was performed with one of the code (Relap5). Then uncertainty

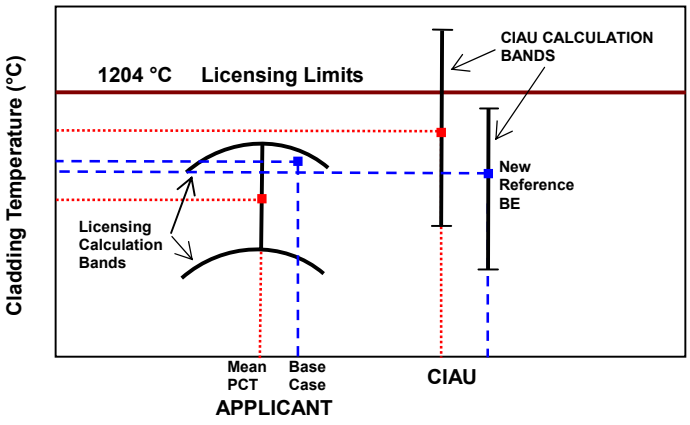

Fig. 8: LBLOCA licensing study for Angra-2 PWR.

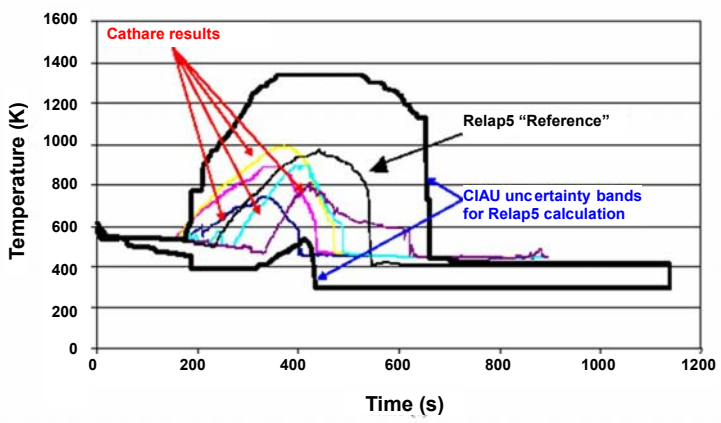

Fig. 9: CIAU application to demonstrate that Cathare and Relap5 results coincide as far as the prediction of a safety relevant parameter is concerned.

bands were derived by CIAU in relation to the output of the first code and the calculation by the second code (Cathare) was performed. The success of the application consisted in demonstrating that uncertainty bands of one code- calculation (Relap5) envelope the results from the other (Cathare) code-calculation.

The third selected CIAU application was requested by the same utility in Bulgaria as in the second discussed case above. The same NPP (Kozloduy, unit 3, VVER-440) constituted the object of the study and a Double Ended Guillotine Break (DEGB) LBLOCA transient scenario was concerned, [26]. A twofold objective for the CIAU application was identified: a) to demonstrate the compliance of the selected scenario with the licensing threshold (namely, the 1204 °C limit); b) to demonstrate the actual "conservatism" of a conservative calculation. The second objective could be achieved because the 'conservative' calculation was carried out by the same code used in the BEPU approach and all 'conservative' boundary and initial conditions were made accessible. The results are presented in Fig. 10. A BE calculation was performed and upper and lower uncertainty boundaries were calculated by CIAU (continuous curves in the figure). Four additional straight lines are reported in the same figure and constitute results of the conservative calculations. The two thick full lines represent the PCT and the reflood time obtained by the first of the conservative calculations, identified as 'driven-conservatism'. The two thick dotted lines represent the PCT and the reflood time obtained by the second of the conservative calculations, identified as 'rigorous-conservatism'. Now, the 'rigorous conservatism' includes input parameter values that were already accepted by the regulatory body of Bulgaria in a previous submission by the same utility. Vice-versa, the 'driven-conservatism' implied a (arbitrary) reduction of the amount of conservatism in order to comply with the licensing threshold. In other words, the calculation at the basis of the results indicated by the full thick lines is still conservative, but

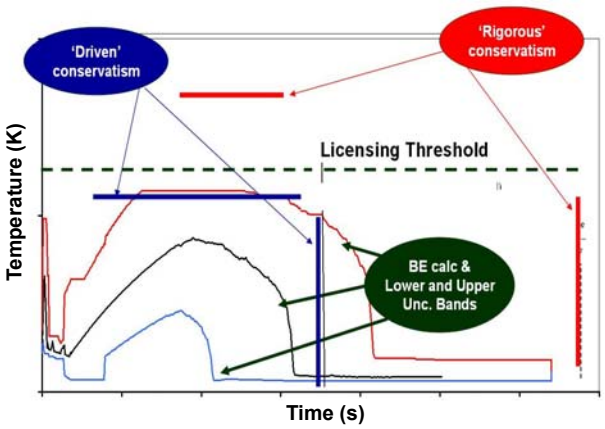

Fig. 10: LBLOCA, DEGB application of CIAU to Kozloduy unit 3 VVER-440. Differences between BEPU and conservative approaches.

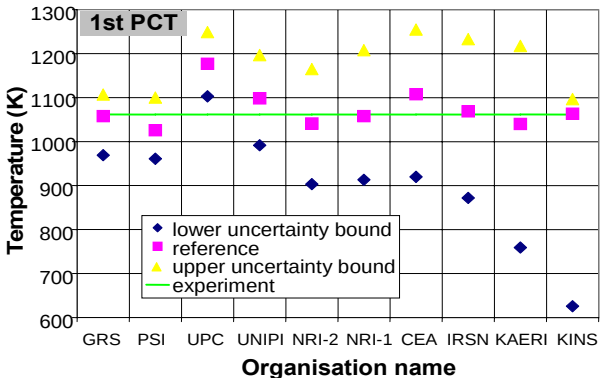

Fig. 11: Outcome of the BEMUSE project: uncertainty bounds from each participant ranked by increasing band width from left to right related to the 1st PCT' of the LOFT experiment L2-5.

the amount of conservatism is not endorsed (by the regulatory body). The following additional comments apply;

a) the BEPU calculation results envelope the 'driven-conservatism' calculation results: thus the amount of 'conservatism' is inadequate (second objective for the analysis);
b) the difference between results from 'rigorous conservatism' and BEPU show the potential advantage of using the BEPU approach;
c) the BEPU approach complies with the licensing threshold (first objective of the analysis).

The fourth selected CIAU application constitutes a qualification study, that at the same time allows a comparison with results of different uncertainty methods. At the international level, within the OECD (Organization for Economic Cooperation and Development) framework, two main activities have been performed (actually the second one is still in progress) as already mentioned: the UMS and the BEMUSE, [8] and [18], respectively. The objective of the project was to predict the LBLOCA performance of the LOFT experimental nuclear reactor (i.e. test L2-5). The process included two steps: the derivation of a reference calculation, involving a detailed comparison between experimental and calculated data, and the derivation of uncertainty bands enveloping the reference calculation. The success of the application consisted in demonstrating that the uncertainty bands envelope the experimental data. Ten international groups participated to the activity [18]. A sample result from the BEMUSE project is outlined in Fig. 11.

The application of the CIAU was performed by the UNIPI (dotted vertical line in Fig. 11) while all other participants used an uncertainty method based on the propagation of the input errors supplemented by the use of the Wilks formula. The consistency between the CIAU results and the experimental data can be observed as well as the spread of results obtained by the use of Wilks formula.

CONCLUSIONS

The uncertainty evaluation constitutes the ending necessary step for the application of a system thermal-hydraulic code to the nuclear technology. Therefore, any application of a best estimate code without the uncertainty evaluation is meaningless because an error is unavoidable for any prediction. The differences between accuracy, uncertainty and sensitivity have been emphasized and the origins of, or the reasons for, uncertainty (see e.g. ref. [10]) should be clearly in mind when developing an uncertainty approach.

Three main independent ways have been described in the paper to evaluate the uncertainty:

- The propagation of code input errors: this can be evaluated as being the most adopted procedure nowadays, endorsed by industry and regulators. It adopts the statistical combination of values from selected input uncertainty parameters (even though, in principle an unlimited number of input parameters can be used) to calculate the propagation of the errors throughout the code.
- The propagation of code output errors: this is the only demonstrated independent working alternative to the previous one and has also been used for industrial applications. It makes full and direct reference to the experimental data and to the results from the assessment process to derive uncertainty. In this case the uncertainty prediction is not propagated throughout the code.

The deterministic approach based on the ASAP and GASAP extended to performing uncertainty evaluation in conjunction with Data Adjustment and Assimilation: all parameters that affect any prediction, being part of either the code models or the input deck can be considered; proper experimental observations are needed to provide an improved estimate of the probability distribution functions of those parameters through the combination with code predictions and the respective errors. The reduction of the uncertainties in both the system parameters and responses is obtained by the

Bayesian inference procedure that is at the basis of Data Adjustment and Assimilation.

The maturity of the methods at the first two bullets may be considered as proved also based upon applications completed within the framework of initiatives of international institutions (OECD/NEA and IAEA). The method at the third bullet constitutes an innovative uncertainty procedure but should not yet be considered as an established technology. However, it constitutes an established idea and framework to pursue a mathematically based road to evaluate the uncertainty in system code predictions.

The industrial relevance of the BEPU approach compared with the conservative approach and with the potential still unexplored benefits that it may produce for the nuclear industry should has been emphasized by the results of the application of the CIAU. Realistic systems availability and the use of three-dimensional neutron kinetics to establish the realistic peak linear power as boundary and initial conditions, should be re-discussed (among the other things) in the light of the capabilities of codes and uncertainty methods here presented.

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