Progress in Uncertainty Analyses Methods

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Abstract:
Methods have been developed and presented to quantify the uncertainty of computer code results. The basic techniques first proposed by GRS and used worldwide, including IRSN, is a statistical method. It is presented together with examples of applications. A controversial international discussion took place about the number of code calculations to be performed comparing calculation results with more than one acceptance criterion, e.g. maximum clad temperature, maximum local and core wide clad oxidation. GRS concludes that one can use the same number of computer code runs for (95%, 95%) tolerance limits, independent of the number of acceptance criteria to be compared with. Usually, probability distributions are specified to express the imprecise knowledge. There may, however, be cases where a specification of a unique probability function is not possible for an uncertain parameter, and where considering all possible dependencies between the uncertain parameters is not always known. Therefore, IRSN develops a new method for uncertainty evaluation, called the Random Fuzzy (RAFU) method. It allows mixing different kinds of knowledge representations in order to take into account the available information about these uncertain parameters, i.e. mixing probabilities and possibilities. The increasing available computing capacity has opened up new frontiers in safety analysis.

1 INTRODUCTION

Best estimate computer codes are used to calculate postulated loss of coolant and transient accidents in a realistic way. There is an increasing interest in computational reactor safety analysis to determine conservatisms for licensing applications by quantifying the uncertainties of the computer code results. The USA Code of Federal Regulation (CFR) 10 CFR 50.46 [1], for example, allows either to use a best estimate code plus identification and quantification of uncertainties, or the conservative option using conservative computer code models listed in Appendix K. In many other countries best estimate codes are approved in licensing submissions in combination with conservative initial and boundary conditions. That approach is also documented in the IAEA Safety Guide No. NS-G-1.2, § 4.89 [2]. Paragraph 4.90 of the same IAEA Guide adds, when a combination of best estimate computer code and realistic assumptions on initial and boundary conditions is applied, the uncertainties should be statistically combined. The calculated results shall not exceed the acceptance criteria with a specified high probability.

Code predictions are uncertain due to several sources of uncertainty, like code models as well as uncertainties of plant and fuel parameters. These uncertainties, for example, come from scatter of measured values, approximations of modelling, variation and imprecise knowledge of initial and boundary conditions. Computer code models are developed based on experiments which can simulate the complex behaviour of a reactor plant under accident conditions in a simplified way only. Most of the experiments are performed in small scale compared to plant size. Uncertainty due to imprecise knowledge of parameter values in calculations are quantified by ranges and probability distributions. These distributions should be taken into account for input parameters instead of one discrete value only.

The aim of the uncertainty analysis is at first to identify and quantify all potentially important uncertain parameters. Their propagation through computer code calculations provides probability distributions and ranges for the code results. The evaluation of the margin to acceptance criteria, e.g. the maximum fuel rod clad temperature, should be based on the one-sided limit of this distribution for the calculated temperatures, for example which is closer to an acceptance criterion, Figure 1. Uncertainty analysis is needed if useful conclusions are to be obtained from best estimate thermal-hydraulic code calculations, otherwise single values of un-quantified conservatism would be presented for comparison with limits for acceptance.

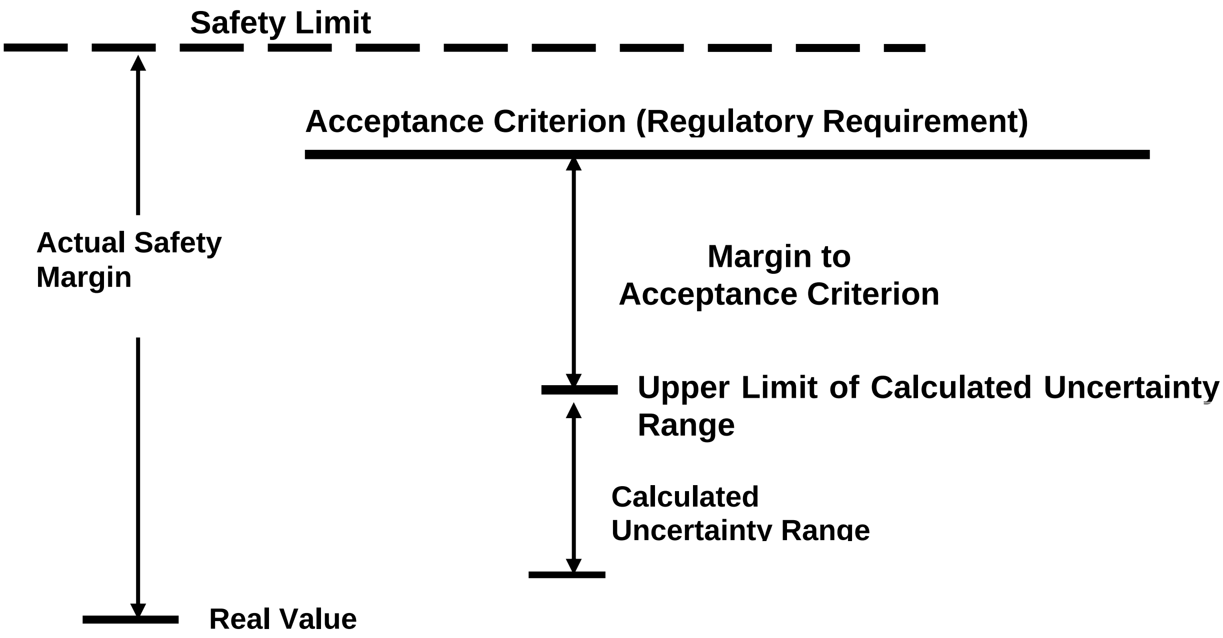

Figure 1: Margin illustration

2 DESCRIPTION OF STATISTICAL UNCERTAINTY METHOD

GRS was the first organization to propose ordered statistics to be applied for the determination of uncertainties of code results and to determine sensitivities of the input parameters to the uncertainty of the results [3, 4]. IRSN used the same procedure for their uncertainty method [5]. The state of knowledge about all uncertain parameters is described by ranges and probability distributions, Figure 2. In order to get information about the uncertainty of computer code results, a number of code runs have to be performed. For each of these calculation runs, all identified uncertain parameters are varied simultaneously. Uncertain parameters are uncertain input values, models, initial and boundary conditions, numerical values like convergence criteria and maximum time step size, etc. Model uncertainties are expressed by adding on or multiplying correlations by corrective terms, or by a set of alternative model formulations. Uncertainties in nodalisation to describe the important phenomena should be taken into account preferably during the code validation process comparing code results with data of experiments or reactor transients. An optimised nodalisation should be developed during that process. However, alternative nodalisation schemes can be included in the uncertainty analysis. Code validation results are a fundamental basis to quantify parameter uncertainties.

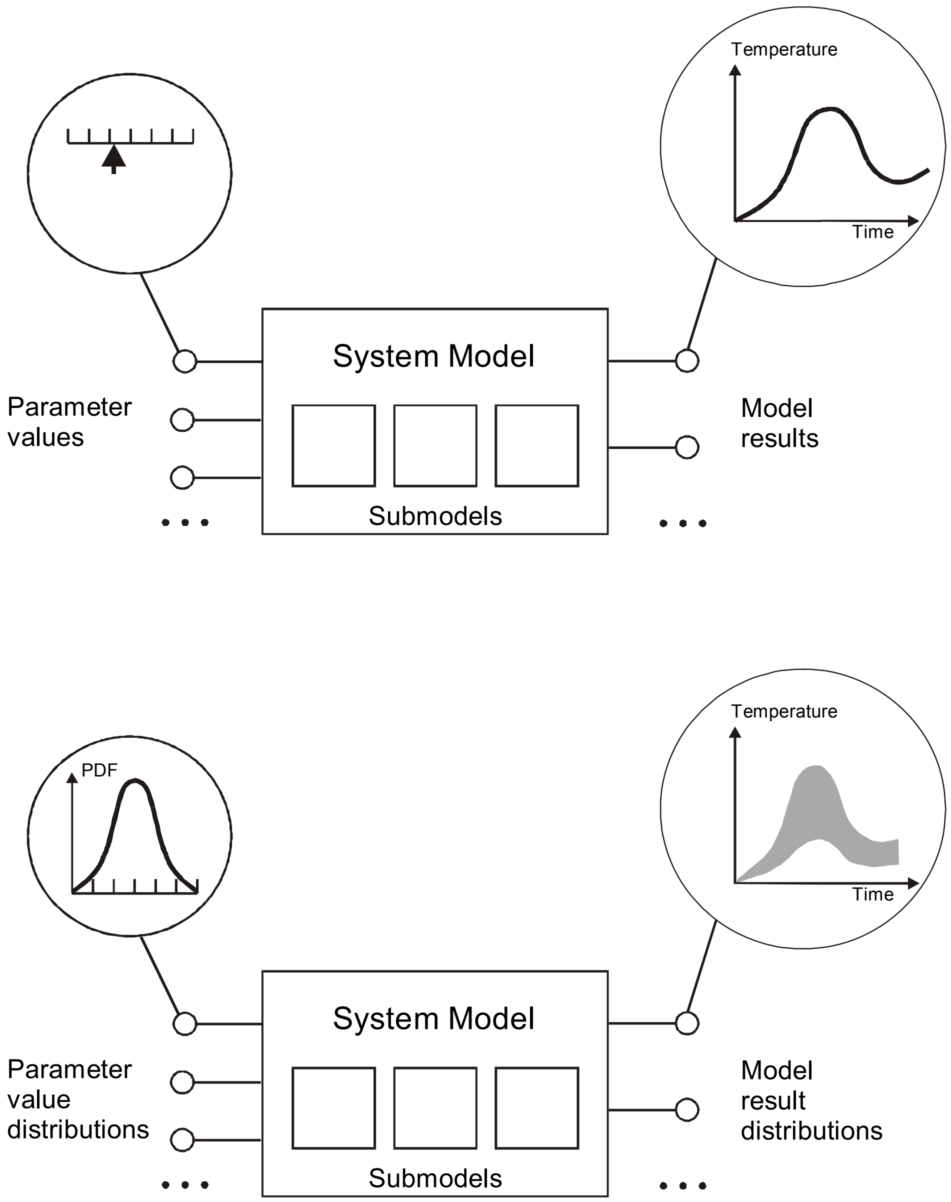

Figure 2: Consideration of input parameter value ranges instead of discrete values in the statistical uncertainty method

The selection of parameter values according to their specified probability distributions, their combination and the evaluation of the calculation results requires a method. Following a proposal by GRS the central part of the method is a set of statistical techniques. The advantage of using these techniques is that the number of code calculations needed is independent of the number of uncertain parameters. In each code calculation, all uncertain parameters are varied simultaneously. In order to quantify the effect of these variations on the result, statistical tools are used. Because the number of calculations is independent of the number of uncertain parameters, no a priori ranking of input parameters is necessary to reduce their number in order to cut computation cost. The ranking is a result of the analysis as described later.

The number of code calculations depends on the requested probability content and confidence level of the statistical tolerance limits used in the uncertainty statements of the results. The required minimum number n of these calculation runs is given by Wilks' formula [6, 7], e.g. for one-sided tolerance limits: $\mathbf{1 - a^n \geq b}$, where b x 100 is the confidence level (%) that the maximum code result will not be exceeded with the probability a x 100 (%) (percentile) of the corresponding output distribution which is to be compared to the acceptance criterion. The confidence level is specified to account for the possible influence of the sampling error due to the fact that the statements are obtained from a random sample of limited size. For two-sided statistical tolerance intervals the formula is: $\mathbf{1 - a^n - n\,(1-a)\,a^{n-1} \geq b}$. The minimum number of calculations can be found in Table 1. For the interesting 95%/95% one-sided tolerance limit in licensing analysis at least 59 variation calculations are needed.

The probabilistic treatment of parameter uncertainties allows quantifying their state of knowledge. This means, in addition to the uncertainty range, the knowledge is expressed by probability density functions or probability distributions. This interpretation of probability is used for a parameter with a fixed but unknown or inaccurately known value. The classical interpretation of probability as the limit of a relative frequency, expressing the uncertainty due to stochastic variability, is not applicable here.

Table 1: Minimum number of calculations n for one-sided and two-sided statistical tolerance limits

	One-sided statistical tolerance limits				Two-sided statistical tolerance limits		
b / a	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
0.99	44	90	459		64	130	662

The probability distribution can express that some values in the uncertainty range are more likely to be the appropriate parameter value than others. In the case that no preferences can be justified, uniform distribution will be specified, i.e. each value between minimum and maximum is equally likely to be the appropriate parameter value. As the consequence of this specification of probability distributions of input parameters, the computer code results also show a probability distribution, from which uncertainty limits or intervals are derived.

A high level of probability is needed that acceptance criteria would not be exceeded [1, 2]. The "high level of probability" is specified in the US NRC Regulatory Guide 1.157 to 95% or more [8]. The IAEA Safety Report Series No. 23 "Accident analysis for Nuclear Power Plants" [9] recommends sensitivity or uncertainty analyses if best estimate codes are used in licensing analysis. Therefore, statistical statements may be made for not exceeding regulatory acceptance criteria.

In order to demonstrate to be within licensing limits, statements are made that a calculated value will, for example, not be exceeded with 95% probability and 95% confidence, i.e. providing a (95%, 95%) statement. The confidence level 95% denominates that the 95th percentile is overestimated conservatively with 95% probability.

Another important feature of the method is that one can evaluate sensitivity measures of the importance of input parameter uncertainties for the uncertainties of the results. These measures give a ranking of input parameters. This information provides guidance as to where to improve the state of knowledge in order to reduce the output uncertainties most effectively, or where to improve the modelling of the computer code. Sensitivity measures like Standardised Rank Regression Coefficients, Rank Correlation Coefficients and Correlation Ratios permit a ranking of uncertainties in model formulations and input data, etc. with respect to their relative contribution to code output uncertainty. The difference to other known uncertainty methods, e.g. [10], is that the ranking is a result of the analysis, and not of prior estimates and judgements. This prior set-up of a Phenomena Identification and Ranking Table (PIRT) by extensive expert staff-hours in [10] is known to be very costly. Uncertainty statements and sensitivity measures are available simultaneously for all single-valued (e.g. peak clad temperature) as well as continuous valued (time dependent) output quantities of interest. The method relies only on actual code calculations without using approximations like fitted response surfaces.

The different steps of the uncertainty analysis are supported by the software system SUSA (**S**oftware System for **U**ncertainty and **S**ensitivity **A**nalyses) developed by GRS [11] and the SUNSET by IRSN [5]. They provide a choice of statistical tools to be applied during the uncertainty and sensitivity analysis. The statistical method is used by several countries, like France for the European Pressurised Water reactor (EPR) large break loss off coolant analysis [12], USA, Korea, Lithuania, Brazil, and the Netherlands. The German Reactor Safety Commission (RSK) recommended using uncertainty analysis for emergency cooling analyses in their meeting in July 2005. Uncertainty analysis is included in the draft revision of the German regulation. The application of these methods in licensing is discussed in Reference [13].

3 COMPARISON WITH MORE THAN ONE ACCEPTANCE CRITERION

The question came up if one can use the same number of computer code runs performed for (95%, 95%) tolerance limits for more than one output parameter to be compared with acceptance criteria simultaneously, i.e. maximum clad temperature, maximum local and core wide clad oxidation. The controversial international discussion of different concepts for “multi-dimensional” outputs [14], [15], [16], [17], [18] shows that a direct and satisfactory extension of the concept of tolerance limits for applications in reactor safety is very difficult or even impossible.

For example Wald [19] extended Wilks’ concept [6], [7] to several output variables. However, it suffers from substantial shortcomings, e.g. it requires a considerably increased number of code runs and depends on the order in which the output variables are treated and extreme values are omitted. For a one-sided upper tolerance limit, for example, when the first output variable is peak clad temperature (PCT), the complete run with the highest PCT is eliminated for the evaluation of the next output variable. Consequently, the second variable is evaluated without that eliminated run, and so forth.

A slightly modified concept of the basic considerations has therefore been proposed which incorporates the safety limits directly into the uncertainty statement. Instead of joint tolerance limits for the multiple outputs of interest one considers the lower statistical confidence limit (e.g. of at least 95%) for the probability of "complying with the safety limits for all output parameters", or "satisfying all licensing requirements or acceptance criteria for all parameters". It turns out that

1. In the one-dimensional case, i.e. one single output parameter, this concept is equivalent to the known concept of one-sided upper tolerance limit,
2. The necessary minimum number of calculation runs (sample size) is also in the general multi-dimensional case the same, i.e. independent of the number of output parameters and related criteria involved, and consequently, independent of the type of interrelationships or correlations between these output parameters and criteria.

Therefore, the number of necessary computer code runs is the same as in the one-dimensional tolerance limit case, even if several output parameters are involved. This is a significant advantage of the method compared to the various extension concepts of multi-dimensional tolerance limits.

4 PROCEDURES TO OBTAIN DISTRIBUTIONS FOR INPUT UNCERTAINTIES

The specification of ranges and distributions of values of uncertain input parameters is the most important task for a statistical uncertainty analysis. These distributions are gained from relevant information of direct or indirect experimental measurements and corresponding computational model calculations during validation of the computer codes, or from indirect expert judgement.

Essentially five procedures are available:

1. "Bayesian prediction" procedure [20, 21, 27]
2. Vinai procedure [22, 23]
3. "CIRCE" procedure [24, 27]
4. "PARFUM" procedure [25, 26, 27]
5. RAFU method, explained in section 6 of this paper.

Procedure (1) may be appropriate when direct model calculations and direct data from informative experiment for the results of the uncertain models are available, i.e. the experimental and computational data refer directly to the uncertain quantities of interest.

Procedure (2) may be appropriate when direct data from experiments are available, like procedure (1). The experimental data are transferred by statistical procedures to densities of parameter values. A newly developed non-parametric estimator and a multi-dimensional clustering technique are used.

Procedure (3) may be appropriate when indirect model calculations and experimental data are available, i.e. the data do not refer directly to the uncertain model quantities of interest but rather to particular functions of them, called responses, which may be given by complex and computationally intensive sub-models.

Procedure (4) may be appropriate when instead of data from experiments and model computations indirect uncertainty quantification on parameter level is available, i.e. full probability distributions are given, usually obtained from expert elicitation, associated with particular simple functions of the uncertain model parameters of interest.

Procedure (5) is used to quantify probabilities and possibilities of uncertain parameter values, and is explained in this paper.

5 RESULTS OF THE BEMUSE APPLICATION

The scope of the Best Estimate Methods Uncertainty and Sensitivity (BEMUSE) Programme of the Committee on the Safety of Nuclear Installations (CSNI) is to compare results of uncertainty analyses performed by different participants for the same Large Break Loss-Of-Coolant Accident (LB-LOCA) experiment on the LOFT facility as well as for the Zion Nuclear Power Plant (NPP). Eleven participants coming from ten organizations and eight countries participated in the exercise using the LOFT experiment [28]. One organisation sent their contribution too late to be included in the comparison.

Except University Pisa, all the participants use an ordered statistics approach with propagation of the uncertainties of input parameters and performing a number of code runs according to Wilks' formula. The method of University of Pisa determines the differences of calculation results to a number of relevant experimental data. These differences or accuracies are extrapolated to the reactor calculation, or to the LOFT experiment in the first BEMUSE application.

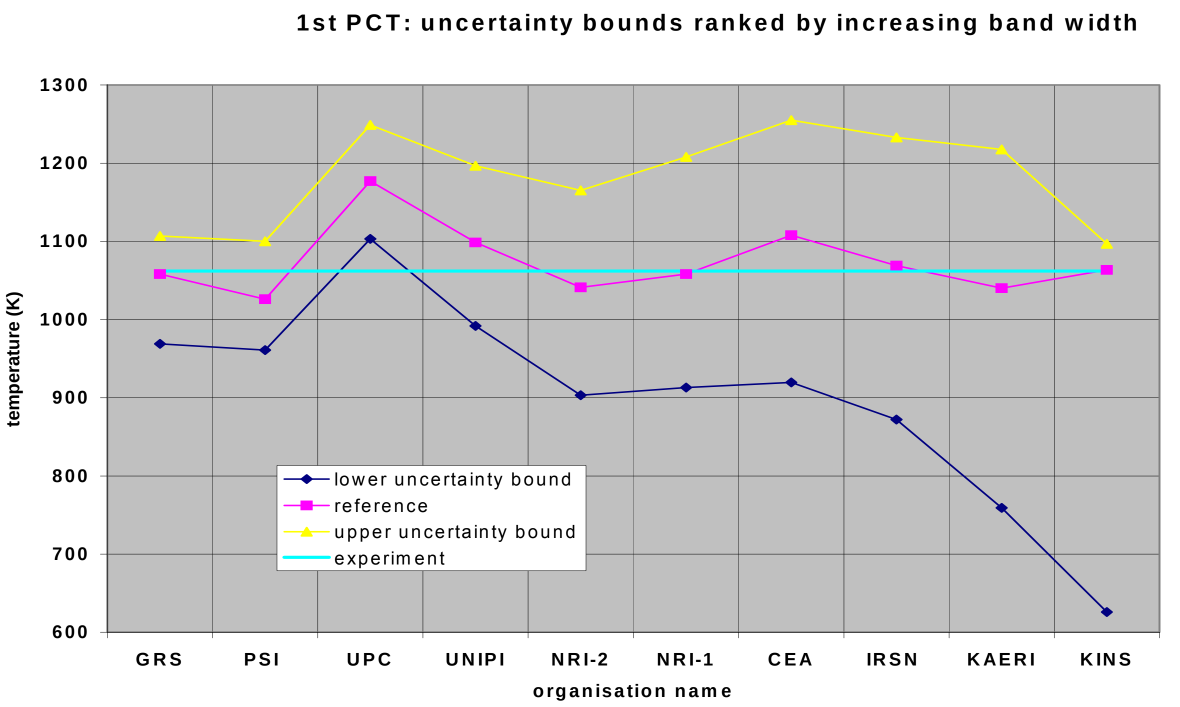

Figure 3: Results of BEMUSE participants for the 1st peak clad temperature

The following observations with regard to results of the first peak clad temperature (PCT) in Figure 3 can be made:

- Only one participant (UPC) does not envelop the experimental PCT, due to a too high lower bound. Two reasons can explain this result: Among all the participants, on the one hand, UPC has the highest reference value; on the other hand, its band width is among the narrowest ones. The difference of the basic calculations of the participants is up to 150 K. The difference of the upper (95%/ 95%) uncertainty bands between the participants is up to 150 K. The difference of the upper band minus reference value is 50 – 170 K.

Two main reasons for the spread of the calculation results are:

1) Insufficient quality of the reference calculation
2) Uncertainties of the input parameters:
   - Missing some influential parameters
   - Too narrow uncertainty bands of the input parameters.

The sensitivity analysis results give more information for which parameters the uncertainty has to be determined with more accuracy, especially for the important ones which can be identified by sensitivity measures.

6 RANDOM FUZZY (RAFU) METHOD

6.1 Probability and possibility

The BEMUSE Programme as well as other applications show that the specification of uncertain input parameters is very important and may have significant influence on the uncertainty band of the code results. Therefore, beside others, IRSN is working on the determination of the distribution of uncertain input parameters.

Sometimes, measurements of an uncertain parameter are available but systematic errors are not precisely known. Consequently, such uncertainties are due to imprecision instead of variability. Usually, probability distributions are specified to express the imprecise knowledge. There may, however, be cases where a specification of a unique probability function is not possible for an uncertain parameter, and where considering all possible dependencies between the uncertain parameters is not always known. The lack of knowledge of the dependence between two variables does not necessarily mean independence.

For safety purposes, it may be worthwhile to provide a methodology which does not need to specify one probability distribution for an uncertain parameter. Therefore, IRSN is developing a new method for uncertainty evaluation, called the Random Fuzzy (RAFU) method. It allows mixing different kinds of knowledge representations in order to take into account the available information about these uncertain parameters, i.e. mixing probabilities and possibilities. It also integrates an efficient numerical strategy to reduce the number of computations to a minimum.

6.2 Quantification of the knowledge about uncertain parameters

The Random Fuzzy (RAFU) method [29] is developed by IRSN to supplement the classical statistical methods. Necessary assumptions with regard to the choices of probability densities can be relaxed. An outcome, however, is larger ranges of the calculated results. The method is based on the Dempster-Shafer theory which is a generalization of probability and possibility theories. The possibility theory [30] provides an attractive framework to model the epistemic uncertainty of a fixed but partial known variable. It introduces a set of probabilities out of a range of variations. A possibility distribution is particularly well fitted to represent a parameter which is only incompletely known. In this sense, a fuzzy interval and of their induced possibility distribution can be seen as a model of partial probabilistic information. For example, in figure 4 is the probability set represented by a triangular possibility distribution. The set of probability distribution functions (pdfs) induced by a triangular possibility distribution contains all pdfs with the same mode (the same most likely value 3) and the same support between 2 and 4 in the example.

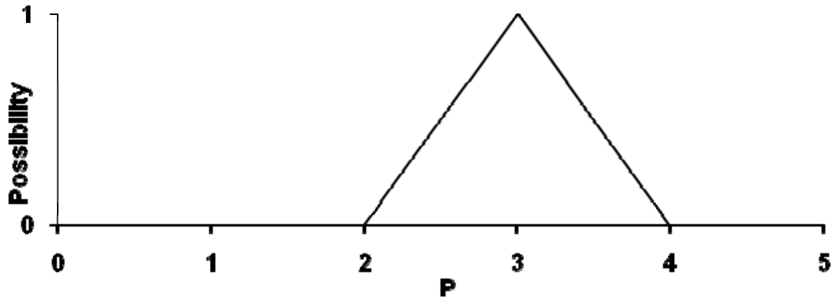

Figure 4: Example of possibility distribution of values of parameter P, triangular possibility

It turns out that the possibility theory is a convenient way to quantify lack of knowledge (epistemic) uncertainty but it can lead also to unrealistic uncertainty margins when enough information is available to determine a unique probability distribution. Therefore, the IRSN method allows the analyst to select a probability distribution or a possibility distribution with respect to the amount of information about uncertain parameters and the nature of uncertainty. This is achieved by working in a unified framework for probability and possibility called the theory of evidence [31]. In the same way that the probability theory assigns weights to the different values for each uncertain parameter due to the distribution, the idea of the theory of evidence is to put weights on subsets of values.

Another important issue may be the choice and the quantification of dependencies between uncertain parameters. An assumption of independence is often assumed when little information about dependencies is known but this may not always be justified. It may lead to compensate uncertainties and can affect the uncertainty ranges, therefore, uncertainty accumulation may be appropriate if there is no information about compensating effects. This is possible within the RAFU method due to a special propagation strategy.

The RAFU method is derived to allow the applicant answering independently the following two questions:

- *Probability or possibility?*
In the case of imprecision of knowledge about the distribution of uncertain parameter values, possibility distributions are used in order to take into account assumptions currently made on the choice of the densities of specific uncertain parameters. If a substantial amount of information is available about the uncertainty, appropriate probabilistic distributions can be used.

- *Compensation due to independence of parameters or accumulation of uncertainties by taking into account dependencies?*
When the amount of information to take into account compensating effects is sufficient, one might assume independence, whereas uncertainty accumulation may be used in case of poor information.

6.3 Propagation of uncertainties through the computer code and treatment of responses

The propagation of uncertainties is based on an extension of Monte-Carlo simulations, and therefore requires at first a sampling of uncertain parameter variables. Note that sampling a variable results in a distribution, Figure 5 left, as in classical Monte-Carlo simulations. For partial-known variables, the sampling in Figure 5 right is performed based on the possibility distributions associated to each variable. We focus in this work on possibility distributions which are common in practical investigations. Therefore, sampling partial-known variables leads to a set of nested intervals called α-cuts, Figure 5 right.

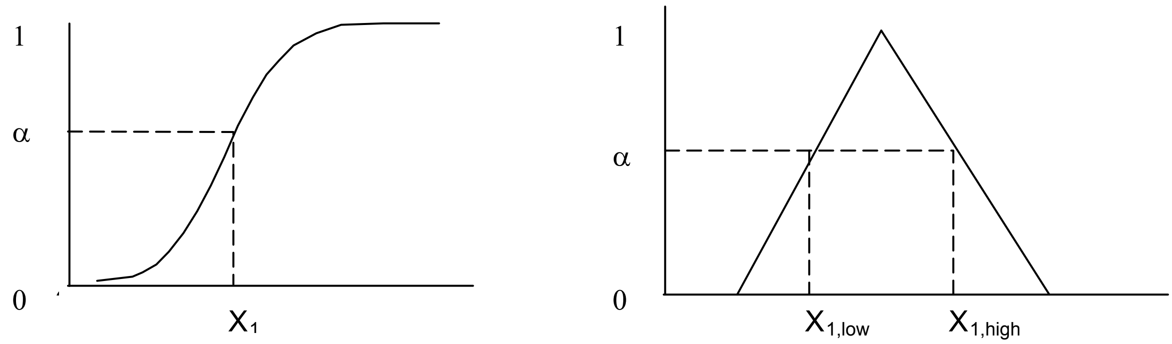

Figure 5: Sampling probability (left) and possibility (right) distributions.

Monte-Carlo simulations are performed on intervals, i.e. calculations are performed with values at the extreme of each sampled interval. Thus, the uncertainty of output quantities derived by this methodology cannot be summarized by a probability density function or a cumulated density function (CDF) but by a pair of lower and upper CDFs, called probability boxes [32]. The difference between these CDFs comes from the lack of knowledge modelled by possibility distributions.

There exist several recent investigations that handle both probabilities and possibilities and derive a pair of CDFs. Among them, one can mention the work of Ferson and Ginzburg [33] and Baudrit *et al* [34] that propose a post-processing technique to extract the relevant information from the resulting random fuzzy variable. Up to now, they concern very simple models or are computationally costly, which limits their efficiency in fields such as nuclear safety where computational cost has to be taken into account.

Opposite to that, the RAFU methodology integrates a computational cost reduction strategy. The underlying idea is that in many investigations, analysts are interested in particular statistical statements (such as α-percentiles) which can be evaluated without building the whole random fuzzy variable. Since the RAFU propagation can be seen as an extension of Monte-Carlo simulation to the theory of evidence framework, each statistical quantity of interest is directly estimated using standard results coming from the probabilistic modelling. Moreover, one can exploit convergence theorems to derive the statistical or numerical accuracy associated to the limited sample size. The computational cost reduction strategy of the RAFU is then to set a decision step before propagating uncertainties and leading to an optimal sampling in terms of number of code runs. More precisely, the RAFU method is pre-defined by a triplet of parameters $(\gamma_S, \gamma_E, \gamma_A)$ specified by the analyst:

Parameter γ_S is related to the statistical uncertainty. It provides the statistical quantity the analyst is interested in, usually α-percentiles in safety studies.

Parameter γ_E is related to the possibilistic uncertainty. It determines how α-cuts are drawn from possibility distributions.

Finally, parameter γ_A measures the desired numerical accuracy on the final result. In the case of α-percentile estimation, γ_A comes from the use of order statistics, and is the “confidence level” in section 2 of this paper.

According to the analyst, the RAFU method then determines the minimal sample size and the nature of the required sampling to obtain the response. The number of calculations is thus reduced to its minimal number, dependent on the analyst's choice. Moreover, computational cost can be easily evaluated, allowing the analyst to eventually revise these choices before uncertainty propagation. It is also possible for the analyst to provide the maximum number of code runs to be made and the numerical accuracy can be determined.

6.4 Application of the RAFU method to calculation results of the LOFT L2-5 experiment

For the application of the RAFU method, we are interested to evaluate the 95% percentile of the peak clad temperature. The method was applied in the frame of an uncertainty analysis performed within the OECD/CSNI programme on Best Estimate Methods for Uncertainty and Sensitivity Analysis (BEMUSE). The uncertainty of post test calculation results of the LOFT L2-5 experiment was determined. IRSN considered 27 uncertain input parameters. Three test calculations are compared, including the 3 most influential parameters as well as the complete set of 27 parameters. For the 27 parameters uniform and histogram distributions are compared. An example for that distribution is given in Figure 6. The uniform distribution is non-symmetric to the nominal value 1.0. For the histogram distribution the 50% percentile is the nominal value, the nominal value is the median of the distribution.

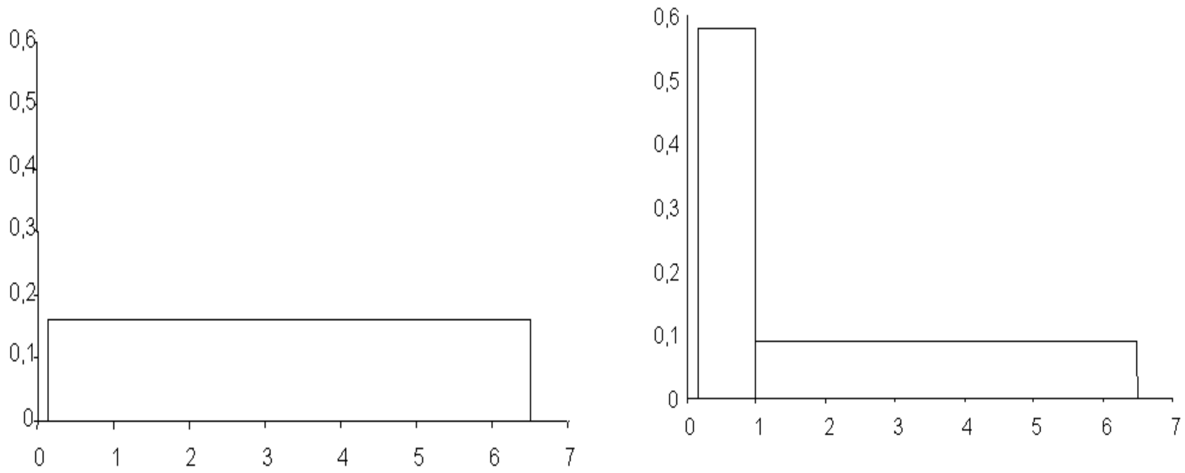

Figure 6: Uncertainty of the film boiling heat transfer coefficient. Left: Uniform distribution, right: Histogram distribution, range from 0.15 to 6.5, nominal value: 1.0

Figure 7 shows the result of the BEMUSE reference calculation by IRSN compared with the experimental data. Figure 8 shows the best estimation of the 5% percentile, noted BE 5% and the 95% percentile, noted BE 95%, using beta laws for the distribution of clad temperature. The corresponding upper and lower values of the uncertainty range at the 5% percentile are BE 5% min and BE 5% max as well as at the 95% percentile are BE 95% min and BE 95% max. The reference value corresponds to setting the uncertain parameters to their nominal values. In addition, the measured experimental values are included.

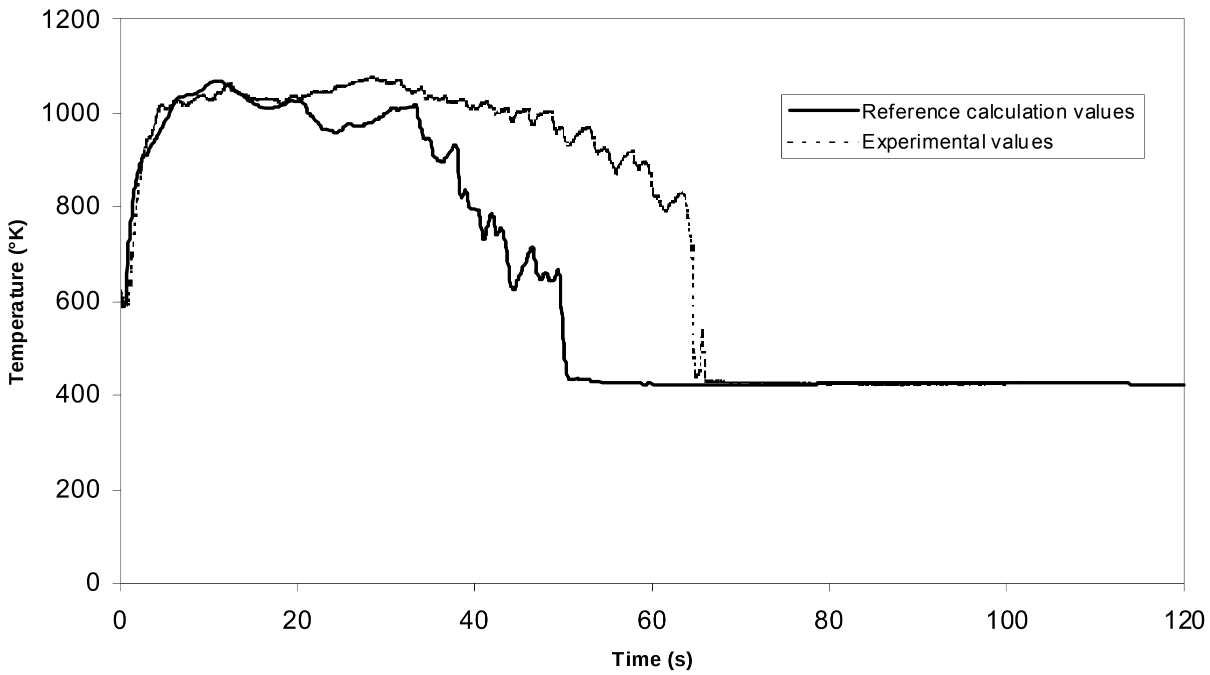

Figure 7: Peak cladding temperature of hot rod in a hot channel, comparison of data and CATHARE V2.5 mod 6.1 calculation

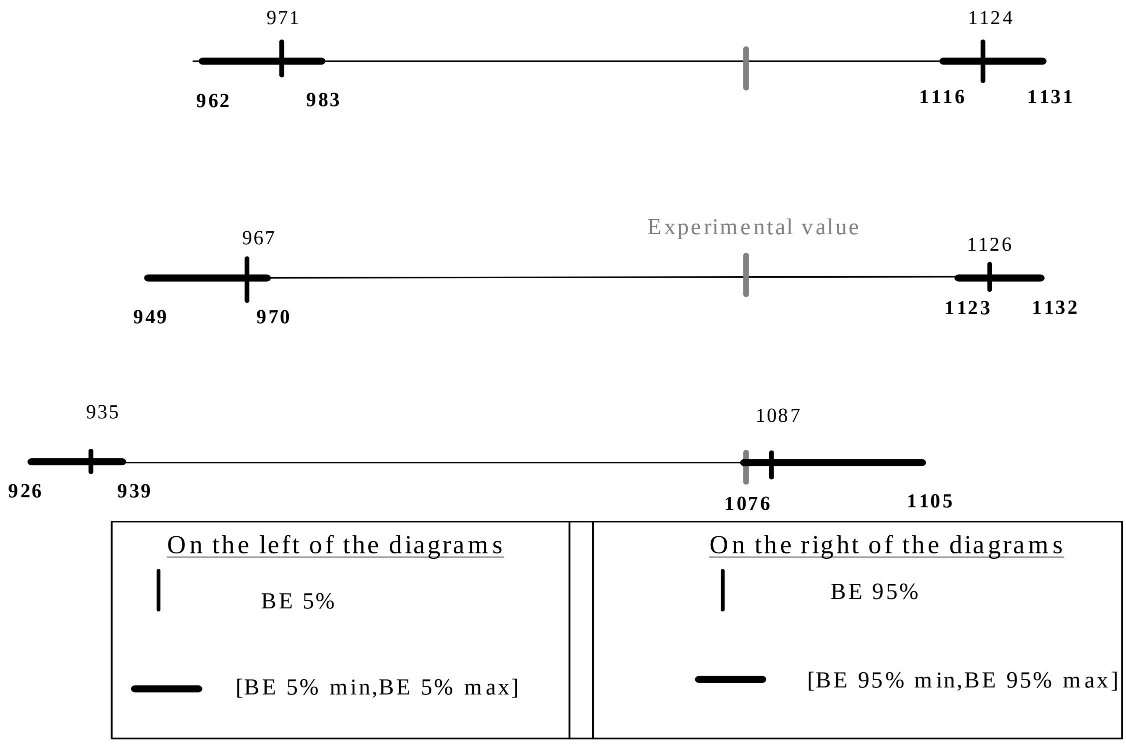

Figure 8: Best estimate and uncertainty values: From top to bottom:

1. 3 parameters, histogram distribution;
2. 27 parameters, histogram distribution;
3. 27 parameters, uniform distribution.

The main conclusions are:

1. There is no significant effect of the number of parameters, the three most influential uncertain parameters result in similar uncertainty ranges of the peak clad temperature. The most influential parameters here are: Liquid wall friction, vapour-wall heat transfer (forced convection) and film boiling (Berenson/ Bryce correlation).

2. The uncertainty range of the calculated peak clad temperature is highly dependent on the distribution of the uncertain input parameters.

Due to the influence of the distributions of the uncertain parameters, the uncertainty of the first peak clad temperature was compared using the standard statistical approach and the Dempster-Shafer procedure. Each of these procedures is performed with two independence assumptions: Uncertainty compensation or "stochastic independence" (P_SI and DS_SI) and uncertainty accumulation or "epistemic independence" (P_EI and DS_EI).

The number of uncertain parameters is three. Histogram distributions are used for the statistical procedure, while the fuzzy variables in the Dempster-Shafer approach are following triangular distributions. Consequently, the Dempster-Shafer approach bounds all choices of the used probability density functions with the same support and the same mode.

Monte Carlo simulations are performed and fuzzy intervals are used for the Dempster-Shafer procedure. The results for the statistical approach are complementary cumulative density functions of the PCT. The lower and upper complementary cumulative density functions are derived using the Dempster-Shafer approach. The curves of the statistical treatment lie between the lower and upper curves derived by the Dempster-Safer procedure for the same dependency assumptions, Figure 9. The confidence level is here defined as (1 – percentile).

The results are:
1. The triangular distribution of the Dempster-Shafer approach leads to a difference of 100 K of the 95% percentile of the first PCT.
2. The difference between uncertainty accumulation and classical uncertainty compensation leads to a difference of 30 K for the 95% percentile.

The Dempster-Shafer theory is considered to be an efficient approach to quantify statistical and possibility effects. It is no more required to select a probability distribution for uncertain parameters when not sufficient information is available. It is possible to cumulate the uncertainties when no knowledge is available, so that the uncertainty estimations do not take into account a priori independence, and on the other hand, can benefit from compensating effects when justified.

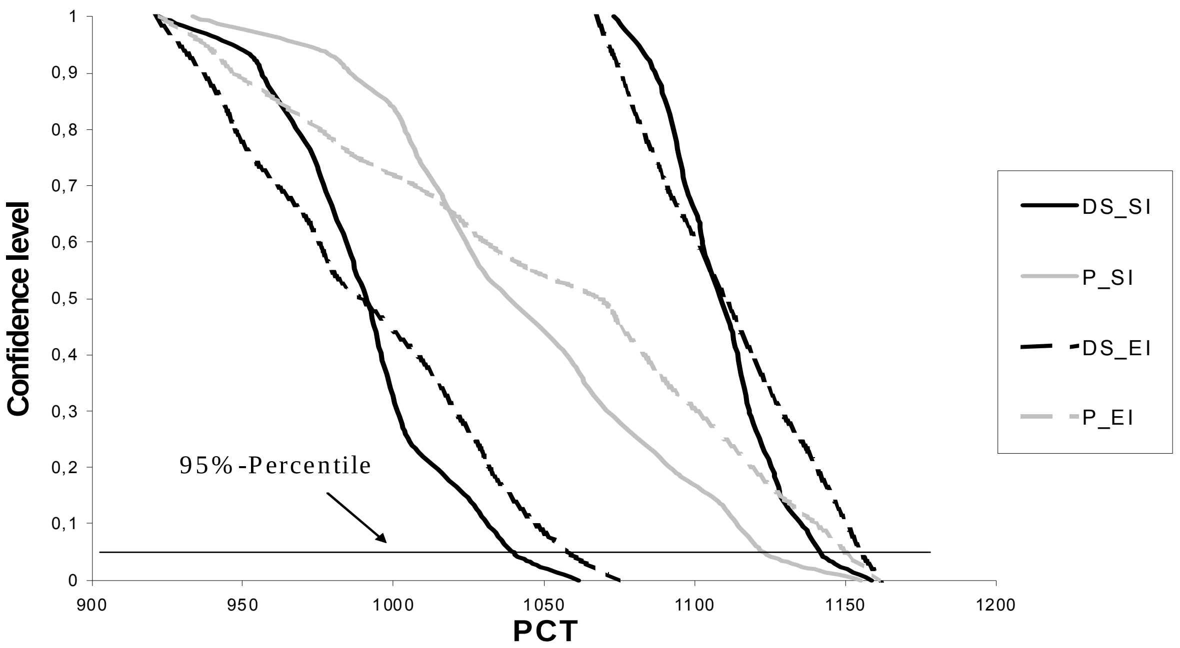

Figure 9: Complementary Cumulative Density Functions of the 3 most influential uncertain parameters

7 SUMMARY

A statistical method for performing uncertainty analysis is presented. A significant advantage of this methodology is that no a priori reduction in the number of uncertain input parameters by expert judgement or screening calculations is necessary to limit the calculation effort. All potentially important parameters may be included in the uncertainty analysis. The method accounts for the combined influence of all identified input uncertainties on the results. This would be difficult or even impossible to achieve by a priori expert judgement of loss of coolant accidents or transients. The number of calculations needed is independent of the number of uncertain parameters accounted for in the analysis. It does, however, depend on the requested tolerance limits, i.e. the requested probability coverage (percentile) of the combined effect of the quantified uncertainties, and on the requested confidence level of the code results. The tolerance limits can be used for quantitative statements about margins to acceptance criteria. Another important feature of the method is that it provides sensitivity measures of the influence of the identified input parameter uncertainties on the results.

After a controversial international discussion about the number of code calculations to be performed comparing calculation results with more than one acceptance criterion, e.g. maximum clad temperature, maximum local and core wide clad oxidation, GRS concludes that one can use the same number of computer code runs for (95%, 95%) tolerance limits, independent of the number of acceptance criteria to be compared with. incorporates the safety limits directly into the uncertainty statement. Instead of joint tolerance limits for the multiple outputs of interest one considers the statistical confidence limit for the probability of complying with the safety limits for all output parameters.

The statistical method relies only on actual code calculations without the use of approximations like fitted response surfaces. The method has been used by many organisations world-wide. These applications include licensing calculations as well as contributions to international analysis comparisons, like the CSNI Best Estimate Methods Uncertainty and Sensitivity (BEMUSE) Programme. Eleven participants coming from ten organizations and eight countries participated in the exercise performing uncertainty analyses of post test calculations on a LOFT experiment.

A challenge in performing uncertainty analyses is the specification of ranges and probability distributions of input parameters. Investigations are underway to transform data measured in experiments and post test calculations into thermal-hydraulic model parameters with uncertainties. Care must be taken to select suitable experimental and analytical information to specify uncertainty distributions.

A new approach, called the RAFU method, has been developed and applied to uncertainty analysis when only incomplete knowledge is available about the uncertain input parameters. Its construction is based on the theory of evidence framework that allows expressing uncertainties of the real state of knowledge. It is coupled with an optimal numerical treatment based on an extension of Monte-Carlo simulations to the theory of evidence framework and on the introduction of a decision step before the propagation that minimizes the required computation and allows the analyst to possibly revise the specification. In addition, this method offers a way to control the numerical accuracy of the result. The RAFU method was applied in the frame of the BEMUSE OECD Programme to derive uncertainty bounds for the LOFT L2-5 large break LOCA experiment. These results are less precise, i.e. provide an interval instead of a value for the percentiles, but may give useful information for safety investigations. The effect of different choices of distributions can be evaluated. It is considered to cope with demands of computer run time using complex computer codes such as thermal-hydraulic system codes.

8 REFERENCES

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