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COMBINING PROBABILISTIC AND DETERMINISTIC METHODS FOR ACCIDENT ANALYSIS

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ABSTRACT

This study describes a practical method applied to nuclear reactor safety analysis (NRSA), based on an approach so-called best estimate plus uncertainty (BEPU). The innovative analysis approach involves statistical methods integrated with deterministic rules to fuel licensing code (FLC). The goal of NRSA is to improve safety margins in the nuclear reactor operation, which has partially achieved with uncertainty treatment. Previously, BEPU analysis was widely used to study the loss of coolant accident (LOCA), via inclusion in thermal-hydraulic codes (THC). The systems can measure the impact caused by uncertainties spread in core reactors with a coupling of THC and optimization packages. This paper shows the result of applying the UA/SA technique to FRAPCON, joined with DAKOTA toolkit. This integration will offer the probabilistic analysis coupled with empirical rules. A perfect fusion of the concepts permits the exploration of parametric uncertainties and calibration of physical models. We can use the combined utilization of FLC systems and the DAKOTA toolkit to produce sensitivity analysis. The first step in this approach is to identify all uncertainty sources of the physical models, the reactor design, and manufacturing parameters. It is subsequently used into an FLC, such as FRAPCON, as input parameters. The uncertainties usually distributed using the Wilks formula, which determines the number of samples required for unilateral tolerance. According to Wilks' method, it needs 59 data samples to achieve a confidence level of 95%. Results from Wilks formula found via Monte Carlo simulation, which applies to FLC coupled with sensitivity analysis.

1. INTRODUCTION

The last tendency of NRSA has promoted the integration of features of both methodologies to build a complete framework. Deterministic models are dominant in the U.S. Code of Federal Regulations, Title 10, Part 50 (10 CFR§50), Appendix K, last updated in 1988. Then it is using the DSA paradigm to the loss of coolant accident (LOCA) evaluations.

In 1996, when was introducing the Code Scaling, Applicability, and Uncertainty (CSAU) method. Where the concepts are in the norm (Quantifying Reactor Safety Margins Application of Code Scaling, Applicability, and Uncertainty). Later, THC codes were used in the licensing process, but it was still necessary to measure the uncertainty effects. During the service life of reactors, all forces are essential considering the uncertainty treatment introduced by Best-Estimate Plus Uncertainty (BEPU).

These analyses can use several statistical methods to perform procedures for all transients and facilities. The BEPU procedures must adequate transient scenarios, including the input parameter selection of uncertainty propagation over the safety criteria. This power framework permits compliance responses using both parametric and non-parametric uncertainty analysis methods. The focus of nuclear safety has been on accident scenarios for power units, especially the Pressurized Water Reactor (PWR). The main topic of research is on PWRs under a Large Break Loss of Coolant Accident (LB LOCA) and in a spent fuel storage condition.

1.1. Long Irradiation Cycles

The zirconium alloys exhibit oxidation, hydride, oxide spallation, degradation of features because of irradiation damage. However, the nuclear specialist must increase fuel discharge burnup, maintaining safety margins. Extended cycles could reduce fuel costs and waste management. Advanced material as iron-chromium-aluminum FeCrAl and ceramic silicon carbide (SiC) should replace zircaloys. In the last decades, because of the same drawback developed options such as Zirlo, M5, MDA, duplex cladding.

1.2. Nuclear Licensing Process

A set of norms form the guidelines that contain the descriptions used to nuclear reactor operations that must obey the limits endorsed. The U.S Nuclear Regulation Commission (USNRC) is the federal agency that must suggest safety requirements to protect the health of the public. Nuclear safety guidance must follow the Code of Federal Regulations (CFR) that contain all regulations issued by the U.S. government regarding atomic energy. The most comment is the (10CFR§50.46), proposed in 1974 [1]. The norms defined acceptance criteria for emergency core cooling systems (ECCS) in light-water reactors (LWRs). The ECCS contains a set of limits that formed at least five practical rules. ECCS requirements intend to guarantee the integrity of the reactor core in any operating conditions.

After the 1990s, started replacement of unrealistic safety margins used in the license of nuclear reactors drove the need for using uncertainty methods. Deterministic rules, often excessive, inducing limits the actual capabilities of the industry to increase energy production. These rules established corrosion limits for cladding oxidation at < 17% of cladding thickness, also defining limits to hydrogen generation. The PCT value shall be below 1200°C and explored for loss-of-coolant accidents. The Deterministic Safety Analysis (DSA) is a consequence of the rules defined in CFR §50.46, conducted under empirical methods. However, deterministic practices could provide unrealistic safety margins for nuclear services. The NRSA had shown the methods BE, and BEPU models, which are accessible in Monte-Carlo codes, also implemented in several THC systems, and fuel performance codes [2].

The International Atomic Energy Agency (IAEA) recommends global safety standards that serve as a reference for protecting the civilian population and the environment. The IAEA specifies that the rules for nuclear operations should base on the recommendations of the BEPU for the licensing process. The NRC establishes a series of regulations known as the US Regulatory Guide (RG), which comprises strategies for creating uncertainty models in the licensing process. Also, it is known as the calculation of the best estimate of performing the central emergency cooling system (BE-ECCS) or RG-1.157. Regarding safety analysis, the RG-1.157 was a turning point in the safety concept followed by the nuclear industry. Several THCs now cover several of these recommended guidelines. Figure 1 shows the uncertainty quantification process.

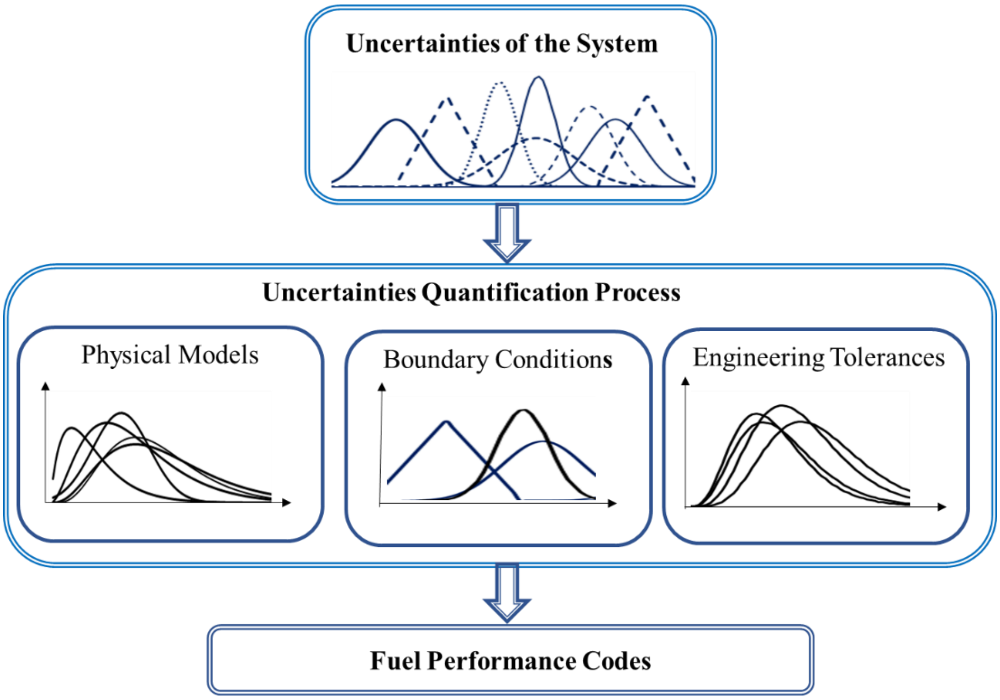

Figure 1: Uncertainty quantification process used for fuel performance codes

The NRC also established the code scaling, applicability, and uncertainty method, using the phenomena identification and rank table (PIRT). A procedure developed by the Technical Program Group for the USNRC in the late 1980s [3]. A group led by Westinghouse sponsored the NRC established CSAU method. Then, European company Areva S.A. developed the Gesellschaft fur Anlagen und Reaktorsicherheit (GRS) method for LOCA analysis, based on a non-parametric statistical approach that articulate inequality branded with a confidence level. Many thermal-hydraulics systems adopted BEPU models to improve safety as the Reactor Excursion and Leak Analysis Program (RELAP). Therefore, fuel performance codes have accurate safety assessments. Sensitivity analysis (SA) provides a study between the cause-and-effect spreader inner-system and how the output can trigger all sources of input deviations [4].

The procedure described here combines the uncertainty analysis and sensitivity analysis (UA/SA), which can also apply to FRAPCON and other licensing codes [5]. The fuel licensing systems inherited features of the BEPU approach because of the use of interfaces with statistical tools. It can quantify the uncertainties based on the mechanical tolerances and also include the propagation for physical models, the method used to calculate fuel responses to different situations. Sensitivity analysis also aids in understanding the failures of accident scenarios. This method offers several benefits and uses a global sensitivity analysis (GSA) to predict fuel response.

1.3. Review Sensitivity Analysis Methods

Sensitivity analysis is the study of how the uncertainty of the output of a model can identify effects from many sources of uncertainties from the system analyzed [6]. GSA technique permits the measurement of the importance of the input parameters within the whole input space. In contrast, another type of analysis is a variance-based sensitivity analysis (VBSA). Variance models are derivations from GSA, including other approaches like regression analysis and the so-called Sobol method [7]. Complicated systems such as a nuclear reactor can use variance-based indices for safety analysis. The study of variance (ANOVA) model leads to the Sobol' indices used for independent input variables, [8]. In the 1970s, the global sensitivity analysis (GSA) practices used the Fourier amplitude sensitivity test (FAST). Global methods contain variability for all input parameters occurring at the same time. Here, sampling of the input parameters following models from Fourier analysis of the output can produce sensitivity indices for each input variable [9]. Figure 2 illustrates a block diagram of the UA/SA method.

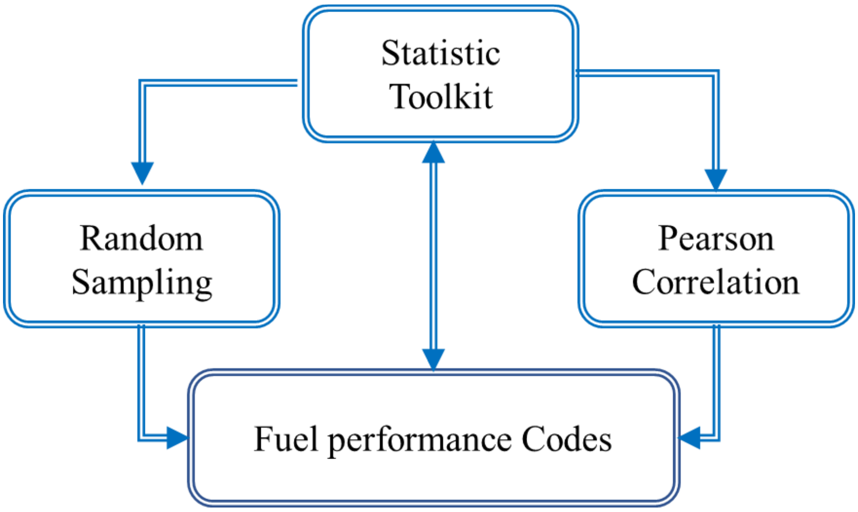

Figure 2: Sensitivity analysis process applied o fuel performance codes

Today, several away use computational tools to perform variance-based analysis for the first order. The first order indices appoint the primary effect of each model input towards the output for prioritizing these inputs. However, Sobol methods have adherence in the nuclear field and for sensitivity measures. In the beginning, sensitivity analyses used standard statistical purposes like scatter plots. Where scatter plot graphics displayed the influence of a variable of the output against each input variable.

Further methods used regression analysis, where regression coefficients qualify the linear sensitivity of each input and correlation analysis. The next step studied used one-at-a-time ways, where one input variable is changed while keeping all others at a constant level.

Therefore, information only for that region in the input space knowledge correlated from local sensitivity methods.

2. MATERIAL AND METHODS

2.1. Reactivity Initiated Accident

The reactivity initiated accident (RIA) is a transient lesser investigated than LOCA. A transient typified as a nuclear accident that involves a pulsed increase in reactor power. The RIA modeling follows the adiabatic Nordheim-Fuchs formulations (NFF), which describe an analytical expression. NFF comprised pulse width and shape under conditions of prompt criticality. The full width at half maximum (FWHM) defines the enthalpy pulse inserted during RIA, equation (1) exhibits the point reactor kinetics model and equation (2) expresses the equation for precursors.

$$\frac{dn(t)}{d(t)} = \frac{\rho(t) - \beta}{\wedge} n(t) + \sum_i \lambda_i C_i \tag{1}$$

$$\frac{dCi(t)}{dt} = \frac{\beta i}{\wedge} n(t) - \lambda_i C_i(t) \tag{2}$$

where, $\rho(t)$ is the reactivity at time t, $n(t)$ is the time-dependent neutron density (t) the effective concentration of delayed neutron group i, β is the total effective delayed neutron fraction, β_i is the effective delayed neutron fraction of group i, λ_i is the effective decay constant of group i, and Λ mean neutron generation time The abrupt power increase can lead to damage to the reactor core and fuel cladding, and in severe cases, even lead to disruption of the reactor. Design-basis accident (DBA)for RIA scenarios will cause a rapid increase of the reactivity represented as higher fuel enthalpy deposited in the fuel following vast horizons such as cladding failure and severe consequences as fuel melting on core reactor. Equation 3 shows a simple correlation for the pulse width of the fuel enthalpy inserted. The transient model using adiabatic NFF contain an approximation to the energy injected in the fuel during power pulse has dependence with the heat capacity of fuel enthalpy. The modeling used for the power added during pulse width from equation (4), also had the energy deposited in the fuel in equation (5).

$$\tau = \frac{3.5255}{\Delta\rho - \beta} \tag{3}$$

where τ represents the power pulse $\Delta\rho$ is a spike of reactivity, β represents the active fraction of delayed neutrons, and Λ is the useful neutron lifetime.

$$P(t) = P_{\max} \operatorname{sech}^2\left(\frac{(\Delta p - \beta)(t - t_{\max})}{2\wedge}\right) \tag{4}$$

where P_{max} is the maximum power, and t_{max} is the time of the maximum power.

$$E = \frac{2C_f(\Delta\rho - \beta)}{\partial\rho / \partial T_f} \tag{5}$$

where E is energy inserted in the fuel mass, $(\Delta\rho\text{-}\beta)$ represents prompt reactivity insertion, and C_f is the heat capacity of UO_2 fuel. Figure 3 illustrates the pulse of enthalpy inserted under RIA conditions.

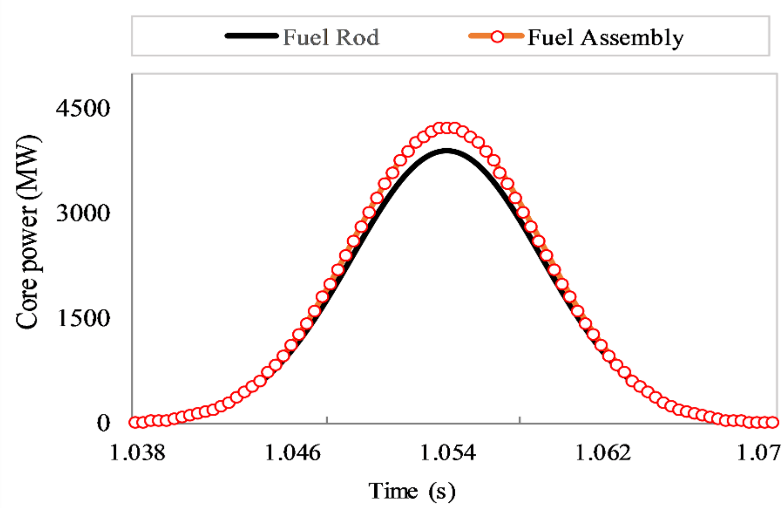

Figure 3: Pulse enthalpy inserted in the fuel rod and fuel assembly

During a steady-state, under regular operations happen changes in the physical properties of the zirconium-based alloys occur. The cladding materials suffer degradations because of a combination of oxidation, hydride, and radiation damages. In this scenario, clad alloys could reach corrosion levels near deterministic limits of 17%.

2.2. Initiated Accident Acceptance Criteria

The new amended the §50.46c comprising guidelines about the loss of elasticity of coating caused by hydride effects. The acceptance criteria used for safety analyses involving thermal-hydraulic, neutron-kinetics, also thermal-mechanic response. However, acceptance criteria used for RIA conditions comprised the compiled results performed during the 1970 decade. The first criteria produced from experiments performed in pulse reactors established on SPERT and TREAT programs, 1974. The conservative limit measured in testing zero or low burnup rods identified the failure, also setting the enthalpy limit of 280 cal/g-UO_2 reevaluated to 230 cal/g-UO_2, 1981. The fuel rod failure threshold related under RIA condition; also shows dependencies with burnup level, clad corrosion, the peak of enthalpy inserted, and fission gas release (FGR)

2.3. Computer Systems

The USNRC promulgated the licensing procedures based on reactor kinetics codes, THC system, and FLCs to audit nuclear power units.

Regarding fuel licensing codes, the Fuel Rod Analysis Program Conservative (FRAPCON) displays the goal of testing the thermal-mechanical behavior of oxide fuel rods for steady-state analysis [10]. FRAPCON performed a cooperative task with another program, the Fuel Rod Analysis Program Transient (FRAPTRAN), which simulates accident conditions [11]. Regulation criterium considers a single fuel rod for licensing analysis in any light-water reactors (LWRs).

Over the years, the U.S. Nuclear Regulatory Commission (NRC) developed a broad benchmark that proves the efficiency of fuel codes. This licensing code can predict a single fuel rod response to a steady-state and provide data on accident scenarios. The NRC recommended its own nuclear fuel rod simulation capabilities. The updated version of the code, FRAPCON-4.0, is the latest version of the NRC tool.

Both FLCs follow on the Materials Property Library (MATPRO), also used for THC codes. The codes worked with a toolkit defined to optimize engineering designs, which is a tool developed by Sandia National Laboratory (SNL) for multi-purpose designs. The result is a flexible system, known as the Design Analysis Kit for Optimization and Terascale Applications (DAKOTA) [12]. The system is a toolkit based on high-performance computation (HPC). Other uses for this system are sensitivity and variance analysis, which are the basis of the methods presented here.

The DAKOTA toolkit implements a stochastic procedure that can optimize nuclear systems and quantify the margins and uncertainty. The simulation process was comprising FRAPCON, FRAPTRAN, and DAKOTA to perform uncertainty and sensitivity analysis.

2.4. Overview of Sensitivity Analysis Methods

Nuclear systems deal with multiple parameters containing uncertainties, sorted according to the origin. There is an uncertainty classification divided into mechanical tolerances, boundary conditions, and risks from physical models. Changes from thermal conductivity can produce a large amount of variability into mechanical and thermal models, including FGR and hydraulic models. The probability density function (PDF) describes the relative likelihood that a random variable takes on a value within a range. The probability density function in the range between two limits a and b, in equation (6).

$$P[a < x < b] = \int_{a}^{b} f(x)dx \tag{6}$$

where P is a probability for support space defined between bound x_{min} and x_{max}.

The PDF defines a non-negative function, such that the integral over the whole support space of $\boldsymbol{x}$ is 1. The same definitions are generalizing for multivariable functions of random variables $\boldsymbol{x} = [x_1, x_2, \dots, x_n]$, in which case the PDF refers to the joint density. In the case of multivariate function using equation (7).

$$P[a_1 < x_1 < b_1,\ a_2 < x_2 < b_2,\ ...,\ a_n < x_n < b_n] = \int_{a_n}^{b_n} ... \int_{a_2}^{b_2} \int_{a_1}^{b_1} f(x) dx_1 dx_2 dx_3 \quad (7)$$

The sensitivity treatment must measure the effects of variations produced on each item of interest. Some models, such as correlation and variance analysis, are the models used to measure SA. The sensitivity, S, of a variable, P, represents the partial derivative of S divided by the partial derivative of P, shown in equation (8).

$$S = \frac{[\partial x / x]}{[\partial P / P]} \quad (8)$$

where x is the variable of interest.

2.5. Local And Global Sensitivity Analysis

In the local sensitivity analysis, the response of a model varies the sample-one inputs while keeping the other input data fixed. The overall sensitivity analysis considers the full range of the input parameter variations to account for all output uncertainty, according to the different sources of changes in the inputs of the model.

The methods used for UA focuses on the task defined to quantify and propagate uncertainties. SA measures how to change the output of a model from multiple variabilities correlated with the input model [13], [14].

If the model does not have linear characteristics but still exhibits monotonic behavior, one could apply a rank transformation to the sample sets. Afterward, to find the analogy between the linear cases, the model can use the Spearman’s Rank Correlation Coefficient (SRCC), the Standard Rank Regression Coefficient (SRRC), and the Partial Rank Correlation Coefficient (PRCC). However, many models are non-linear and non-monotonic. Here, a deconstruction of the output variance can lead to helpful indices for single inputs or even subsets of data.

The methods adopted are SRCC, coupled with sensitivity indices. The DAKOTA toolkit estimated correlations using the Pearson Product Momentum Correlation (PPMC) and SRC. The nonparametric statistic can identify free distributions. The correlation indexes used to detect the strength of a monotonic relationship were PPMC and SRCC. The formulation used to Pearson coefficient in equation (9), where *R* signifies the degree to which *X* and *Y* vary together, divided by the degree to which X and Y can vary separately.

$$R_i^2 = \frac{\mathrm{cov}(X_i, Y)^2}{\mathrm{var}(X_i)\,\mathrm{var}(Y)} \quad (9)$$

where R_i is the Pearson coefficient of correlation, for an input Xi and Y are random variables of the input data and output responses, respectively.

The Spearman Rank Correlation Coefficient extends the PPMC measure to detect the strength of a monotonic relationship. The Spearman rank index measure for the ranks of the inputs and output methods. The model used to Spearman rank using equation (10).

$$\rho_i^2 = \frac{\operatorname{cov}(X_i^{rnk}, Y^{rnk})^2}{\operatorname{var}(X_i^{rnk})\operatorname{var}(Y^{rnk})} \tag{10}$$

where ρ_i is the Pearson measure for input and X_i^{rnk}, and Y^{rnk} are the ranks of the inputs i and the outputs, respectively.

The trouble with the PPMC is the linearity assumption regarding only adequately explaining the variance's contribution to the response variance for linear, additive functions. Both the Pearson and the Spearman coefficient only consider the effect of one input variable at a time and may not include higher-order input interaction effects, which may be necessary.

2.6. Variance Decomposition Procedures

The uncertainty propagation of a model is useful to assess the sensitivity of results from individual parameters or combinations of settings. The variance-based decomposition (VBD) method, developed initially by Sobol, is a higher-order method used to calculate the fraction of the output variance attributed to a specific input, or set of input data. The total variation of an output expresses a finite sum of output variances dependent on fixed input. First-order Sobol indices are a function of conditional variance upon a single input data using equation (11), also is supposing that the smoothed curve is represented by $E_{x\sim i}(y|x_i)$.

$$S_i = \frac{Vx_i(E_{x\sim i}(y\,|\,x_i))}{V(y)} \tag{11}$$

The advantage of this decomposition is that it allows us to determine what fraction of variance in Y is for each contributor. The VBD model can isolate and estimate the effects of each input variable's interaction with other inputs; therefore, giving a much more comprehensive view of which outcomes are essential to variance. However, VBD has a disadvantage regarding decomposition, in that the integrals embedded within it become expensive to calculate, depending on the uncertainty method applied.

2.7. Wilks Method

Uncertainty and sensitivity analysis UA/SA divided into five simple steps. First, based on all input variables, define the statistical distribution used for each parameter into an empirical range. The second phase comprises the generation of samples of the input variables. The next step measures the spread of uncertainty for each sample in the models under consideration through the utilization of fuel codes. The fourth phase involves analysis of propagated performance uncertainty. In the last step, measure GSA using statistical correlations or variance analysis.

Wilks formulation governs a minimum sample size of wanted lower and upper tolerance limit. The modeling can support multivariable statistics used for BEPU applications. The order statistic is a nonparametric technique that defines the minimum number of samples required to reach the intended significance and confidence levels. The order statistic method (OSM) must describe an ideal free distribution, in equation. (12) defines Wilks formulation.

$$\sum_{j=0}^{n-k}\binom{n}{j}\alpha^{j}(1-\alpha)^{(n-j)} \geq \beta \tag{12}$$

where α is the quantile level, β is the confidence level for the upper bound of the quantile, and N *i*s the number of simulations.

The statistical method, Latin hypercube sampling (LHS), can build robust random sampling [18]. The Wilks formula provides the number of examples needed to reach a confidence level and a probability of 95%. The Wilks formula calculates to find first-order statistics with a minimum of 59 cases [15-19]. The BEMUSE project studied the best distributions to adopt and the practical ranges of deviations[20-21]. Random generators from DAKOTA may create a series of the input samples using the LHS method. Fuel code implements the Monte Carlo (MC) simulations used for the propagation process. The SA process uses the statistical correlation coefficients calculated by the DAKOTA toolkit. A probability distribution can help build the mathematical representation of the input parameters created by the DAKOTA toolkit using the Latin hypercube sampling model. Table 1 shows the lowest number of trials for the given quantiles and confidence levels most used for the BEPU models.

Table 1: Number of trials given as a function of the quantile and confidence levels

α	β	$1^{nd}N_1$ (α, β)	2^{nd} N_2 (α, β)	3^{rd} N_3 (α, β)	4^{th} N_4 (α, β)
90%	90%	45	77	105	132
95%	95%	59	93	124	153
99%	99%	90	130	165	198

Random distributions could represent all physical tolerances of the input parameters. UA/SA method uses LHS models to create input sampling, where a set of samples used to perform Monte Carlo simulation should spread the inner system input uncertainties.

3. DISCUSSION AND RESULTS

2.2 Characterization of Fuel Rod Uncertainty

The aim of the CABRI International Program (CIP) executed in 2000, comprised fourteen RIA experiments performed in the CABRI research reactor. Reports collected from CIP programs appointed follow parameters form CIP0-1 rod test. The CIP0-1 using fuel system type (UO_2/ZIRLO). In the first phase, the fuel rod reached to 75 GWd/MTU, clad oxide thickness of (60-70) µm, fill gas pressure of 0.3 MPa under regular operation. In the second phase, the fuel rod suffered an enthalpy inserting a pulse width of 32 ms, reach a peak of enthalpy of 389 J/g(UO_2), and does not occur failure of the fuel rod [22]. In the experiment, the cladding maximum hoop strain reached 05.%. Fuel codes deal with various uncertainties, such as mechanical tolerances and operating conditions. The CIP0-1 comprised many interest effects also were calculated uncertainty quantification, propagation, and sensitivity analyses. The practical values assigned to the coating show deviations from $\pm 2\sigma$. System configurations also can support cladding uncertain defined to axial growth, hydrogen uptake, corrosion, and strengthen rates. Besides, sensitivity values set for FGR, and swelling of ($\pm 2\sigma$). Table 2 displays the uncertainties used in the simulation. We selected the inputs of primary importance from FRAPCON, and FRAPTRAN follows the method of Wilks producing 59 samples, which compose 59 run-codes. Figure 4 illustrates the sensitivity analysis from FRAPCON and FRAPTRAN.

Table 2. Uncertainty input parameters used in simulation FRAPCON and FRAPTRAN

Input Parameters	Nominal (μ)	Upper Bound (μ±σ)	Lower Bound (μ±σ)
Rod Length (mm)	1.7749	1.8104	1.7394
Fuel Pellet diameter (mm)	8.1900	8.3538	8.0262
Radial gap thickness (mm)	0.0825	0.0842	0.0809
Plenum void volume (mm^3)	1910	1948.2	1871.8
Rod diameter (mm)	9.5000	9.6900	9.3100
Pellet High (mm)	9.8300	10.0266	9.6334
Depth of pellet dish	0.0081	0.0083	0.0080
The radius of the pellet dish (mm)	0.2399	0.2447	0.2351
Fuel roughness (mm)	0.0020	0.0020	0.0020
Fuel pellet density (%)	95.7000	97.6140	93.7860
Fuel cold work (%)	0.5000	0.5100	0.4900
Cladding roughness (mm)	0.0005	0.0005	0.0005
Rod gas pressure (MPa)	2.3500	2.3970	2.3030
Fuel rod pitch (mm)	12.3000	12.5460	12.0540

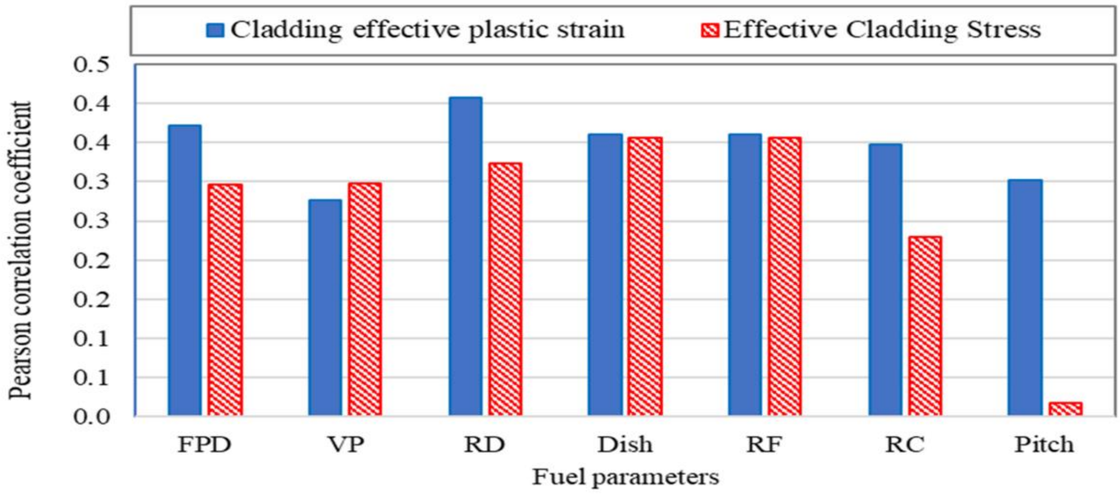

Figure 4: Sensitivity analysis of cladding mechanical behavior with input parameters

Interest parameters observed during simulations that show the Pearson indexes for cladding effective plastic strain and effective cladding stress regarding input parameters. The parameters investigated are fuel pellet diameter (FPD), the volume of the plenum (VP), rod diameter (RD), dish, rough of fuel (RF), rough of cladding (RC), pitch. Energy stored in the fuel and cladding shows small variability for the space of samples simulated around 0.13%. The cladding outsider oxidation layer thickness also shows reduced variability of around 0.80%. The explanation about occurs because of RIA shows less than one second. Figure 5 illustrates cladding mechanical deformation analyzing cladding axial, hoop, and radial strains.

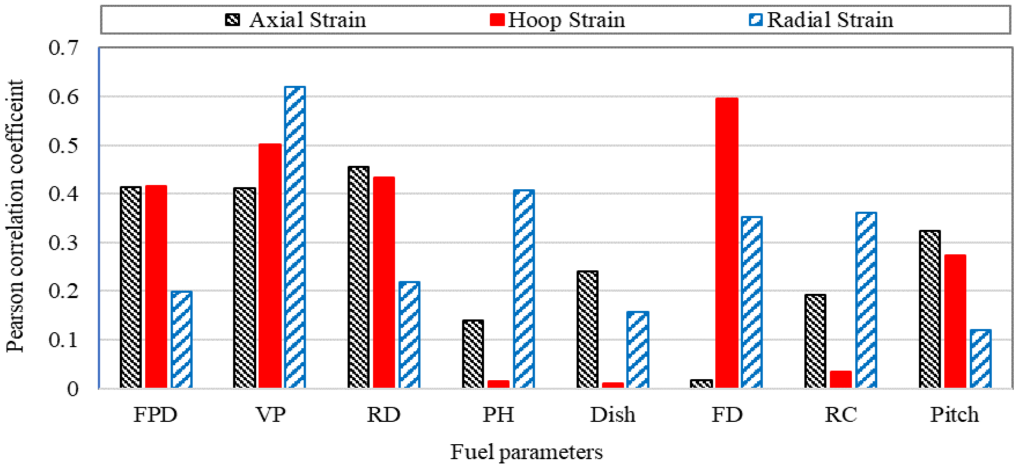

Figure 5: Sensitivity analyses of cladding axial, hoop, and radial strain

However, several parameters used in FRAPCON can rewrite for FRAPTRAN showed in the table. During reactivity accidents, a few inputs variables do not have a correlation with enthalpy pulse inserted. Figure 6 demonstrates that SA measures form plenum pressure and average fuel temperatures.

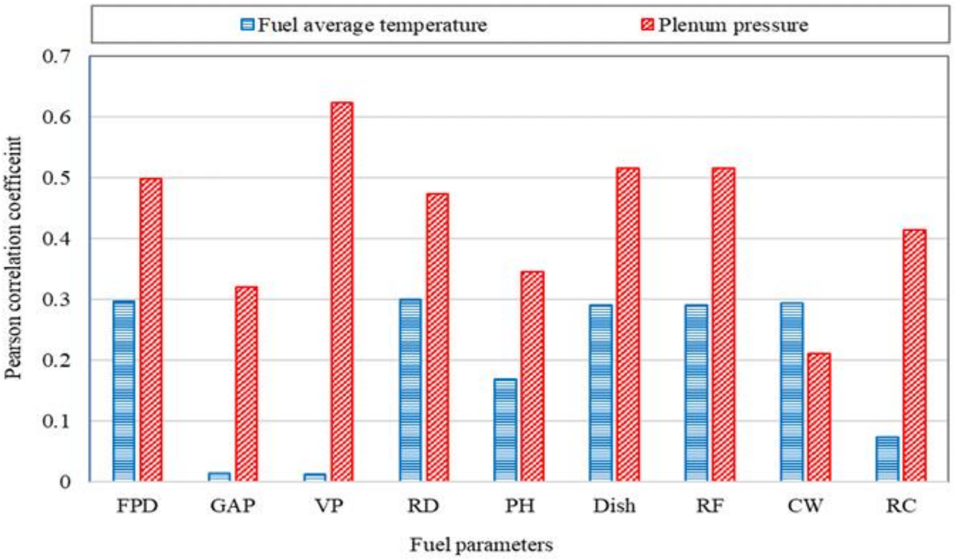

Figure 6: Sensitivity analyses of plenum pressure and fuel average temperature;

4. CONCLUSION

There are several LOCA experiments tested with BEPU models, but in this investigation is being the same concepts to RIA scenario. The collection of methods here so-caller UA/SA can integrate the fuel licensing code using DAKOTA toolkit. In this study, were vastly used FRAPCON, FRAPTRAN, and DAKOTA also coupled with fuel safety rules with statistical concepts to produce the results funded. The fuel rod simulated under RIA conditions combining the UQ and the PPMC measure SA. Uncertainty quantification based on normal distributions based on the mean values and standard deviations of the variables. During simulations, uncertainty spread from input parameters with small variations introduced to the output. As the number of simulations increased, output parameters showed strong tendencies to expand the possibilities. We performed the sampling based on the effects because of the engendering tolerances combined with the boundary conditions, including uncertainties from physical models. We used the proposed m to predict the results of the idealized fuel rod experiment.

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