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Selecting benchmarks for reactor calculations.

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ABSTRACT

Criticality, reactor physics, fusion and shielding benchmarks are expected to play important roles in GENIV design, safety analysis and in the validation of analytical tools used to design these reactors. For existing reactor technology, benchmarks are used to validate computer codes and test nuclear data libraries. However the selection of these benchmarks are usually done by visual inspection which is dependent on the expertise and the experience of the user and thereby resulting in a user bias in the process. In this paper we present a method for the selection of these benchmarks for reactor applications based on Total Monte Carlo (TMC). Similarities between an application case and one or several benchmarks are quantified using the correlation coefficient. Based on the method, we also propose an approach for reducing nuclear data uncertainty using integral benchmark experiments as an additional constrain on nuclear reaction models: a binary accept/reject criterion. Finally, the method was applied to a full Lead Fast Reactor core and a set of criticality benchmarks.

Key Words: **Criticality benchmarks, ELECTRA, TMC, nuclear data, GENIV, reactor calculations**

1. INTRODUCTION

The International Handbook of Evaluated Criticality Safety Benchmark Experiments (ICSBEP) contains criticality safety benchmarks derived from experiments that were performed at various nuclear critical facilities around the world [1]. Other benchmarks used for nuclear data and reactor applications include the Evaluated Reactor Physics Benchmark Experiments (IRPHE) which contains a set of reactor physics-related integral data and the Radiation shielding experiments database (SINBAD) which contains a compilation of reactor shielding, fusion neutronics and accelerator shielding experiments. These benchmarks are used for the validation of calculation techniques used to establish minimum subcritical margins for operations with fissile material; for the design and establishment of a safety basis for the next-generation of nuclear reactors, and for quality assurance necessary in developing cross-section libraries and radiation transport codes [2]. For existing

reactor technology, benchmarks can be used to validate computer codes, test nuclear data libraries and also for reducing nuclear data uncertainties [3]. One such example is the extensive testing of nuclear data libraries with a large set of criticality safety and shielding benchmarks by Steven C. van der Marck [4].

Since these benchmarks differ in geometry, type, material composition and neutron spectrum, the selection of these benchmarks for specific applications is normally tedious and not straightforward [5]. Until now, the selection process is based on visual inspection which is dependent on the expertise and the experience of the user. This results in user bias making benchmarks selected, different from one research group to the other as a result of different expertise, purpose of the evaluation and accessibility to benchmarks [5]. Also, this approach is not suitable for the Total Monte Carlo (TMC) methodology which lays strong emphasis on automation, reproducibility and quality assurance. To solve the problem of user dependency in the benchmark selection process, a novel method based on the TMC approach was proposed and presented in Ref [6] for benchmark selection. The selected benchmarks can be used for validating computer codes for reactor calculations and for reducing nuclear data uncertainty for reactor applications as can be seen in Fig. 1.

The method was subsequently applied to, on a limited scale, fresh core calculations [6] and burnup evaluation of the European Lead Training Reactor (ELECTRA) [7]. ELECTRA is a plutonium fueled, low power reactor design proposed within the GENIV research on-going in Swedish Universities [8]. A 25% reduction in inventory uncertainty due to Am-241 nuclear data was achieved for ELECTRA End of Life (EOL) while a 40% reduction in k_{eff} uncertainty due to ^{239}Pu was achieved at Beginning of Life (BOL) by using the PU-MET-FAST-001 benchmark [1] information to constrain random files. It was recommended in Ref [6] that the method be tested on a larger set of benchmarks. Also, as a consequence of this methodology, several correlations can also be observed: nuclear data vs. benchmarks, benchmark vs. benchmark, nuclear data vs. neutron or gamma leakage, neutron or gamma leakage vs. criticality benchmarks among others as suggested in Ref [9]. In this work, we present a detailed description of the methodology proposed and its application to ELECTRA and a set of criticality benchmarks obtained from the ICSBEP Handbook [1]. We also propose a method for uncertainty reduction using criticality benchmarks experiments as an additional constrain for nuclear reaction models. It is our believe that if this method is implemented in the Total Monte Carlo chain, nuclear data uncertainty in reactor safety parameters can be reduced significantly.

2. Total Monte Carlo

The Total Monte Carlo concept was developed at the Nuclear Research and Consultancy Group (NRG), Petten [10] for the production of nuclear data libraries and for uncertainty analysis. Differential data from the Experimental Nuclear Reaction Data (EXFOR) database [11] are used as a visual guide to constrain model parameters in the TALYS Nuclear Physics code [12] by applying a binary accept/reject method where an uncertainty band is placed around the best or global data sets such that the available scattered experimental data falls within this uncertainty band. After enough iterations, a full parameter covariance matrix can be obtained [10]. Random nuclear data libraries that fall within experimental data uncertainties are accepted whiles those that do not fulfill this cri-

terion are rejected. In order to cover the nuclear reactions for the entire energy region from thermal up to 20 MeV, a large set of resonance parameters are added using the TARES code [13]. The random files generated are processed into ENDF format using the TEFAL code [14] and into ACE format with the NJOY processing code [15]. These files are used in neutron transport codes to obtain distributions for different quantities such as k_{eff}, inventory, temperature feedback coefficients, and kinetic parameters, etc with their corresponding standard deviations. It has been observed that, this methodology opens several perspectives for the understanding of basic nuclear physics and for the evaluation of risk assessment of advanced nuclear systems [16].

3. Methodology

The method we propose in this work is presented in Fig. 1, a flowchart which summarizes the whole benchmark selection idea. It should be noted that while the methodology presented in this work hinges on random files generated with the TMC method, the concept is in principle, independent of the method used for random file generation.

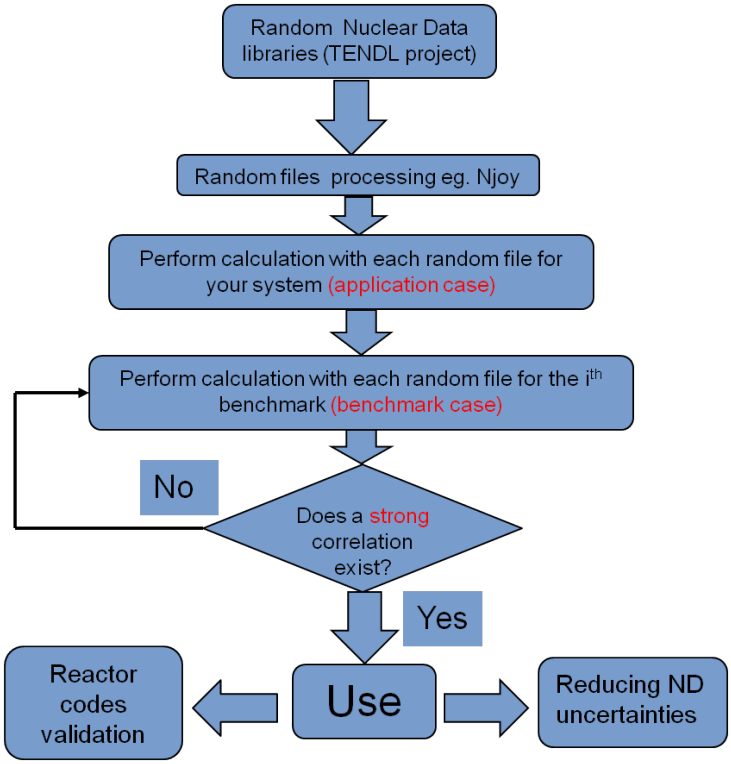

Figure 1. Flow chart diagram for the benchmark selection process. Random files obtained from the TENDL project are processed into ACE format and used for reactor code validations and for reducing nuclear data (ND) uncertainties. Similarities between benchmarks and application cases are quantified using the correlation coefficient.

The basic steps involved are:

(1) Generation of random nuclear data libraries produced. There are several approaches available for random nuclear data generation. One such approach is the TMC methodology [10] where a large

set of random nuclear data libraries for different nuclides can be produced by varying nuclear model parameters in the nuclear reactions code TALYS within predetermined widths derived from comparison with experimental data. These random files are processed into ENDF-6 format using the TEFAL code. This approach has e.g the advantage that valuable feedbacks can be given to nuclear reaction models. Another approach is based on full Monte Carlo sampling of nuclear data inputs based on covariance information that come with new nuclear data evaluations. The method includes uncertainties of multiplicities, resonance parameters, fast neutron cross sections and angular distributions etc and has been been successfully implemented in the AREVA GmbH code NUDUNA (NUclear Data UNcertainty Analysis) [17]. In practice, this step can be skipped as random nuclear data libraries are readily available for different nuclides from the TENDL project [18].

2) The next step is the processing of random nuclear data libraries into usable formats for nuclear reactor codes. Normally, for use in neutron transport codes such as SERPENT and MCNP, the following sequence of modules for the NJOY processing code: MODER-RECONR-BROADR-UNRESR-HEATR-PURR-ACER is used to convert the ENDF-6 formatted random nuclear data into the ACE format.

3) The third step is to perform simulations for the application case and one or several benchmark cases using the same set of processed random nuclear data. The application case is defined as the engineering system under consideration - for this, a model of the system with full geometry, elements, concentrations, isotopic compositions etc. is required. The benchmark case is the i^{th} benchmark which can be obtained from available handbooks such as the ICSBEP handbook which contains criticality safety benchmarks, IRPHE which contains a set of reactor physics-related integral data and SINBAD which contains a compilation of reactor shielding, fusion neutronics and accelerator shielding experiments. For the application of the proposed methodology, only criticality benchmarks from the ICSBEP handbook were used in this work. For simulations, the geometry, type, material composition and neutron spectrum of benchmarks should be considered. Since most reactor spectra cut across a wide range of energies, this methodology can be considered novel as it offers the possibility of quantifying the relationships and similarities between application cases and benchmarks, benchmarks and benchmarks, benchmarks and nuclear data and application cases and nuclear data.

4) As a final step, several correlations between reactor parameters such as the k_{eff} can be extracted and observed: a) benchmark case against benchmark case b) application case against benchmark case and c) nuclear data against benchmark case. To quantify the relationship between two systems, the Pearson correlation coefficient which is a measure of the strength of the linear dependence between two variables and its value given between +1 and -1 is computed. If a strong correlation exists between the benchmark case and the application case, the benchmark can be considered as a good representation of the reactor system under consideration.

3.1. Reducing nuclear data uncertainty using integral benchmarks experiments

The current nuclear data uncertainties observed in reactor safety parameters for some nuclides calls for safety concerns especially with respect to the design of GENIV reactors and should therefore be reduced significantly [19]. In this section, we present a binary accept/reject method for further

reducing nuclear data uncertainties using a set of integral safety benchmarks obtained from the ICSBEP Handbook [1]. Even though information on differential measurements together with their uncertainties are included (implicitly) in the production of random files in the TMC methodology, wide spreads have been observed in the parameter distributions (known here as our 'prior distribution') leading to large uncertainties in reactor parameters for some nuclides for the European Lead-Cooled Training Reactor [6, 20]. Due to safety concerns and the development of GENIV reactors with their challenging technological goals [21], these uncertainties should significantly be reduced.

As earlier stated in section 2, differential experimental data were used as a guide to constrain model parameters in original TMC. This serves as our first level of constrain for the model parameters used in the TALYS code. To accomplish our goal of further reducing nuclear data uncertainties, we propose a second level of constrain using criticality benchmark experiments. It was demonstrated earlier in Ref [6] that, by setting a more stringent criteria for accepting random files based on integral benchmark information, nuclear data uncertainty could be reduced further. In Ref [6] however, arbitrary χ^2 limits were set on accepting random files using criticality benchmarks without including evaluated benchmark uncertainty information. As an improvement to this method, we included benchmark uncertainty information to the process.

The method we propose here makes use of prior information included in the random nuclear data libraries produced using the TALYS based system, which implicitly include nuclear data covariance information. We then further reduce the uncertainties in the observed prior by constraining the files with integral experimental data (this constitutes the 'a posteriori' uncertainties on the response parameters).

To include benchmark uncertainty information, we propose an acceptance interval (F_E) which is directly proportional to the evaluated benchmark uncertainty (σ_E):

$$F_E \propto \sigma_E \Rightarrow F_E = \kappa\sigma_E \tag{1}$$

Where κ, the proportionality constant which defines the magnitude of the spread, is given as the inverse of the correlation coefficient (R) between the application case and the benchmark:

$$\kappa = \frac{1}{|R|} \tag{2}$$

With;

$$R = \frac{\sum_{x=1}^{n}(k^{sys}_{eff(x)} - \overline{k^{sys}_{eff}})(k^{E}_{eff(x)} - \overline{k^{E}_{eff}})}{\sigma_{k^{sys}_{eff}}\sigma_{k^{E}_{eff}}} \tag{3}$$

Where k^{sys}_{eff} and k^{E}_{eff} are the k_{eff} values for the x^{th} random file for the application case and the benchmark respectively, $\overline{k^{sys}_{eff}}$ and $\overline{k^{E}_{eff}}$ are their mean values and $\sigma_{k^{sys}_{eff}}$ and $\sigma_{k^{E}_{eff}}$ are their standard deviations.

If x denotes our random files (random nuclear data), we consider the following probability distribution function $k_{eff}(x)$ bounded by an acceptance band $[-F_E, +F_E]$. Let the maximum value of

$k_{eff}(x)$ be denoted by $k_{eff}^{Max} = k_{eff}^{E} + F_E$ and the minimum value, $k_{eff}^{Min} = k_{eff}^{E} - F_E$. If we define an acceptance range as $k_{eff}^{Min} \leq k_{eff}(x) \leq k_{eff}^{Max}$, then if any random file falls within this range, we accept x as a realization of $k_{eff}(x)$ and therefore we assign it a binary value of one whiles those that do not meet this criteria take binary values of zero and are therefore rejected. A posterior distribution in a parameter of interest (k_{eff} in our case) can now be obtained (using the accepted files) together with the mean and standard deviation which in principle should be narrower in spread than the prior distribution.

By setting $\kappa = 1/|R|$, we assign smaller acceptance intervals (F_E) to strongly correlated benchmarks whiles weakly correlated benchmarks are assigned with larger acceptance intervals (F_E). We choose to accept a lot more random files for the weakly correlated benchmarks because such benchmark(s) are not a true reflection of the application case. Even though some of these random files might contain large uncertainties for example in the thermal region, this effect will be relatively small in the fast region where our application case (ELECTRA) is used. For example, if there exist a strong correlation (say an $R \simeq 1.0$) between an application case and a particular benchmark, this will give a $\kappa = 1$ implying that random files that fall within $1\sigma_E$ of the evaluated benchmark uncertainty are accepted, similarly a weakly correlated benchmark with say $R = 0.5$, gives an acceptance interval of $2\sigma_E$. As a rule of the thumb, we propose an acceptance limit of $3\sigma_E$, this corresponds to an $R = 3.0$. Since very weakly correlated or uncorrelated benchmarks will not add much information to the calculation, they can be rejected.

There are however possible drawbacks to this methodology:

1) For this method to be applicable, correlation coefficients between the application case and the benchmarks must be known and this involves a large number of reactor calculations and hence, computer time. This problem can however be solved by establishing a lookup validation database with information on the random files performance on a wide range of different benchmarks.

2) There is also the possibility of running into a situation where the number of random files that lie within F_E are so small that the uncertainty of the nuclear data uncertainty computed for the posterior distribution becomes very large. In such a situation, valuable feedback information is given to the prior for a further reduction of sampling widths used in sampling model parameters in the TALYS code.

3.2. Application of methodology

The application case chosen for this study is the European Lead-Cooled Training Reactor (ELECTRA, a conceptual 0.5 MW lead cooled reactor fueled with (Pu,Zr)N with an estimated average neutron flux at beginning of life of $6.3 \times 10^{13} n/cm^2 s$ and a radial peaking factor of 1.45 [8]. The fuel composition is made up of 60% ZrN and 40 mol % of PuN. The core is hexagonally shaped and consists of 397 fuel rods and it is 100% cooled by natural convection. The control assemblies and the absorbent part of control drums are made of ^{10}B enriched to 90% in ^{10}B, having a pellet density of g/cm^3. A more detailed description of the reactor is presented in Ref [8]. Since ELECTRA is plutonium fueled, the benchmarks used in this work are a set of Plutonium Metallic Fast (pmf1, pmf2, pmf5, pmf8, pmf9, pmf10 and pmf11) benchmarks obtained from the International

Handbook of Evaluated Criticality Safety Benchmark Experiments (ICSBEP). Nuclear data varied in this work are ^{239,240,241}Pu isotopes. All other nuclides were maintained as JEFF-3.1 nuclear data library. For the application case, criticality calculations were performed for a total of 500 k_{eff} cycles with 50,000 source neutrons corresponding to 25 million particle histories whiles for the benchmark cases, 10,000 source neutrons for a total of 110 k_{eff} cycles were used.

4. Results and Discussion

4.1. Correlations

As a consequence of our benchmark selection methodology, several correlations can be observed and quantified. These correlations are important for nuclear data adjustments and for criticality studies [9]. In Table I, II and III, we present correlation coefficients computed between selected plutonium metallic fast benchmarks denoted by "pmf", for varying ^{239}Pu, ^{240}Pu and ^{241}Pu nuclear data respectively. For ^{239}Pu variation, relatively strong positive correlations are recorded for all benchmarks with pmf1(^{239}Pu Jezebel) vs. pmf2 (^{240}Pu Jezebel) recording the highest value of 0.98. This signifies a strong similarity between the two benchmarks. This is not surprising as the plutonium composition of ^{239}Pu Jezebel is made up of 95.2% ^{239}Pu, 4.5% ^{240}Pu and 0.3% ^{241}Pu whiles that of ^{240}Pu Jezebel is made up of 76.4% ^{239}Pu, 20.1% ^{240}Pu and 3.1% ^{241}Pu and 0.4% ^{242}Pu. The lowest correlation coefficient of 0.68 was however observed between pmf1 and pmf8. Similarly, relatively high correlation coefficients were recorded between benchmarks due to ^{240}Pu variation as can be seen in Table II. In Table III however, weak correlations were observed for all benchmarks. This is not surprising as the wt.% of ^{241}Pu in the core for all benchmarks under consideration is relatively small; ranging from 0.3% to 3.1%.

Table I. Correlation between benchmark and benchmark due to ^{239}Pu nuclear data variation. (pmf) denotes plutonium metallic fast benchmarks. Only case 1 of each benchmark is used.

	pmf1	pmf2	pmf5	pmf8	pmf9	pmf10	pmf11
pmf1	1						
pmf2	0.98	1					
pmf5	0.96	0.96	1				
pmf8	0.68	0.68	0.71	1			
pmf9	0.98	0.97	0.98	0.70	1		
pmf10	0.96	0.96	0.98	0.70	0.97	1	
pmf11	0.94	0.94	0.95	0.68	0.96	0.94	1

In Table IV, we present correlation factors computed between selected benchmarks and the application case (ELECTRA) for varying ^{239,240,241}Pu nuclear data. As can be seen in the table, relatively strong correlations were obtained for all benchmarks due ^{239,240}Pu nuclear data. This can be attributed to the substantial amounts of ^{239}Pu and ^{240}Pu found in the core for both benchmark and application cases. Also, ELECTRA and all the benchmark cases under consideration exhibit similar reaction rate spectra for both fission and capture. However, because of the small amounts of ^{241}Pu in the fuel in both ELECTRA and the benchmark cases, weak correlations were observed. In Fig. 2, two examples of correlations are presented; ELECTRA vs. pmf9 and between ELECTRA

Table II. Correlation between benchmark and benchmark due to ^{240}Pu nuclear data variation. Only case 1 of each benchmark is used.

	pmf1	pmf2	pmf5	pmf8	pmf9	pmf10	pmf11
pmf1	1						
pmf2	0.73	1					
pmf5	0.71	0.70	1				
pmf8	0.74	0.72	0.70	1			
pmf9	0.75	0.74	0.73	0.71	1		
pmf10	0.75	0.71	0.71	0.72	0.74	1	
pmf11	0.73	0.74	0.71	0.74	0.72	0.72	1

Table III. Correlation between benchmark and benchmark due to ^{241}Pu nuclear data variation. Only case 1 of each benchmark is used.

	pmf1	pmf2	pmf5	pmf8	pmf9	pmf10	pmf11
pmf1	1						
pmf2	0.03	1					
pmf5	-0.008	0.04	1				
pmf8	0.094	0.09	-0.03	1			
pmf9	0.095	0.03	0.05	0.04	1		
pmf10	0.081	0.15	0.07	0.10	0.04	1	
pmf11	0.14	0.03	0.14	0.12	0.06	0.06	1

and pmf10 benchmark. Strong correlations are observed in both cases signifying a strong similarity between ELECTRA and the two benchmarks.

In Fig. 3, we present correlation between the k_{eff} of two benchmarks (pmf1 and pmf8) and ^{239}Pu nuclear data against incident neutron energies. A sensitivity method based on the Monte Carlo evaluation developed at Nuclear Research and Consultancy Group (NRG) [10] was used to extract correlation between the k_{eff} and different reaction channels averaged over 44 energy groups. This method has been applied to lead cross sections and presented in more detail in Ref [20]. As can be observed in Fig. 3, pmf1 and pmf8 are all strongly correlated with the (n, f) cross section with the highest correlation occurring at about 1MeV. With the (n, g) cross section however, relatively weak anti correlations are observed for the entire incident energy region.

Table IV. Correlation factors computed between benchmark and application case (ELECTRA) due to the variation of ^{239,240,241}Pu nuclear data. Only case 1 of each benchmark is used.

Application case with isotope varied	pmf1	pmf2	pmf5	pmf8	pmf9	pmf10	pmf11
ELECTRA-^{239}Pu	0.83	0.84	0.93	0.65	0.88	0.92	0.85
ELECTRA-^{240}Pu	0.84	0.83	0.81	0.83	0.82	0.83	0.82
ELECTRA-^{241}Pu	0.27	0.25	0.14	0.24	0.25	0.27	0.25

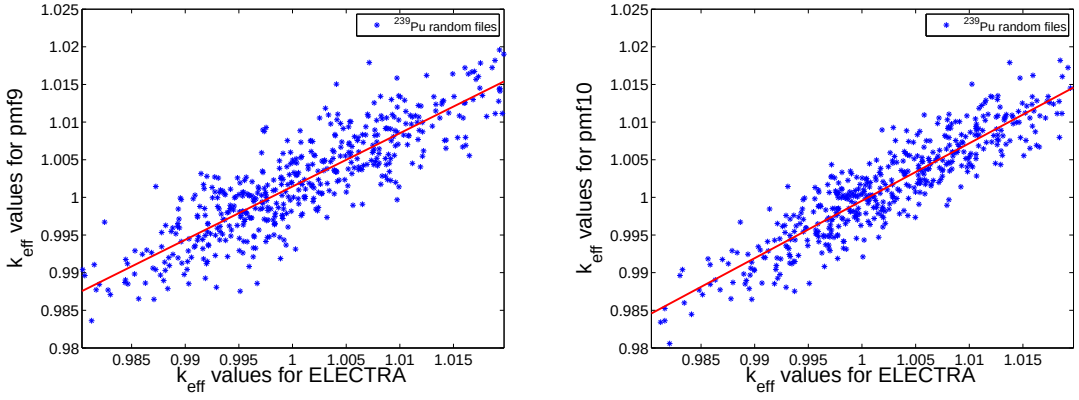

Figure 2. Example of correlation between benchmark and application case (ELECTRA) due to ^{239}Pu nuclear data variation. Left: pmf9 benchmark vs. ELECTRA (Correlation coefficient computed R=0.88 and Right: pmf10 benchmark vs. ELECTRA (R=0.92).

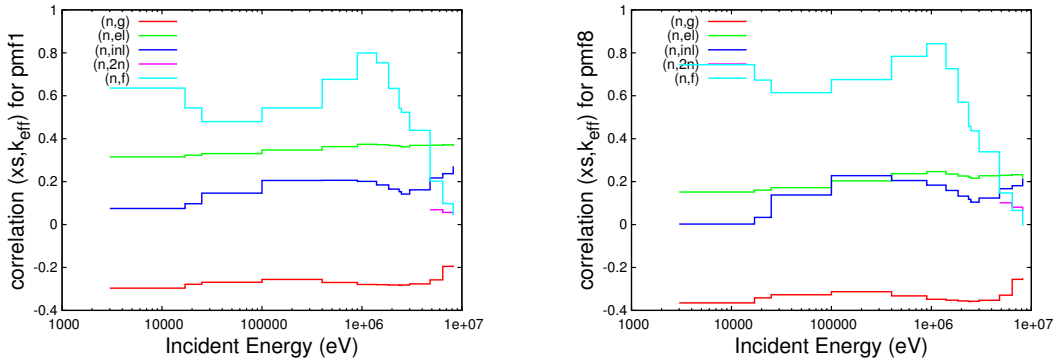

Figure 3. Example of correlation between benchmark and nuclear data. Correlation factors are given between five reaction channels: $(n, g), (n, el), (n, inl), (n, 2n)$ and (n, f) and the k_{eff} for the pmf1 (left) and pmf8 (right) benchmarks against incident nuclear energies.

4.2. Nuclear data uncertainty reduction

Using Equation (1), acceptance intervals(F_E) were computed for ELECTRA using different benchmarks and ^{239,240,241}Pu nuclear data and presented in Table V. Results in terms of the magnitude of the evaluated benchmark uncertainty are given in brackets. It can be observed that, the acceptance intervals for ^{241}Pu are relatively larger when compared to values for ^{239,240}Pu nuclear data for all benchmarks with the largest value recorded at $7.0\sigma_E$ which corresponds to 905 pcm. The large value observed is as a result of the weak correlation coefficient (R=0.14) recorded between the application case (ELECTRA) and the pmf5 benchmark.

In Fig. 4, we present probability distributions in k_{eff} for ^{239}Pu (left) and ^{240}Pu (right) after implementing our binary accept/reject method. The plots show both prior and posterior distributions after including pmf1 benchmark information for constraining random nuclear data for ELECTRA.

Table V. Criticality safety benchmarks with their corresponding acceptance intervals for the variation of ^{239,240,241}Pu nuclear data using ELECTRA as the application case. Values in bracket represent the magnitude of the evaluated benchmark uncertainty(σ_E).

Benchmark type	σ_E [pcm]	$F_E(^{239}\text{Pu})$ [pcm]	$F_E(^{240}\text{Pu})$ [pcm]	$F_E(^{241}\text{Pu})$ [pcm]
pmf1	200	241($1.2\sigma_E$)	238($1.1\sigma_E$)	728($3.6\sigma_E$)
pmf2	200	237($1.2\sigma_E$)	241($1.2\sigma_E$)	796($4.0\sigma_E$)
pmf5	130	139($1.1\sigma_E$)	160($1.2\sigma_E$)	905($7.0\sigma_E$)
pmf8	60	92($1.5\sigma_E$)	72($1.2\sigma_E$)	253($4.2\sigma_E$)
pmf9	270	307($1.1\sigma_E$)	330($1.2\sigma_E$)	1086($4.0\sigma_E$)
pmf10	180	195($1.1\sigma_E$)	216($1.2\sigma_E$)	673($3.7\sigma_E$)
pmf11	100	118($1.2\sigma_E$)	122($1.2\sigma_E$)	405($4.0\sigma_E$)

It can be observed that, the posterior distribution for ^{239}Pu (left) has a much narrower spread compared to ^{240}Pu (right). This is because of the strong correlation observed between the pmf1 and ELECTRA systems for ^{239}Pu nuclear data variation.

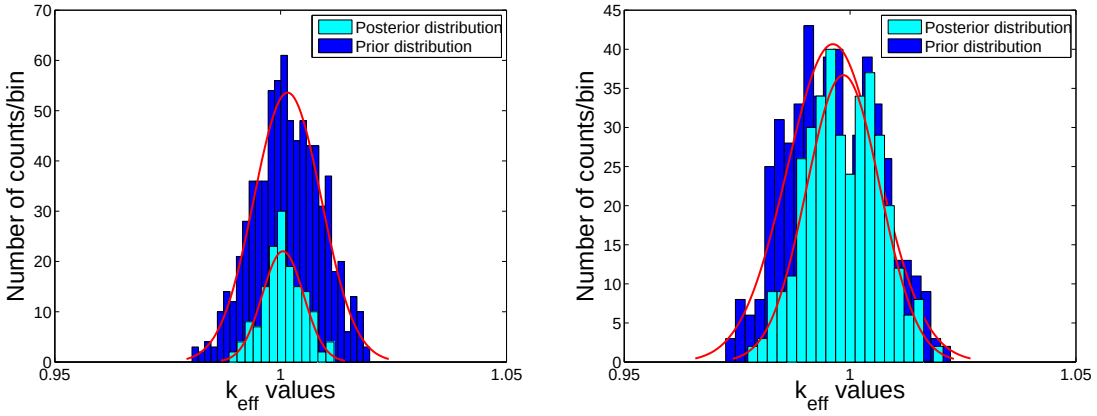

Figure 4. Example of results showing k_{eff} distributions for varying k_{eff} for ^{239}Pu (left) and ^{240}Pu (right) nuclear data after combining the prior information with integral information from pmf1 benchmark (σ_E=200pcm) for ELECTRA.

In Table VI, ^{239,240,241}Pu nuclear data uncertainty results computed for the prior distribution using original TMC are compared with results of the posterior distribution using the binary accept/reject method for the ELECTRA.

As can be seen from the table, an uncertainty reduction of 40% is recorded for ^{239}Pu while a 20% reduction is observed for ^{240}Pu after implementing the accept/reject method in the TMC chain. No reduction in nuclear data uncertainty was however observed for ^{241}Pu. This is not surprising since the weak correlation coefficient observed between ELECTRA and pmf1 benchmark due to ^{241}Pu variation, gives an acceptance interval of $3.6\sigma_E$ and therefore almost all random files were accepted.

Table VI. Table showing results from prior distribution (original TMC) compared to the posterior (binary accept/reject method). Results in brackets represent the percentage reduction in nuclear data uncertainty achieved after implementing the method.

Isotope	prior [pcm]	Binary accept/reject [pcm]
^{239}Pu	748±19	447±12(40%)
^{240}Pu	1011±32	809±26 (20%)
^{241}Pu	1175±37	1175±37(0%)

5. CONCLUSION

A method is proposed for the selection of benchmarks which may serve as a validation database for more complex reactor calculations based on the Total Monte Carlo. Relationship between application cases and benchmarks are quantified using the correlation coefficient. By including criticality benchmark experiment information using an accept/reject method, a 40% and 20% reduction in nuclear data uncertainty in k_{eff} for ELECTRA was observed for ^{239}Pu and ^{240}Pu respectively.

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