Journal of Engineering Science and Technology
Vol. 15, No. 2 (2020) 946 - 956

DEVELOPMENT OF UNCERTAINTY ANALYSIS IN FUEL PERFORMANCE ANALYSIS OF TRIAC-BATAN

T. SETIADIPURA*, N. A. WAHANANI,
A. PURWANINGSIH, A. A. WASKITA

Centre for Nuclear Reactor Technology and Safety, BATAN Indonesia,
Puspiptek Area Building 80th, Tangerang Selatan, Banten, Indonesia
*Corresponding Author: tsdipura@batan.go.id

Abstract

Uncertainty analysis was developed in the TRISO TRIAC-BATAN fuel performance code including the Latin Hypercube Sampling (LHS) and Standard Random Sampling (SRS). The study of the comparison of the two uncertainty analyses was also carried out. One of the main challenges for improving the performance of Tristructural-Isotropic (TRISO) fuels is the ability to accommodate uncertainties related to TRISO fuel design. In addition to SRS, the LHS method was added because it allows for the extraction of information in sufficient quantities with a relatively small sample size that is suitable for challenges in analysing the performance of TRISO fuels. In this study, LHS and SRS are used as sampling methods, while uniform and triangle probability density (PDF) functions are used to represent the characteristics of uncertainty from design data. It was found that LHS was better than SRS in terms of representing PDF uncertainty. However, in the TRISO fuel performance analysis, the LHS results with a higher standard deviation compared to the SRS method.

Keywords: Latin hypercube sampling, Standard random sampling, TRISO fuel performance.

1. Introduction

In designing the Experimental Power Reactor (RDE) [1], the Indonesian National Nuclear Energy Agency (BATAN) must also pay attention to fuel safety analysis. Therefore, the safety analysis code for the performance of tristructural-isotropic (TRISO) based fuels has been developed [2]. The code is equipped with a Latin Hypercube Sampling (LHS) module for uncertainty analysis. This module is applied because of the characteristics of TRISO-based fuel design that have uncertainty in its dimensions [3] and are based on earlier versions developed using Java [4]. Therefore, it is important to analyse how uncertainty will affect fuel failure fraction.

In terms of uncertainty analysis, several previous studies have been carried out in various fields. Chen et al. [5] analysed randomness of gravel flow in the HTR type reactor and its effect on reactor key parameters. In addition, Chen et al. [6] also investigated the uncertainty of the filling fraction of gravel beds. This uncertainty will also affect key parameters. In the research activity, Chen et al. [6] used the uncertainty probability distribution function of the experimental results in conjunction with theoretical analysis using several sampling methods namely important sampling, simple random sampling (SRS) and LHS.

Uncertainty analysis has also been applied to the aerospace industry for design optimization [7], geological disposal of radioactive waste [8], as well as land mapping [9-11]. Among many applications, the LHS method in various types shows excellence among other sampling methods. By using LHS, a small number of samples are sufficient to run the simulation [12]. This is due to the ability of LHS in taking samples, which are distributed evenly throughout the area of interest [13].

In general, the uncertainty analysis can be classified into forward and inverse analysis [14]. Forward analysis (uncertainty propagation) concern on quantifying the output as a consequence of the uncertainties in the input. On the other hand, inverse analysis (model calibration) is used to identify the unknown variables at the input using the mathematical models. From this perspective, TRIAC-BATAN equipped by the sampling module concerns only on investigating the failure fraction of the TRISO-based fuel due to the uncertainties in its dimensions. Because of TRIAC-BATAN [2] was developed based on PANAMA [15, 16], consequently, only dimensional characteristics of TRISO particle are suitable for uncertainty analysis.

2. Design of the Uncertainty Module

The sampling module applied in the TRIAC-BATAN provides uniform and triangle types of distributions. Before the main TRIAC-BATAN calculation is conducted, the user must choose the option whether or not sampling will be used. The user is also required to provide an option whether LHS or SRS will be used.

The difference between LHS and SRS in TRIAC-BATAN lies in the P_m calculation. Only LHS needs to calculate P_m. If the sampling module is used, TRIAC-BATAN will generate samples as required.

For each sample, TRIAC-BATAN calculates a single value of the TRISO failed fraction. Then TRIAC-BATAN will produce failed fraction as many as samples that are inserted by the user.

Interaction between the additional uncertainty sampling method and the main TRIAC-BATAN calculation is shown in Fig. 1. The green line in Fig. 1 represents the sampling module. Though the sampling module is drawn in an integrated manner with the main TRIAC-BATAN calculation, it can be used separately for other purposes if there is a suitable interface provided.

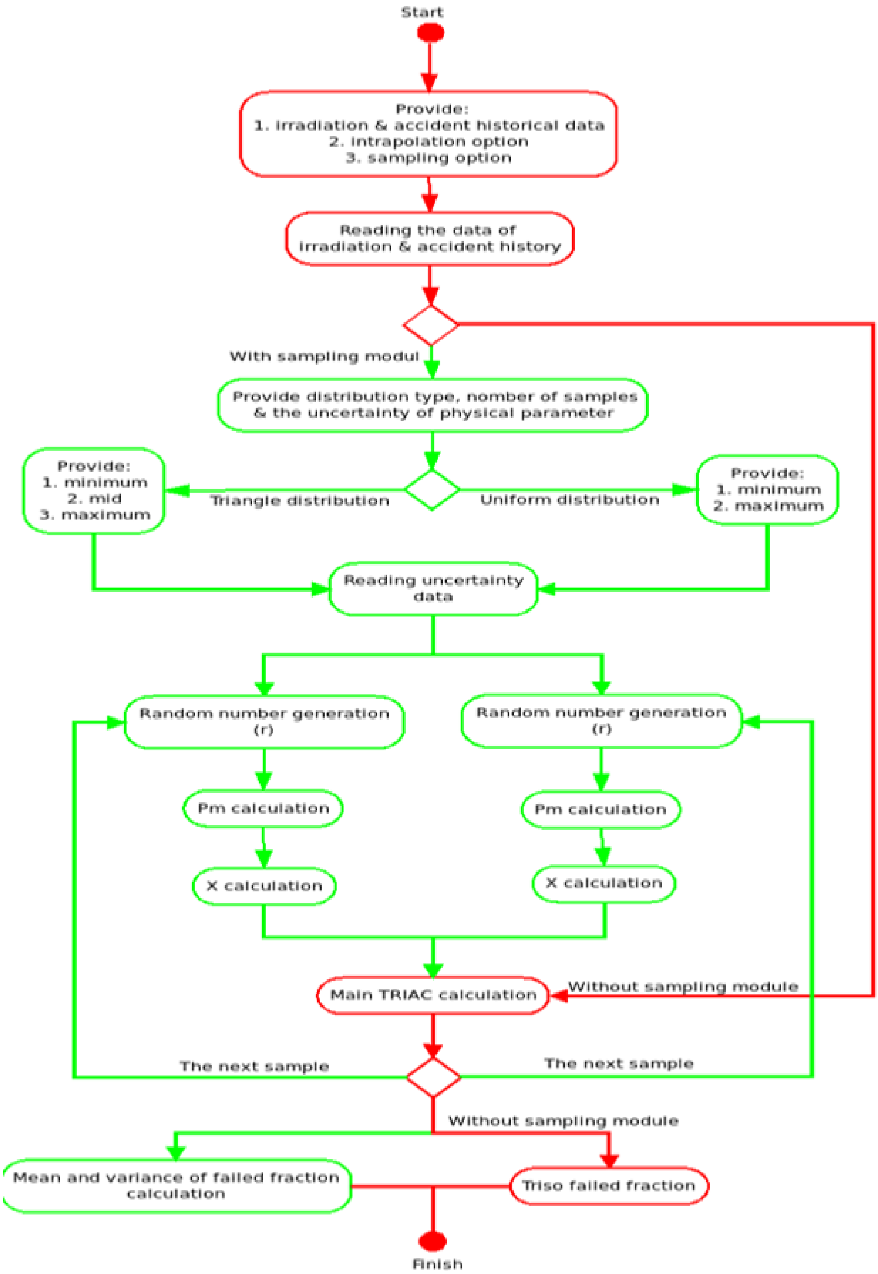

Fig. 1. Flow chart of TRIAC-BATAN with additional uncertainty sampling module.

Variable P_m is intended to distribute the sample along the physical parameters containing uncertainty. It can be denoted as Eq. (1). r is the random number between 0 and 1, i is the sequence of sample and n is the number of samples involved. The index i has the possible value of 0 up to n.

$$P_m = \frac{r+i}{n} \quad (1)$$

After that, the value of P_m will be converted to x, which is the sampling value. Converting function will vary from one distribution to another distribution. In the case of uniform distribution, where the sample will be distributed equally along with the range of uncertainty, the converting function is denoted as Eq. (2). Max and min are the maximum and minimum value of the uncertainty range respectively, with x as the resulting sample value.

$$x = P_m(Max - Min) + Min \quad (2)$$

For triangular distributions, there are two areas that must be represented by different equations, namely the left and right sides of the midpoint, as shown in Fig. 2(a). Whether the sample is assigned to the left or right of that point depends on the distribution itself. The distribution of triangles can be represented by the parameter k. If Min = Mid, then k = 0.0 and the triangle will have the shape, which is shown in Fig. 2(b). On the other hand, if Mid = Max, then k = 1.0 and the triangle will have the shape, which is shown in Fig. 2(c). Otherwise, k will be denoted as Eq. (3).

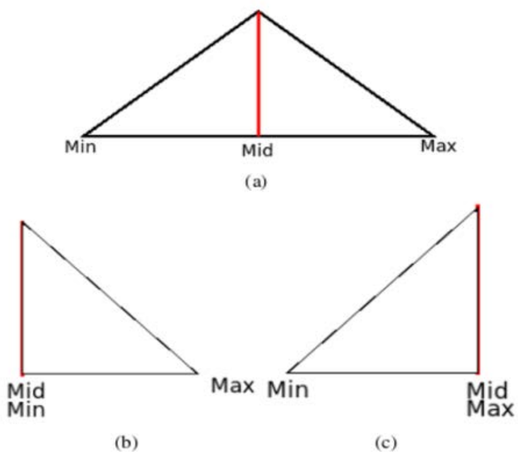

Fig. 1. Variation in a triangular shape that affects the value of *k*.

$$\boldsymbol{k} = \frac{(\boldsymbol{Mid-Min})}{(\boldsymbol{Max-Min})} \quad (3)$$

If $P_m \leq K$, then the value of x equal to Eq. (4). On the other hand, if $P_m > K$, then the value of x equal to Eq. (5).

$$x = Min + \sqrt{P_m(Max - Min)(Mid - Min)} \quad (4)$$

$$x = Min + \sqrt{(1 - P_m)(Max - Min)(Max - Mid)} \quad (5)$$

Figures 3(a) and (b) present the distribution of 1000 samples using a uniform distribution. They are sampled with LHS and SRS respectively. The 1000 samples are then divided into 50 classes with 20 samples for each class. The figures show the number of samples exists in each class. Figure 3(a) shows that each class contains 20 samples. While Fig. 3(b) shows that only the 32nd, 48th and 50th classes contain 20 samples.

While Figs. 4(a) and (b) show the distribution of 1000 samples using triangle distribution, which is sampled with LHS and SRS respectively. The 1000 samples are also divided into 50 classes as previously shown in Figs. 3(a) and (b). From Figs. 3 and 4, we can conclude that LHS performs better in sampling with certain distribution than SRS does.

Figure 5 presents the structural relationship between the distribution class of Uniform and Triangle with their superclass triac LHS. While Fig. 6 presents the interaction between main TRIAC-BATAN class with the sampling module shown in Fig. 5. The LHS calculation is an interface to the sampling module, even when we do not use TRIAC-BATAN application.

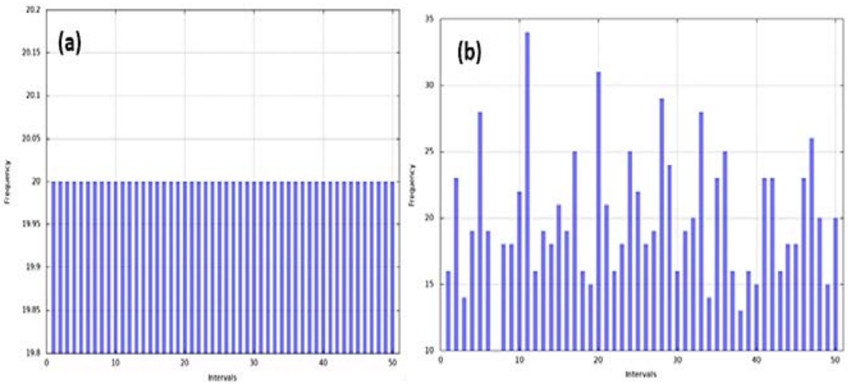

Fig. 3. Distribution of 1000 samples using uniform distribution: (a) LHS and (b) SRS.

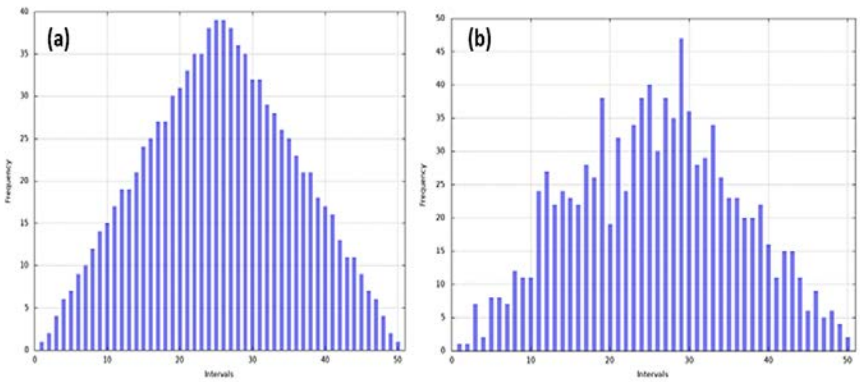

Fig. 4. Distribution of samples using triangle distribution: (a) LHS and (b) SRS.

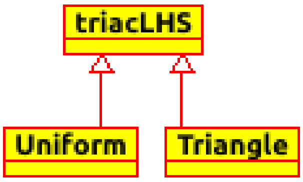

Fig. 5. Class diagram of the TRIAC-BATAN sampling module.

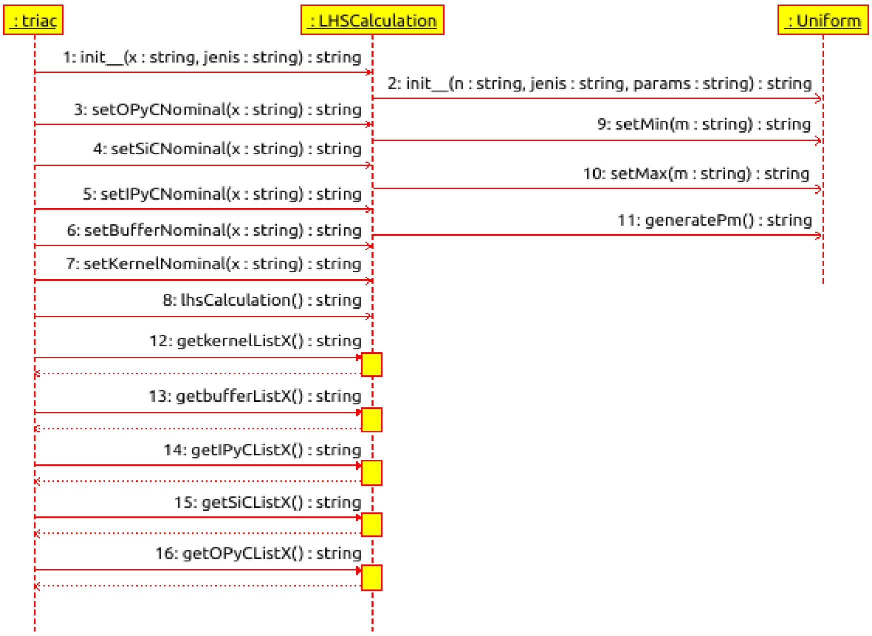

Fig. 6. Interaction between main TRIAC-BATAN class with the sampling module.

Based on Fig. 6, the user must provide the nominal physical parameters that contain uncertainty. In the case of TRIAC-BATAN, the only physical parameters that have uncertainty are those related to the dimensions of the TRISO particles. Then, the nominal values supplied to the sampling module are the dimensions of OPyC, SiC, IPyC, buffer and kernel layer as illustrated in Fig. 7. In Fig. 6, this condition is represented by the sequence of number 3 to 7.

To use TRIAC-BATAN with sampling module, the user is required to supply several parameters related to the uncertainty of the physical parameter in addition with several samples and the type of distribution. The parameters are supplied through the same input file as described by Waskita and Setiadipura [2] with additional uncertainty value. For each nominal value, there are three additional values, namely the value of uncertainty, the type of distribution (uniform or triangular) and variance (in case the user needs to use a normal distribution). However, the normal distribution has not been implemented and will be added in the next version of this sampling module. The last value is the number of samples that is necessary to be simulated. Consequently, if using the sampling module is selected, each TRISO particle will be simulated with the same number of samples.

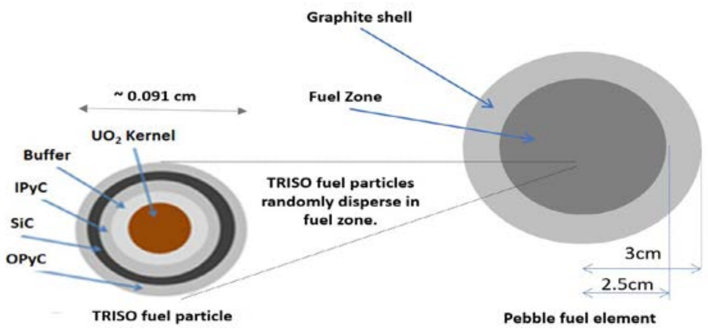

Fig. 7. The illustration of TRISO particle [17].

3. Results and Discussion

In this study, irradiation and accident history were used as previously simulated [2]. Additional data was the uncertainty of the thickness of the TRISO layer as described in the simulation that was conducted with 100 samples. Each TRISO layer was given the same treatment. This means that in one simulation, each TRISO layer will have the same distribution and sampling method. The distribution of nominal and uncertainty of each TRISO layer are presented in Table 1.

Table 1. Nominal and uncertainty of each TRISO layer.

	Nominal	**Uncertainty**
Kernel	2.55e-04	5.00e-06
Buffer	3.45e-04	4.40e-06
IPyC	3.85e-04	1.00e-05
SiC	4.20e-04	2.60e-06
OPyC	4.60e-04	1.00e-05

The TRISO fraction that fails will vary from time to time, based on the timeline of the accident [2]. As a result, different samples will produce different failed fractions at different times. The following figures show the average value of a failed fraction with a standard deviation. In this study, the authors assume that each TRISO layer will have distribution in their own uncertainty. Using 100 samples, failed fraction of TRISO particles with uniform distribution either with LHS or SRS are depicted in Figs. 8(a) and (b). They represent failed fraction mean value and its standard deviation (σ) respectively. The value of σ shown in Fig. 8 is presented numerically in each timeline. It shows that LHS produce higher σ than SRS for uniform distribution.

On the other hand, failed fraction of TRISO particles with triangle distribution either with LHS or SRS are depicted in Figs. 9(a) and (b). They represent failed fraction mean value and its σ value respectively. The value of σ shown in Fig. 10 is presented numerically in each timeline. It shows that LHS produce higher σ than SRS for uniform distribution. With two different distributions, LHS and SRS show the same result. The standard deviation of failed fraction obtained by using LHS is larger than SRS and uncertainty data with triangle distribution will have a smaller standard deviation compared to uniform distribution as shown in Fig. 10. These results are different from the utilization of LHS and SRS on uncertainty analysis on pebble bed loss of cooling accident [17, 18].

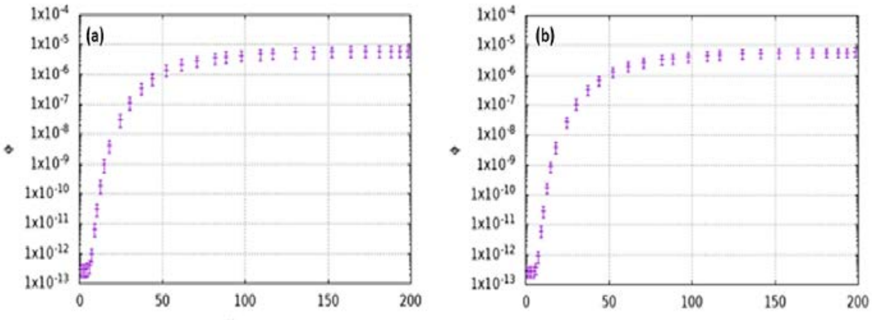

Fig. 8. Failed fuel fraction using uniform distribution: (a) LHS and (b) SRS.

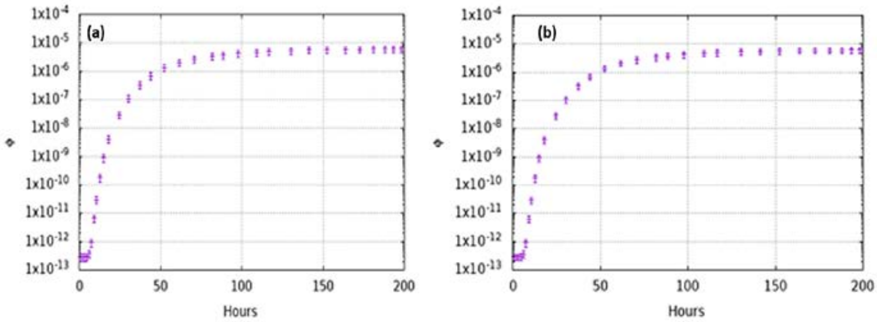

Fig. 9. Failed fuel fraction using triangle distribution: (a) LHS and (b) SRS.

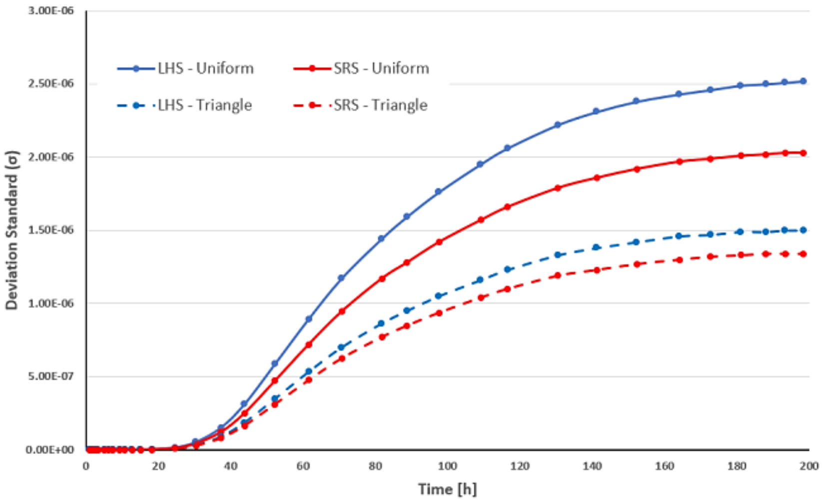

Fig. 10. Comparison of standard deviation from different sampling method and uncertainty data distribution.

The following data plot is obtained by using a much larger number of samples each about 10000, 50000 and 100000. Figures 11(a) and (b) concern on how the distribution of samples affects the TRISO failed fraction.

Based on the above results, we can conclude that the fuel performance of the equipment is typically good. This can solve the current problems regarding non-renewable energy [19, 20]. However, the analysis must be further done to make optimum condition and applicable for realistic apparatus [21, 22].

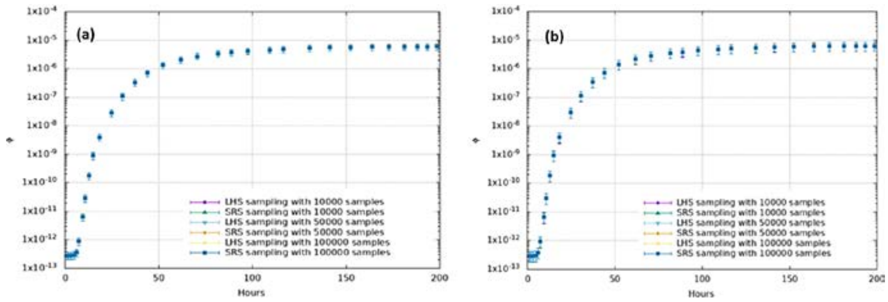

Fig. 11. Failed fuel fraction with higher sample data: (a) LHS and (b) SRS.

4. Conclusions

Development of uncertainty analysis in the TRISO fuel performance analysis, TRIAC-BATAN, has been successfully conducted. By using the sampling module, either LHS or SRS, the obtained samples can be adjusted to follow the certain distribution, which is well-fitted with the physical parameter considered. When the sampling module was integrated with TRIAC-BATAN, it can be used to examine how the failed fuel fraction of a TRISO will work with the uncertainty on the TRISO design parameter. It was found that the LHS method will give a higher standard deviation compared to SRS, although LHS is better in representing the probability density function of the uncertainty data. With the uncertainty analysis module, TRIAC-BATAN is ready to be used as a better simulation tool for TRISO fuel performance analysis by accommodating the uncertainty data of the fuel design.

Acknowledgements

Authors thank the Ministry of Research and Higher Education of the Republic of Indonesia for the financial support given under the Insinas Flagship Program 2018. Authors also thank PTKRN-BATAN for supporting this research through DIPA 2018.

References

1. Setiadipura, T.; Bakhri, S.; Sunaryo, G.R.; and Wisnusubroto, D.S. (2018). Cooling passive safety features of reaktor daya eksperimental. *AIP Conference Proceedings*, 1984(1), 020034.

2. Waskita, A.A.; and Setiadipura, T. (2019). The development of TRIAC-BATAN: a triso fuel performance analysis code. *Journal of Physics: Conference Series*, 1198(2), 022035.
3. Terry, W.K. (2005). Evaluation of the initial critical configuration of the HTR-10 pebble-bed reactor. *Report No. INL/CON-05-00852*. Idaho National Laboratory (INL), United States of America.
4. Wahanani, N.A.; Purwaningsih, A.; and Setiadipura, T. (2009). Latin hypercube sampling for uncertainty analysis. *Journal of Theoretical and Computational Studies*, 8(0408), 1979-3878.
5. Chen, H.; Fu, L.; Jiong, G.; Ximing, S.; and Lidong, W. (2015). Quantitative analysis of uncertainty from pebble flow in HTR. *Nuclear Engineering and Design*, 295, 338-345.
6. Chen, H.; Fu, L.; Jiong, G.; and Lidong, W. (2015). Uncertainty and sensitivity analysis of filling fraction of pebble bed in pebble bed HTR. *Nuclear Engineering and Design*, 292, 123-132.
7. Yao, W.; Chen, X.; Luo, W.; van Tooren, M.; and Guo, J. (2011). Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles. *Progress in Aerospace Sciences*, 47(6), 450-479.
8. Hansen, C.W.; Helton, J.C.; and Sallaberry, C.J. (2012). Use of replicated Latin hypercube sampling to estimate sampling variance in uncertainty and sensitivity analysis results for the geologic disposal of radioactive waste. *Reliability Engineering and System Safety*, 107, 139-148.
9. Clifford, D.; Payne, J.E.; Pringle, M.J.; Searle, R.; and Butler, N. (2014). Pragmatic soil survey design using flexible Latin hypercube sampling. *Computers and Geosciences*, 67, 62-68.
10. Mulder, V.L.; de Bruin, S.; and Schaepman, M.E. (2013). Representing major soil variability at regional scale by constrained Latin Hypercube Sampling of remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, 21, 301-310.
11. Rad, M.R.P.; Toomanian, N.; Khormali, F.; Brungard, C.W.; Komaki, C.B.; and Bogaert, P. (2014). Updating soil survey maps using random forest and conditioned Latin Hypercube Sampling in the loess derived soils of northern Iran. *Geoderma*, 232-234, 97-106.
12. Vořechovský, M.; and Novák, D. (2003). Statistical correlation in stratified sampling. *Proceedings of the 9th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP)*. San Francisco, California, United States of America, 119-124.
13. Husslage, B.; Rennen, G.; van Dam, E.R.; and den Hertog, D. (2011). Space-filling Latin hypercube designs for computer experiments. *Optimization and Engineering*, 12(4), 611-630.
14. Tian, W.; Heo, Y.; de Wilde, P.; Li, Z.; Yan, D.; Park, C.S.; Feng, X.; and Augenbroe, G. (2018). A review of uncertainty analysis in building energy assessment. *Renewable and Sustainable Energy Reviews*, 93, 285-301.
15. Verfondern, K.; and Nabielek, H. (1990). The mathematical basis of PANAMA-1 code for modelling pressure vessel failure of TRISO coated particles under accident conditions. *HTA-IB-03/90*, Germany: Julich Research Center.

16. Verfondern, K.; Cao, J.; Liu, T.; and Allelein, H.-J. (2014). Conclusions from V&V studies on the German codes PANAMA and FRESCO for HTGR fuel performance and fission product release. *Nuclear Engineering and Design*, 271, 84-91.
17. Setiadipura, T.; Irwanto, D.; and Zuhair. (2015). Preliminary neutronic design of high burnup OTTO cycle pebble bed reactor. *Atom Indonesia*, 41(1), 7-15.
18. Strydom, G. (2013). Uncertainty and sensitivity analyses of a pebble bed HTGR loss of cooling event. *Science and Technology of Nuclear Installations*, Special Issue, Uncertainty Analysis in Reactor Physics Modelling, Article ID 426356, 16 pages.
19. Andika, R.; and Valentina, V. (2016). Techno-economic assessment of coal to SNG power plant in Kalimantan. *Indonesian Journal of Science and Technology*, 1(2), 156-169.
20. Ridwan, Y.S.; Supriadi, S.; and Nugraha, W.C. (2019). Traceable value for proficiency test of natural gas. *Indonesian Journal of Science and Technology*, 4(2), 270-279.
21. Eftekhari, S.; and Al-Obaidi, A.S.M. (2019). Investigation of a cruising fixed wing mini unmanned aerial vehicle performance optimization. *Indonesian Journal of Science and Technology*, 4(2), 280-293.
22. Al-Obaidi, A.S.M.; and Sun, L.C. (2014). Calculation and optimization of the aerodynamic drag of an open-wheel race car. *Journal of Engineering Science and Technology (JESTEC)*, EURECA 2013, Special Issue, August, 1-15.