CONTROL ROD DROP TRANSIENT: UNCERTAINTY AND SENSITIVITY ANALYSIS OF THERMAL-HYDRAULIC VARIABLES USING A 3D MODEL WITH TRACE V5.0P3/PARCS 3.0

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ABSTRACT

In this study, a non-intrusive and stochastic method is used to accomplish an *Uncertainty and Sensitivity* (U&S) analysis in a control rod drop transient. This transient is included in the *Anticipated Operational Occurrences* (AOOs). The U&S analysis and perturbation generation is done through the DAKOTA statistical tool, developed at Sandia National Laboratories. As input parameters to the U&S analysis, 43 different thermal-hydraulic variables are chosen. Similarly, three different output parameters are chosen: total reactor power, enthalpy and reactivity. The number of total perturbations (146) is obtained using Wilks' formula considering double tolerance limits with 95% of uncertainty and 95% of statistical confidence for the output parameters. The results include the tolerance bounds of output parameters and sensitivity of input parameters as a function of time. Therefore, the most important thermal-hydraulic variables, regarding this AOO, could be isolated. As a new feature in the thermal-hydraulic model, the core is modeled using fully 3D components. A cartesian vessel is used to model the fuel assemblies (without collapsing) and a cylindrical vessel is used to model the bypass and downcomer zones.

KEYWORDS
U&S analysis, 3D vessel model, TRACE, DAKOTA, Partial Rank Correlation Coefficient

1. INTRODUCTION

The need for safety in nuclear power plants was increased recently due to the Fukushima accident. Extensive relevant literature can be found. For example, [1] and [2] give a good analysis for quantification of uncertainty analysis related to nuclear power plant computer codes. Moreover, relevant state of the art for *Best-Estimate* (BE) safety analysis and uncertainty evaluation can be found in [4] and [3]. In the present study, *Uncertainty and Sensitivity Analysis* (U&S) is applied as described in the literature to identify the uncertainty of the model output parameters and how their variance is apportioned by each model input parameter. This is done propagating the error through some physical model or computer code (thermal-hydraulic and neutronic coupled codes in this case).

U&S is related to safete analysis. The objective of safety analysis is to ensure that enough margin exists between real value and the threshold value at which barriers against radioactive release would fail. See Figure 1 for a graphical definition of safety margins and uncertainty [1]. To accomplish this objective, the *Nuclear Regulatory Commission* (NRC) includes the U&S analysis as additional and required information needed for a *Best-Estimate* (BE) value. Best-Estimate codes are used currently to predict and simulate different kind of transients in nuclear reactors. Thus, U&S analysis studies are becoming more and more common in scientific literature. Uncertainty is inherent to any experiment and computer code, it arises from the lack of physical knowledge, in the implemented computer code, and also the error introduced by the user in the input deck values. Moreover, uncertainty could be divided into two different components [6], 1) stochastic or aleatory uncertainty is irreducible since it is inherent to the aleatory or random behavior of the system under study and, 2) subjective or epistemic uncertainty is reducible but arise from the inability to measure or specify the true value.

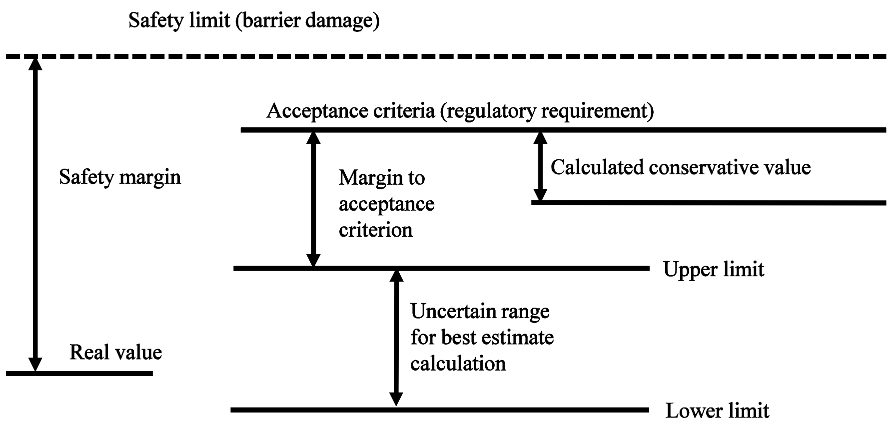

Figure 1: Safety margins and uncertainty definitions [1].

U&S methods could be classified into deterministic or stochastic methods. *Global Perturbation Theory* (GPT) is used in deterministic codes, and sampling methods fall into the stochastic methods. In this study, a sampling method is used to propagate the uncertainty through a thermal-hydraulic code coupled to a neutronic code. The thermal-hydraulic code used is TRACE V5P3 and the neutronic coupled code is PARCS v3.0. For the U&S analysis the toolkit DAKOTA [7], developed at Sandia National Laboratories, is used to propagate the uncertainty and the output uncertainty apportioned by each input parameter (sensitivity).

This paper is divided into five sections. Section two gives the details related to the methodology using DAKOTA. Section three describes the models used in the thermal-hydraulic and neutronic codes. The thermal-hydraulic model makes use of fully 3D components to simulate the fuel assemblies, bypass and downcomer [8]. Next, section four shows the U&S obtained results. Finally, section five contains the conclusions and future work. This study is complemented with a previous study, by the same authors, following the same methodology but for neutronic variables instead [9].

2. UNCERTAINTY AND SENSITIVITY METHODOLOGY

As exposed in section one, the toolkit used for U&S analysis is DAKOTA. It can be used to solve a big range of problems: optimization, parametrical studies, design of experiments, etc. In this study, however, it is used to *Uncertainty Quantification* (UQ) and *Sensitivity Analysis* (SA). The methodology is explained next.

2.1. Uncertainty Propagation

Every computer code or model has certain uncertainty inherent to its randomness or lack of knowledge related to the physical models implemented. This uncertainty can be quantified. If perturbations are applied to each of the code input parameters, using a (quasi-random) sampling method, these parameters could be considered as random variables, called *input uncertainty space* [6]. Thus, the output parameters, due to the input uncertainty propagation through the code, can also be considered random variables. This is called *output uncertainty space*. This is represented in Figure 2, where f represents the computer code under study. This code has several input parameters x_1, to $x_{v_{in}}$, and several output parameters, y_1 to $y_{v_{out}}$, each input parameter is perturbed with a different perturbation factor, δ_i.

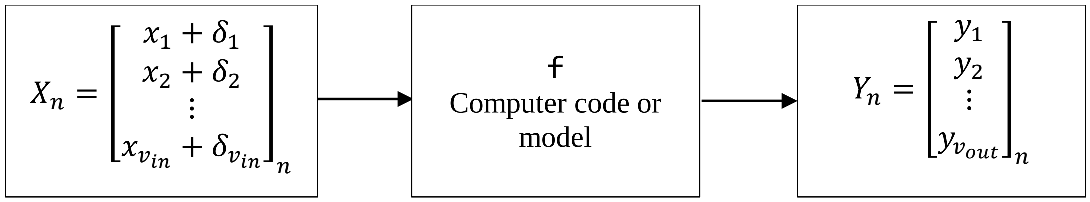

Figure 2: Uncertainty quantification methodology using a computer code or model with several input parameters, X, and output parameters, Y.

These perturbation factors must be generated in a random sampling process, the most common sampling methods used are *Simple Random Sampling* (SRS) and *Latin Hypercube Sampling* (LHS) [9], the latter is discussed more deeply later in this section. An input parameter matrix is needed, each input parameter set is perturbed with a randomly generated perturbation factor and used in a single code run; later an output parameter matrix is gathered, one output set per code run. The whole process is repeated *n* times, the determination of the parameter *n* is an important feature of the methodology. The Wilks' assumption [10] is used to define the number of runs or sample size. Wilks' formula gives the minimum sample size for a certain population coverage with a certain confidence. If we define α as the uncertainty and β as the statistical confidence for the output variables, we can calculate the number of runs, *n*, using Equation 1 for simple tolerance limit and Equation 2 for double tolerance limits.

$$1 - \alpha^n \geq \beta \qquad (1)$$

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

Applying Equation 2 (double tolerance limits), the minimum sample size obtained (or number of runs) with 95% uncertainty and 95% of statistical confidence for the output variables is 93 [10]. However, it was recently published that the minimum number of runs required for a first order double tolerance limit in a 95/95 case is 146 [11]. This is the sample size used in this study.

When a parametric sampling method is used, the sampling is done one at a time and the model code is run once for each sampling. This procedure can require a prohibitive number of runs to obtain good statistics. For parametric approaches, the number of total samples depends on the number of input parameters. Nevertheless, if a nonparametric approach is used all uncertain parameters are sampled together and the number of samples does not depend on the number of input parameters any more [3]. Thus the number of runs can be substantially reduced

The uncertainty method GRS's (Gesellschaft für Anlagen und Reaktorsicherheit) developed in Germany is used. This method determines the number of samples using Wilks' formula, but instead of parametric sampling it uses nonparametric sampling [3]. As a consequence, the number *n* of code runs is independent of the number of input uncertain parameters, it only depends on the uncertainty and the statistical confidence level used [4]. The main drawback is that the input parameters uncertainty must be known in advance. The input uncertainty is defined using a *Probability Distribution Function* (PDF). This is the most risky step in the methodology since it affects directly to the results obtained. Frequently, the PDF definition must be reevaluated after some code runs. These PDFs are used by the sampling method to generate the perturbation matrix. The uncertainties distributions are obtained from the literature or by an expert opinion. The most common PDFs are the normal *N~(μ,σ)* and uniform *U~(m,M)* distribution; although other distributions could be used, such as log-normal, triangular or polygonal for continuous variables and Poisson or binomial for discrete variables.

For this study, 43 different thermal-hydraulic parameters are chosen as input parameters, details are given in section 3.2. Besides, there are only 3 different variables as output parameters: reactivity, power and enthalpy. These output parameters are chosen because they provide enough information to define the reactor state. They involve the main neutronic parameters and predict the current reactor evolution. Moreover, physical limits are set to ensure reactor integrity (enthalpy).

2.2. Sampling Method

Each perturbation set is obtained using a sampling method. In this study two different sampling methods are used and compared: *Simple Random Sampling* (SRS) and *Latin Hypercube Sampling* (LHS). Both are quasi-random methods, however, LHS is considered to be statistically equal or better than SRS. LHS is an efficient stratified Monte Carlo sampling method that allows sampling using the predefined parameter PDF. The main advantage of LHS over SRS is that LHS gets a better sample distribution over the sample space and thus, a better coverage of input uncertainty space [12]. LHS sampling is obtained with three steps, (1) each input PDF is subdivided in *n* subintervals with equal probability according to each PDF, (2) a random point is generated in each subinterval for each input parameter, and (3) a random combination of points generated in previous step, without replacement, is used to generate a sample. The process is repeated until all *n* samples are randomly generated. A couple of advantages could be added to LHS. First, it is more robust for codes or models with non-linear effects. Second, with SRS if there are not enough samples, a subset of low probability but high sensitivity (over output) could be missed. It is shown that the variance of the predicted output mean using LHS is always less or equal than the variance of the predicted output mean using SRS, Equation 3.

$$Var(\hat{E}(y)_{LHS}) \leq Var(\hat{E}(y)_{SRS}) \tag{3}$$

2.3. Sensitivity Measurement

In addition to uncertainty, DAKOTA also provides the calculation for sensitivity analysis. Qualitatively, it defines how the input uncertainty is spread among output parameters. Thus, it is possible to identify which uncertainty among the input parameters should be reduced in order to obtain the biggest reduction in output uncertainty. To this end, DAKOTA provides the *Simple Correlation Coefficient* (SCC) and *Partial Correlation Coefficient* (PCC) in matrix format for all input and output parameters. SCC shows the correlations among different parameters, its value is bounded between -1 and +1. For highly correlation parameters its value would be near +1 or -1 (direct or inverse correlation). Moreover, if the value is near zero, the parameters are poorly correlated. However, the value of SCC could be influenced by other model parameters. To avoid biased SCC, the PCC provides the correlation between two parameters while holding all the other parameters constant. The value meaning is the same as in the SCC case. See Equation 4 for SCC formula between parameters *x* and *y*. Equation 5 provides the formula for PCC between parameters *x* and *y* holding a third parameter, *z*, constant, $r_{xy|z}$.

$$SCC = r_{xy} = \frac{Cov(x,y)}{\sqrt{Var(x)Var(y)}} \qquad -1 \leq SCC \leq +1 \tag{4}$$

$$PCC = r_{xy|z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1-r_{xz}^2)(1-r_{yz}^2)}} \qquad -1 \leq PCC \leq +1 \tag{5}$$

Moreover, this is only valid for linear relationships. For non-linear models the values are ranked, averaged values are used if ties are present. Ranked values could be used with previous formulas. DAKOTA also calculates the *Simple Rank Correlation Coefficient* (SRCC) and *Partial Rank Correlation Coefficient* (PRCC), their values have the same meaning explained before. In this study the PRCC is used to represent sensitivity analysis.

Finally, the DAKOTA methodology to calculate U&S is explained in 4 simple steps. (1) Identify the model inputs parameters whose uncertainty will be propagated and define their PDFs. (2) DAKOTA pre-process: use an appropriate sampling method to sample the input space, x_1 to $x_{v_{in}}$, according to each PDFs. Thus, obtaining *n* perturbation sets, δ_i, (each set contains perturbations for each input parameter). (3) Run the computer code or model *n* times and gather the output space, y_1 to $y_{v_{out}}$, in a matrix. (4) DAKOTA post-process: feed the perturbation and output space matrix to DAKOTA to calculate the related U&S among other statistical data.

3. MODELS & UNCERTAINTIES

3.1. Thermal-Hydraulic Model

TRACE thermal-hydraulic code is used for this study. The model used presents a fully 3D PWR core, it is based on previous studies [8]. It is modeled using vessel 3D components, one cartesian vessel to represent the different fuel assemblies one by one, and one cylindrical vessel for the bypass and downcomer. Thus, this model can better simulate asymmetric phenomena and cross flow between assemblies, the latter is especially important for PWR. Due to the large number of components and input deck work, the process to create this model is automatized using MATLAB.

The cartesian vessel is modeled to have the corner cells with fraction flow area equal to zero, thus it resembles the actual radial mapping used in PARCS neutronic code. One heat structure component is coupled for each fuel assembly with the same axial distribution. Moreover, the cylindrical vessel is discretized in two radial cells and three azimuthal sectors. The inner radial cell represent the bypass and the outer cell the downcomer. Heat structure components are used in the cylindrical vessel to model the heat in the bypass and the core shroud heat transfer (between inner and outer radial cells). Three breaks and three fills are used to simulate a different hot and cold leg respectively, each break and fill is attached to a different azimuthal sector in the cylindrical vessel. Both vessels are connected side-wards by one cell pipe component at all axial levels, and axially by single junctions at bottom and top of each fuel assembly. See Figure 3 for a sketch of a simplified TRACE model using 3D vessel components, the flow path is shown using blue arrows.

In order to test the methodology, a control rod drop transient occurrence is simulated. This transient is included in the *Anticipated Operational Occurrences* (AOOs). An AOO is classified as an occurrence (and not as an accident) because reactivity is removed from the core (control rod is inserted and more neutrons are absorbed). To assure a proper steady state convergence, 50 seconds of null transient are simulated. Then the control rod involved in the occurrence starts being inserted and within 2.06 seconds it is totally introduced.

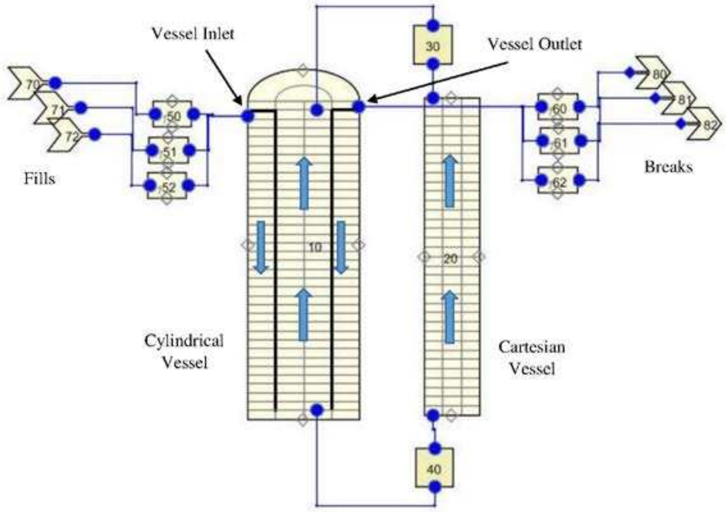

Figure 3: Simplified TRACE model for PWR 3D core representation by means of a cartesian vessel (fuel assemblies) and a cylindrical vessel (inner radial cell bypass and outer cell downcomer), sketch using SNAP tool.

One important fact of this model, as said before, is the simulation of cross flow among different channels and bypass. However, this makes the bypass flow oscillate sharply, obviously this is an unreal effect. To solve this problem the axial and radial friction factors must be adjusted. This process must be repeated for all three azimuthal sectors. Fortunately, an iterative process in MATLAB is developed to adjust the corresponding friction factors [8]. Figure 4 shows an example of bypass flow with different azimuthal sectors comparing the adjusted TRACE 3D model and the equivalent RELAP 1D model. Abscissa axis shows the axial cell number in the axis (z) direction.

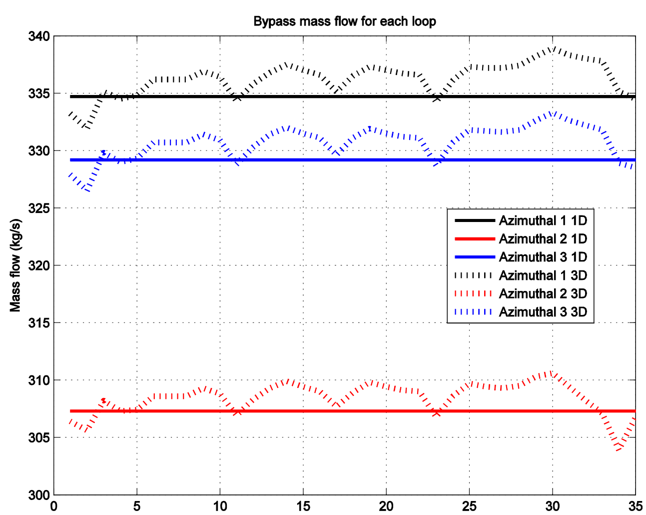

Figure 4: Bypass flow for three different azimuthal sectors comparing TRACE 3D model (dotted lines) and RELAP 1D equivalent model (stright lines), flow as function of axiall cells in axial direction.

3.2. Thermal-Hydraulic Uncertainty

Research in the literature was made to find what thermal-hydraulic variables should be included in the uncertainty propagation, what their uncertainties are and how to fully characterize uncertainty distributions [13-17]. A list of thermal-hydraulic variables is listed in Table 1 and

Table **2** for normal and uniform distributions, respectively. They also show the parameters defining the PDFs and the reference where the information was found.

Table 1: Thermal-hydraulic variables to propagate through TRACE following a normal distribution

Definition	Variable	Mean	Stand deviation	Reference
Output pressure	preso	1.0	0.002	Expert Opinion
Reactor power	power	1.0	0.005	Expert Opinion
Inlet mass flow	massi	1.0	0.002/0.001	Expert Opinion
Wall roughness	wallr	1.0	0.25	Expert Opinion
Assembly flow area	Farea	1.0	0.01	[14], page 13
Pitch to diameter ratio	Pdrat	1.0	0.05	Expert Opinion
Radial fuel peaking factor	frpwd	1.0	0.01	[14], page 13

Table 2: Thermal-hydraulic variables to propagate through TRACE following a uniform distribution

Definition	Variable	Lower limit	Upper limit	Reference
Gap heat transfer coefficient	hgapc	0.65	1.35	[15], page 50
Grid friction factor	kfacf	0.95	1.05	[15], page 50
Hydraulic diameter	hydim	0.995	1.005	[15], page 50
Fuel heat capacity	$mheat_0$	0.99	1.01	[16], page 60
Clad heat capacity	$mheat_2$	0.97	1.03	[16], page 60
Fuel thermal conductivity	$mcond_0$	0.954	1.046	[16], page 60
Clad thermal conductivity	$mcond_2$	0.94	1.06	[16], page 60
Inlet flow temperature	tliqi	-0.5/-0.2	0.5/0.2	[14], page 13/Expert
Gap size	gapsz	-7.4E-6	7.4E-6	Expert Opinion
Critical heat flux multiplier	chfml	-0.4	0.3	[17], page 3.24
Heat fraction to bypass	fbyph	-2.375E-5	2.375E-5	Expert Opinion
Heat fraction to moderator	fmodh	-9.2625E-4	9.2625E-4	Expert Opinion

The variables in italics are treated as different input variables for each assembly type, there are four types (3 fuel types plus bypass). Its PDF definition is not changed for each assembly type. Thus, the total number of input parameters is 43. These data are introduced directly in DAKOTA tool to generate the appropriate perturbation factor matrix. For the variables inlet mass flow and inlet flow temperature, two different sets of parameters are shown (a/b), the former corresponding to the LHS sampling and the latter to the SRS sampling. For both variables the uncertainty was deliberately decreased because some simulations using SRS sampling failed while using the uncertainty defined for LHS sampling.

3.3. Sensitivity approximation

According to [9], two different sensitivity approximations are used. First approximation, called maximum peak approximation, calculates the U&S analysis only for the time where the absolute maximum output parameter value is found. Thus, only three U&S analysis are run, one per output parameter. This approximation gives sensitivity information for the most critical transient time step. The second approximation, called index dependent approximation, calculates the U&S analysis for each time step for the whole simulation and for all three output parameters. This approximation gives sensitivity information for the whole transient simulation, thus, a wider sensitivity view is obtained.

3.4. Neutronic model

PARCS code is used to build the neutronic model. The 3D neutronic model is spatially discretized into 17x17x34 cells. These neutronic cells represent both the core and the bypass. Fourteen different control banks are modeled. Moreover, there are 3 types of fuel assemblies and 1379 different cross section compositions. Two prompt neutron groups and six delayed neutron groups are defined. PARCS is coupled with TRACE thermal hydraulic code.

The cross section libraries are obtained using the coupled codes CASMO4-SIMULATE3 and the SIMTAB methodology, developed together by the UPV and Iberdrola. Cross sections are homogenized and collapsed and have the nemtab/r format.

4. RESULTS

The results are divided in subsections, each one for a different approximation.

4.1. Maximum peak approximation

Figure 5 shows the most sensitive input parameters for each output parameter (enthalpy, power & reactivity) using LHS sampling method. The same is shown in Figure 6 using SRS sampling method. Following the previous study [9], an input parameter is considered to be sensitive enough if its PRCC is bigger than 0.16.

For the maximum peak approximation, see Figure 5, out of the 43 initial input parameters, the number of sensitive input parameters (PRCC bigger than 0.16) are 10 for the enthalpy, 13 for the power and 14 for the reactivity output parameter. That is with LHS sampling method. However, using the SRS sampling method, Figure 6, there are 5 (enthalpy), 16 (power) and 10 (reactivity) input parameters sensitive enough for each output parameter. See Table 3 for more details.

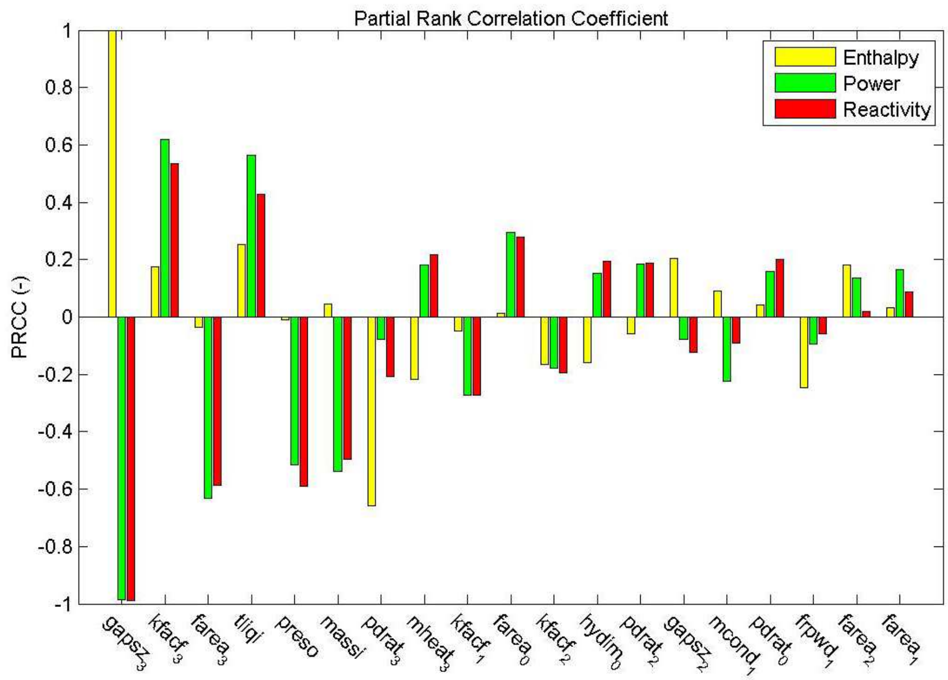

Figure 5: Maximum peak approach, PRCC for the most sensitive input parameters (PCRR > 0.16) using LHS sampling method.

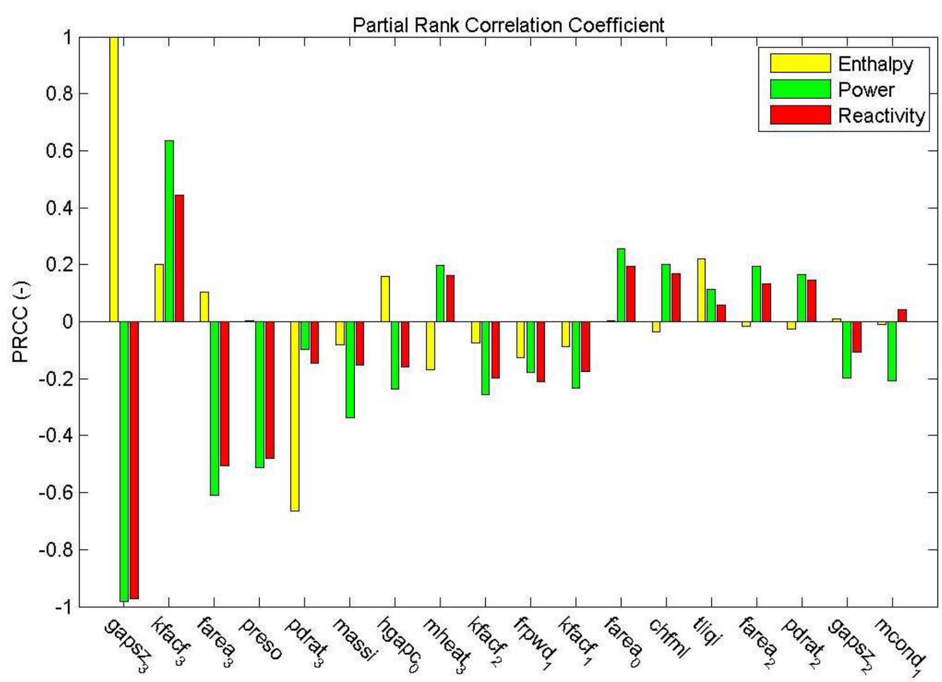

Figure 6: Maximum peak approach, PRCC for the most sensitive input parameters (PCRR > 0.16) using SRS sampling method.

4.2. Index dependent approximation

Figure 7 shows for the enthalpy output parameter, its mean (solid black line), the lower and upper 95% confidence interval (dashed red lines) and the maximum/minimum for each time step among all samples (dot-dashed blue lines). The same information is shown in Figure 8 and Figure 9 for the power and reactivity (power is normalized to one). The left image shows the response for the whole simulation time. Whereas, in the right image, a zoom is used over the peak functions to appreciate the different lines. Only the LHS sampling method results are shown, results for the SRS sampling method are similar. For all results, a null transient for 50 seconds is run prior to the control rod drop transient.

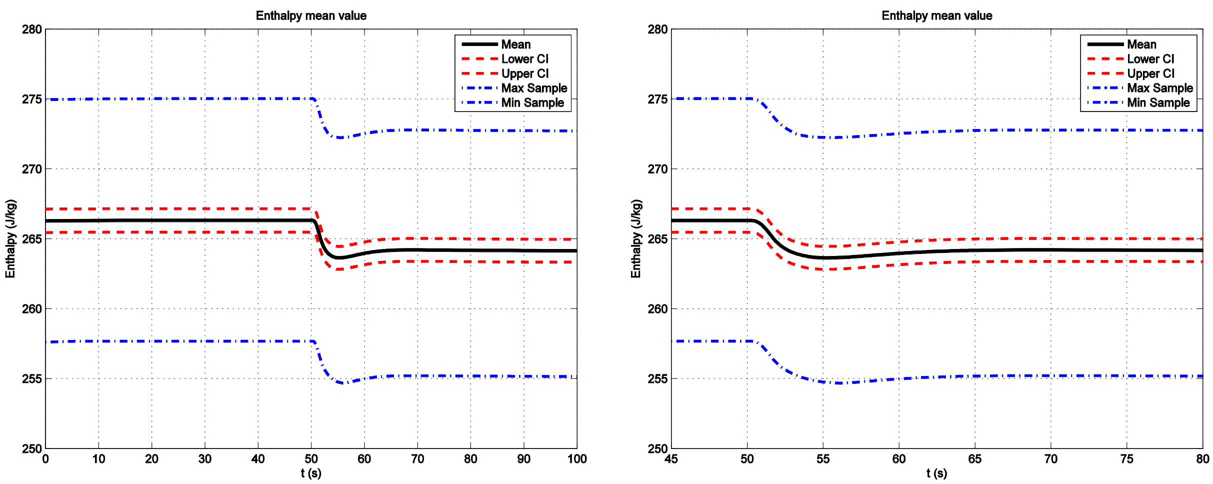

Figure 7: Enthalpy mean (solid black line), the lower and upper 95% confidence interval (dashed red lines) and the maximum/minimum for each time step among all samples (dot-dashed blue lines). LHS sampling results. Peak zoom is shown on the right.

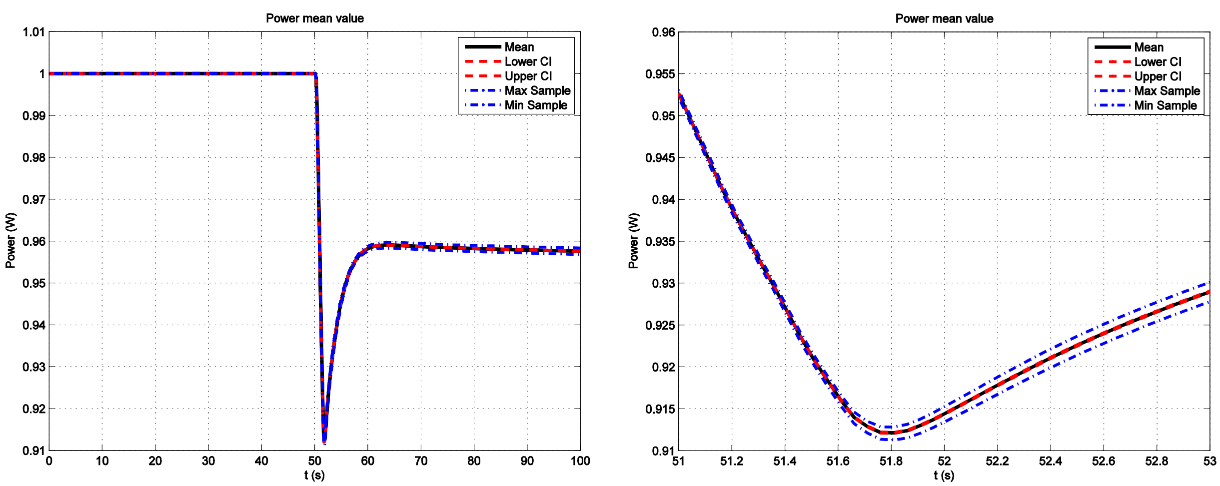

Figure 8: Power mean (solid black line), the lower and upper 95% confidence interval (dashed red lines) and the maximum/minimum for each time step among all samples (dot-dashed blue lines). LHS sampling results. Peak zoom is shown on the right.

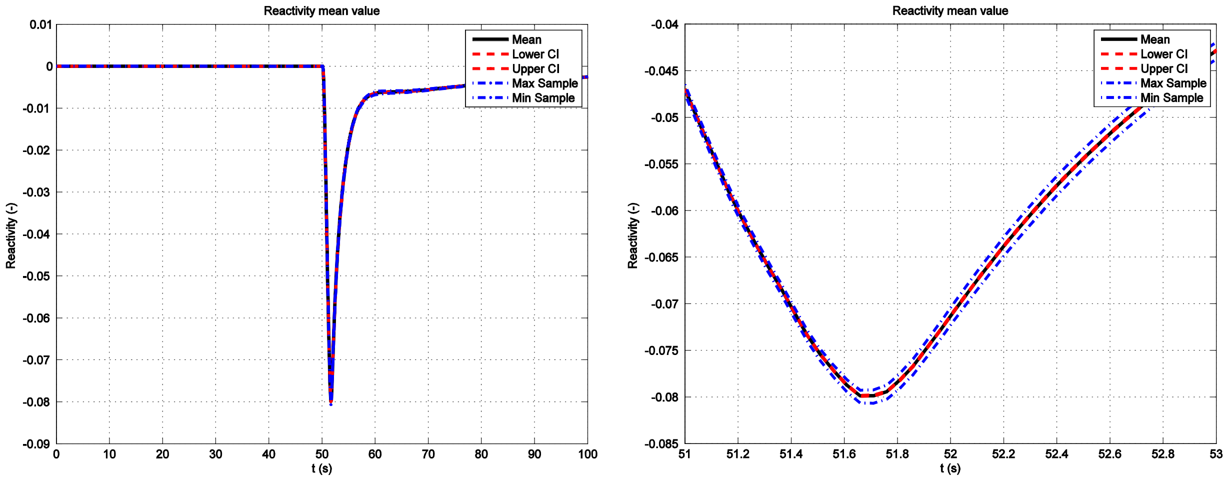

Figure 9: Reactivity mean (solid black line), the lower and upper 95% confidence interval (dashed red lines) and the maximum/minimum for each time step among all samples (dot-dashed blue lines). LHS sampling results. Peak zoom is shown on the right.

Figure 10 contains the standard deviation and its lower and upper 95% confidence interval (dashed red lines) for the enthalpy (left) and reactivity (right) output parameter. Only the LHS sampling method results are shown.

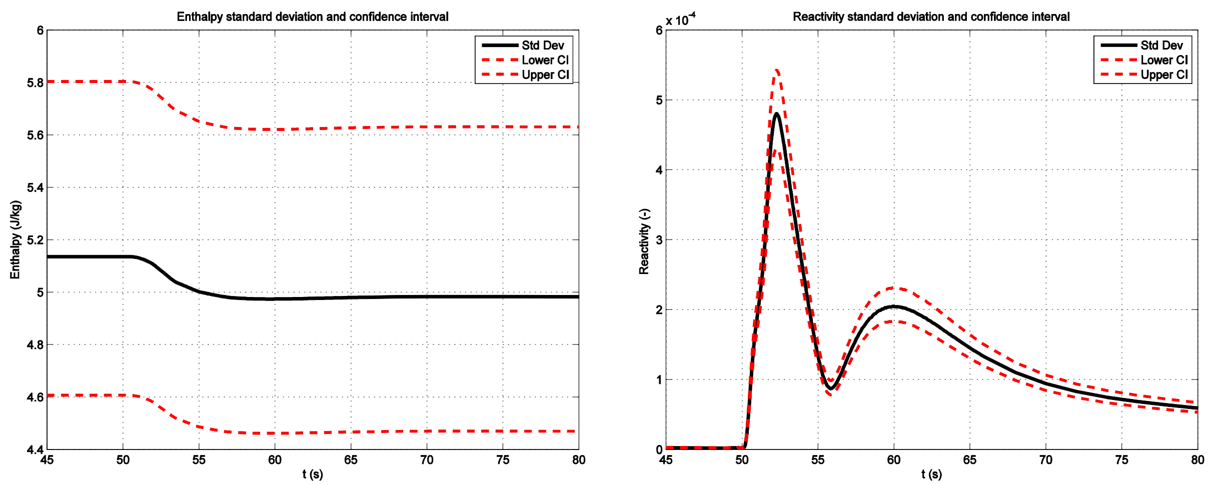

Figure 10: Enthalpy (left) & reactivity (right) standard deviation (solid black line) and the lower and upper 95% confidence interval (dashed red lines). LHS sampling results.

Regarding the index dependent approach, from Figure 7 to Figure 10, it can be concluded that the most uncertain output parameter, using coupled TRACE/PARCS, is the enthalpy. Its uncertainty is almost 2%, whereas that for the power and reactivity is 0.05% and 0.6% respectively.

With respect to the index dependent sensitivity analysis, Figure 11 contains the PRCC values as a function of time for all three output parameters. Only the 14 most sensitive input parameters are shown.

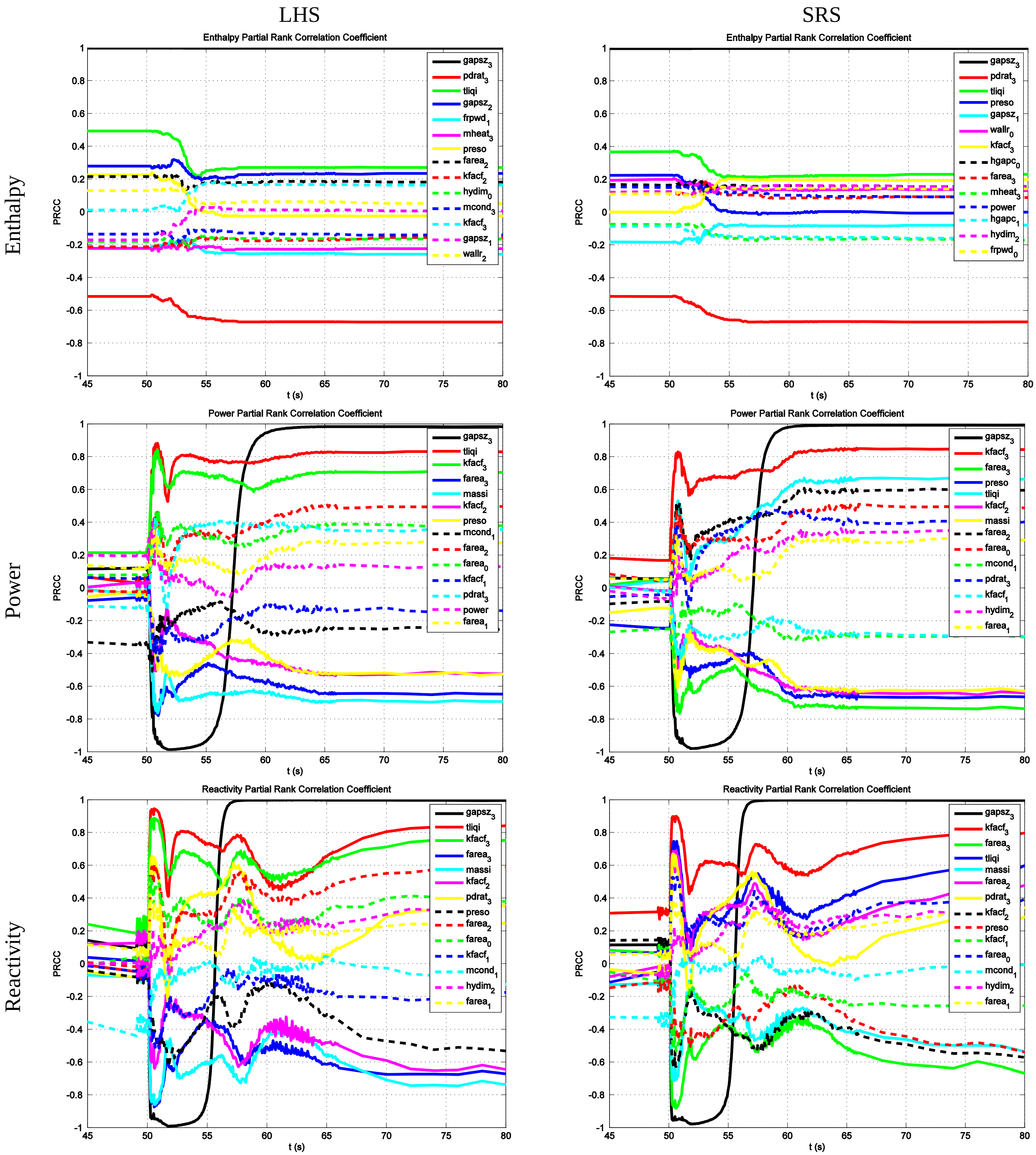

Figure 11: Index dependent approach, PRCC for the most sensitive input parameters and the output parameters (enthalpy, power & reactivity). Left column contain LHS sampling method results, whereas right column shows the results for the SRS sampling method.

Sensitivity analysis, Figure 11, shows that the most sensitive input parameters experience a great change in sensitiveness when the *Anticipated Operational Occurrences* (AOO) occur (50 seconds). The most sensitive input parameter is, again, the gap size for the assembly type 3. For the enthalpy, the gap size is sensitive all the time, whereas, for the power and reactivity, the sensitivity experience a sign change when the rod is dropped.

Other input parameters to consider are the boundary conditions (BC). The inlet liquid temperature is always the most important BC input parameter, except for power using SRS. This is followed by output pressure for enthalpy and inlet mass flow for reactivity. For the power output parameter the second most important input parameter is inlet mass flow or inlet liquid temperature, for LHS and SRS respectively.

5. CONCLUSION & FUTURE WORK

In this study a U&S analysis for 43 different thermal-hydraulic parameters was performed. A probabilistic uncertainty method (GRS) with nonparametric sampling was used, the number of samples or code runs was determined using Wilks' formula. The PDFs for the 43 uncertain input parameters were obtained from the literature whenever possible, see Table 1 and Table 2. Two different approximations were used 1) according to the maximum peak value, and 2) index dependent approach, where the sensitivity coefficients are obtained as a function of time.

Regarding the first approach, Table 3 show in detail the uncertain input parameters according to each output parameter and sampling method used. The input parameters are sorted according to its sensitivity.

Table 3: List of most sensitive input parameters for the maximum peak approach as a function of output parameter and sampling method used.

Enthalpy		Power		Reactivity	
LHS	SRS	LHS	SRS	LHS	SRS
gapsz3 pdrat3 tliqi frpwd1 mheat3 gapsz2 farea2 kfac3 kfac2 hydim0	gapsz3 pdrat3 tliqi kfacf3 mheat3	gapsz3 farea3 kfacf3 tliqi massi preso farea0 kfacf1 mcond1 pdrat2 mheat3 kfacf2 farea1	gapsz3 kfac3 farea3 preso massi farea0 kfacf2 hgapc0 kfacf1 mcond1 chfml mheat3 gapsz2 farea2 frpwd1 pdrat2	gapsz3 preso farea3 kfacf3 massi tliqi farea0 kfacf1 mheat3 pdrat3 pdrat0 kfacf2 hydim0 pdrat2	gapsz3 farea3 preso kfacf3 frpwd1 kfacf2 farea0 kfacf1 chfml mheat3

As seen in this table, the fuel-clad gap size in assembly type 3 is always the most important input parameter for both sampling methods. The difference compared to the second most sensitive input parameter is important. The gap size has a positive PRCC for the enthalpy and negative PRCC value for the power and reactivity. On one hand, if the gap size is increased, then the fuel temperature is also increased and thus, the enthalpy increases. On the other hand, due to the increase of fuel temperature and the Doppler effect, the absorption cross section is also increased and thus, the power and reactivity decreases.

The first three most important input parameters are the same regardless of the sampling method used (for power and reactivity the second and third parameter are swept). However, there are some disagreement with the other input parameters. Sensitivity coefficients are expressed as the fraction of uncertainty apportioned by each input parameter. Thus, the first three input parameter fractions make the biggest contribution to the uncertain output parameters. The other input parameters have a little contribution. Therefore, a little change due to the sampling method could change the sensitivity ranking.

For both approaches, the assembly type 3 is always the assembly with more sensitive input parameters, then assembly 2 and 1 are, roughly, equally sensitive, finally assembly type 0 (bypass) is the less sensitive. The great importance of assembly type 3 input parameters can be assessed using Figure 12. A great fraction of the core is represented using this assembly type, thus, a slight change in its input parameters affects the output parameters significantly. Mainly, the bypass does not have a great effect on the output parameters studied. However, its flow area is significant enough, it greatly affects the core flow and thus the power and reactivity.

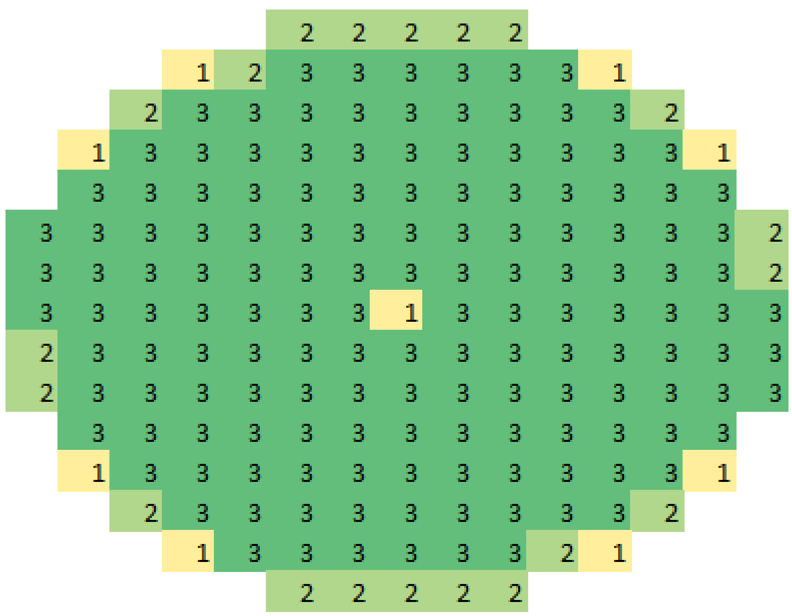

Figure 12: Fuel type radial mapping.

In a previous study [9] the U&S analysis was done using the main cross sections as input parameters. As it was a first methodology try, the PDFs definitions were unreal. In this study it has been shown how to use the same methodology using thermal-hydraulic variables as input parameters and using more accurate PDFs. As a **future work**, uncertainty will be propagated through the cross section process generation: collapse, homogenization and burn-up. Therefore, proper PDFs will be available for the main cross sections in the neutronic code. Thus, the cross section and neutronic parameter uncertainties could be propagated through the burn-up and thermal-hydraulic/neutronic codes.

NOMENCLATURE

$\mathbf{x_i}$: input parameter with index *i*
$\mathbf{y_i}$: output parameter with index *i*
$\mathbf{v_{in}}$: number of total input parameters
$\mathbf{v_{out}}$: number of total output parameters
$\boldsymbol{\delta_i}$: perturbation for input parameter with index *i*
$\boldsymbol{\alpha}$: uncertainty for Wilks' formula
$\boldsymbol{\beta}$: statistical confidence for the output variable
n: total number of runs using Wilks' formula
SCC: Simple Correlation Coefficient, also represented as r_{xy}, sensitivity coefficient between any two general parameters *x* and *y*
$\mathbf{r_{xz}}$: SCC between any two general parameters *x* and *z*
PCC: Partial Correlation Coefficient, also represented as $r_{xy|z}$, sensitivity coefficient between any two general parameters *x* and *y* and holding a third general parameter constant, *z*

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