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Uncertainty Quantification of Engineering Parameters for a Nuclear Reactor Loaded with Dispersed Fuel Particles

Yukun Li [1,2], Zhenping Chen [1,2,*], Chao Yang [1,2,*], Guocai Huang [1,2], Kekun Gao [1,2], Aikou Sun [1,2], Chengwei Liu [1,2] and Zhiqiang Wu [1,2]

1 School of Nuclear Science and Technology, University of South China, Hengyang 421001, China; 20212010210682@stu.usc.edu.cn (Y.L.); 202120082100465@stu.usc.edu.cn (G.H.); 202120082100460@stu.usc.edu.cn (K.G.); 20212010110644@stu.usc.edu.cn (A.S.); 20212010210685@stu.usc.edu.cn (C.L.); 202120101100649@stu.usc.edu.cn (Z.W.)

2 Key Lab of Advanced Nuclear Energy Design and Safety, Ministry of Education, University of South China, Hengyang 421000, China

* Correspondence: chzping@yeah.net (Z.C.); yangc066@163.com (C.Y.)

Abstract: Owing to their high intrinsic safety, dispersed fuel particles are an important fuel pattern for fourth-generation nuclear reactors. Due to the unique cladding layers and the random dispersion characteristics, dispersed fuel particles significantly differ from pressurized water reactors regarding operation-induced uncertainty. This study quantitatively analyzed overall uncertainty while considering a random distribution of dispersed fuel particles, material thickness, and fuel enrichment. The results demonstrated that, for all packing fractions, the uncertainty induced by the random dispersion of dispersed fuel particles was below 0.03%. For every packing fraction, the differences between the results obtained by the regular and the random distribution models increased, and then decreased, until reaching its maximum (1.297%) at 15%. K_{eff} decreased as the radius of the UO_2 kernel increased; K_{eff} increased as the thickness of the cladding layer increased; the uncertainty of K_{eff} was 1.003% when a random distribution of particles, material thickness, and fuel enrichment were taken into consideration; the uncertainty of the power distribution of reactor core assemblies was maximized (1.495%) at the edge of the reactor core. Quantitative analysis of uncertainty provides references for the optimization of design and safety margin analysis for reactors.

Keywords: Monte Carlo; dispersed fuel particles; engineering parameters; uncertainty quantification

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1. Introduction

In the context of global carbon emissions and the development of carbon-neutral energy, clean energy has become crucial in addressing the challenges posed by energy structure and climate change [1]. Nuclear energy is a green and clean source with high energy density, efficient power generation, and low carbon emissions [2]. Compared to other forms of clean energy, such as wind and solar power, nuclear energy is less susceptible to natural environmental factors, and its efficiency and stability more effectively meet the demand for sustainable energy [3,4]. Despite its numerous advantages, nuclear energy has many safety concerns [5]. Therefore, future developments in nuclear technology will prioritize intrinsic safety measures and minimize radioactive material leakage rates [6,7].

With advancements in fourth-generation nuclear technology. Tri-structural isotropic coated fuel particles (referred to as TRISO-dispersed fuel particles) are widely used in advanced reactors [8]. TRISO is an abbreviation of Tri-structural ISOtropic fuel particles, which is a new type of reactor fuel. Tri-structural means that fuel particles are composed of three different structural layers: the fuel core, pyrolytic carbon coating layer and silicon carbide coating layer. The multilayer structure is used to improve the safety and operation performance of nuclear reactors. Isotropic means that the structure of TRISO particles is homogeneous and isotropic in all directions.

The main purpose of TRISO fuel particle design is to improve the intrinsic safety and stability of nuclear reactor fuel. Intrinsic safety means that the reactor has its own safety attributes in design and manufacture. This safety attribute is not disturbed by the outside world and can maintain stable and safe operation even in the case of being out of control or in an accident. For dispersed fuel particles, the coating layer has a certain sealing function, which can effectively prevent the leakage of radioactive fuel and products in the fuel core [9]; the porous structure of the loose pyrolytic carbon coating layer provides storage space for gaseous fission products, while absorbing the core swelling [9] caused by fuel core depletion, reducing the risk of fuel element damage. Consequently, TRISO-dispersed fuel particles offer a new direction in enhancing intrinsic safety features and optimizing the use of nuclear energy. Combined with passive heat removal systems, they become essential technologies for small modular reactors (SMR) and micro-reactors.

However, the engineering application of TRISO-dispersed fuel particles also has many shortcomings. For example, the complex engineering structure introduces a significant number of engineering uncertainties. Research on TRISO-dispersed fuel particle intrinsic uncertainty has become a significant issue. The most recent research project addressing this is the International Atomic Energy Agency's International Coordinated Research Program on Modeling Uncertainty Analysis for High-Temperature Gas-Cooled Reactors (IAEA HTGR UAM CRP) [10]. The results show that the uncertainty induced by the random distribution of TRISO-dispersed fuel particles is not very large, especially for the reactor's effective multiplication factor (K_{eff}), which does not exceed 30 pcm [11]. However, the fuel manufacturing tolerances and geometrical information induce significant uncertainty in the calculation. Chen Youying, Master of Science from Harbin Engineering University, investigated the influences of the packing fraction of dispersed fuel particles and random dispersion on the uncertainty induced by the transport calculation using different models for a high-temperature gas-cooled reactor with a spherical bed at the fuel sphere scale [12]. Lou Lei, a researcher of the Nuclear Power Institute of China, investigated the relationship between the deviation of the dispersed fuel uniform mixing model and the diameter of fuel particles and fuel enrichment using the reactor Monte Carlo program (RMC). When the fuel enrichment or particle size is large, the uniform mixing model will bring a large calculation deviation [13]. Zhang Yongdong, Master of the Shanghai Institute of Applied Physics, Chinese Academy of Sciences, explored the effects of kernel radius and cladding layer thickness distribution on the probability of failure using random sampling [14] and found that the effective combustion depth of fuel was significantly reduced due to the spatial self-shielding effect and the scattering probability of each layer of material thickness. Dr. Fan Kai, from the Institute of Nuclear Energy and New Energy Technology, Tsinghua University, established a geometric model of the appropriate fuel particle random distribution using the MCNP code and compared it with the regular distribution model to analyze the effect of distribution randomness on the effective multiplication factor [15]. The results showed that the fuel particles' random distribution leads to a slightly larger effective multiplication factor than that of the regular model, and the main reason for the deviation between the two models is the difference in the spatial and angular distribution of the two-particle arrangements [15]. G. Kepisty of AGH University of Science and Technology used 100 independent copies of Monte Carlo burnup simulations to study the statistical error propagation of the full-core HTR model [16]. The results show that the actual and apparent changes of K_{eff} are close to each other from the beginning of irradiation to high burnup. It is difficult to use K_{eff} to observe statistical error propagation in high burnup. The increasing real variation of K_{eff} has been detected with a delay after entering the regime of unstable simulation at a high burnup.

The above research demonstrates that the current international research situation mainly studies the influence of single-factor uncertainty, especially for the spatially random effect of dispersed fuel particles. However, there are few studies on the comprehensive influence of multiple factors combined with engineering parameters. Therefore, this study focuses on the quantitative analysis of multi-factor comprehensive uncertainty, specifically the following three points: (1) random dispersion uncertainty of the random distribution model and the difference between models under different packing fractions; (2) the effect of material thickness of each layer of TRISO-dispersed fuel particles; and (3) combined with fuel enrichment random sampling, the overall uncertainty of the combination of the random distribution of material thickness in each layer of particles and the spatially random distribution. In the manufacturing process, the errors introduced by materials, processes, equipment and environmental conditions are difficult to completely control and the accuracy can only be controlled within a reasonable range. Therefore, the uncertainty of engineering parameters studied in this paper is accidental uncertainty, which cannot be avoided and has nothing to do with the calculation process itself.

This study concludes that the overall uncertainty of engineering parameters on the transport calculation and the power distribution, which can help to improve nuclear energy safety, can be comprehensively assessed by uncertainty analysis of key parameters and can retain sufficient margins and corresponding measures to ensure the safe operation of the reactor. In addition, it can help to optimize reactor design and operation and enable understanding of potential fluctuations during operation, thus optimizing system performance and efficiency, improving reactor energy efficiency, reducing operating costs, and minimizing environmental impact. In summary, uncertainty analysis is indispensable to TRISO-dispersed fuel particles in nuclear energy engineering.

2. Uncertainty Quantification

2.1. Statistical Sampling Method

The uncertainty analysis method based on Statistical Sampling Theory is widely used in modeling and simulation to quantify uncertainty. For any nuclear reactor modeling and simulation, the uncertainty of the input parameters will be transferred to the system's response along with the calculation process. The mapping relationship between the system response and input parameters can be simply expressed as follows:

$$\mathrm{R}(\alpha) = [\mathrm{R}_1(\alpha), \mathrm{R}_2(\alpha) \ \ldots \mathrm{R}_{\mathrm{nR}}(\alpha)]^{\mathrm{T}} = \mathrm{f}\ (\alpha)$$

where R is the response vector of the system, nR is the number of system responses, $\alpha = (\alpha_1, \alpha_2 \ldots \alpha_{n\alpha})^{\mathrm{T}}$ is the input parameter vector, $n\alpha$ is the number of input parameters, and f is the system response as a function of input parameters.

Since the true value of the input parameters in the transport calculation is uncertain, and the measured values inevitably have errors, it is usually necessary to assign a specific distribution function to the input parameters to describe the possible value range and probability distribution of the true value of the input parameters. In statistics, the above input parameters are equivalent to continuous random variables, and the entire real number set composed of the value range is the population. Because it is impossible to fully calculate the population, in order to study the impact of the input parameter population, it is necessary to extract a certain number of individuals from the population for calculation. The process is called sampling and the total number of individuals extracted is called the sample, and the number of samples is called the sample size [17]. In the uncertainty analysis of nuclear reactor calculations, how to accurately reflect the distribution characteristics of input parameters through efficient sampling methods is very important.

Latin Hypercube Sampling (LHS) is an improved stratified importance sampling. Its basic idea is to divide the population into several equal probability sub-intervals, and then randomly select a sample in each sub-interval. Latin hypercube sampling combines the advantages of simple random sampling and hierarchical importance sampling. It can not only make the samples cover the distribution range of input parameters evenly, but also does not need to allocate the weight of each layer in advance. Moreover, even in the case of a small number of samples, Latin hypercube sampling can also accurately and reasonably characterize the uncertainty of input parameters [18]. Compared with simple random sampling, Latin hypercube sampling can complete uncertainty quantification with fewer samples and has a significant improvement in the estimation of mean and variance. When obtaining the calculation results at the same confidence level, the calculation time required is significantly reduced [19]. The sampling diagram is shown in Figure 1. Therefore, Latin hypercube sampling is the preferred method for this uncertainty analysis.

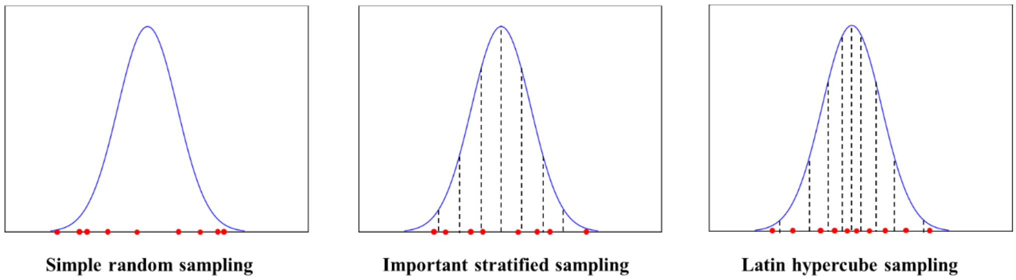

Figure 1. Schematic of different sampling methods.

2.2. Development of an Uncertainty Analysis Tool

This study uses the open-source transport calculation program OpenMC to build a Monte Carlo model of a reactor loaded with TRISO-dispersed fuel particles. OpenMC provides a python module to build transport calculation models for different engineering parameters efficiently. At the same time, this research develops high-performance engineering parameters' sampling tools and related interfaces based on the Linux operating system, using the Python-3.8.10 programming language combined with the NumPy library, pyDOE library, and SciPy library. The number of samples and the overall distribution parameters are set through the input window. The sampling program performs the sampling process and outputs the sample results to the specified output file. The sample results are imported into the OpenMC transport program through the interface to model and calculate. The calculation results are output and statistically analyzed with the sample input. Finally, an automated uncertainty analysis program of parameter sampling-transport calculation-statistical analysis was constructed. The program execution process is shown in Figure 2.

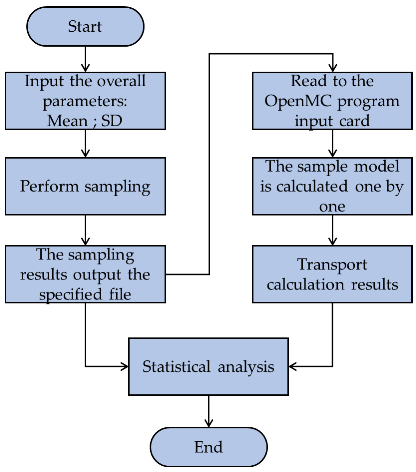

Figure 2. Program execution flowchart.

The research content and methodological flow of this study are shown in Figure 3. The research content includes the quantitative analysis of the comprehensive uncertainty of the packing fraction, material thickness and binding enrichment. The computational condition in this study is 300/50,000/100, where 300 is the number of cycles, 50,000 is the number of source particles per cycle, and 100 is the number of skipped cycles. This allows us to accurately evaluate the engineering parameters' uncertainty of dispersed fuel particles without placing undue strain on computational resources [12].

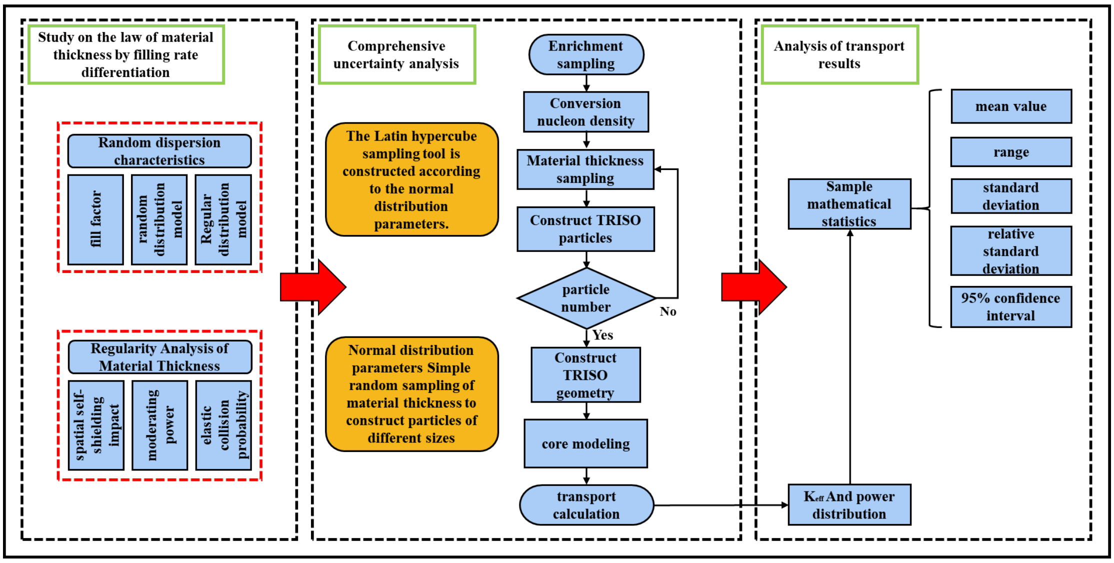

Figure 3. Research methodology flowchart for automatic uncertainty quantification.

3. Quantitative Analysis of Uncertainty

3.1. Transport Calculation Model

Particulate fuel of a small modularized pressurized water reactor (SMR) is used as the calculation model. The reactor core consists of 89 fuel assemblies, each arranged in a 5 × 5 fuel rod arrangement. The specific parameters of the reactor are shown in Table 1, and the model is shown in Figure 4 [20].

The TRISO-dispersed fuel particles are a special type of composite fuel particle commonly used in designing advanced reactor cores, such as high-temperature gas-cooled reactors. TRISO-dispersed fuel particles are composed of a fuel kernel and four cladding layers. The cladding consists of four layers arranged from inner to outer as follows: low-density pyrolytic carbon (Buffer layer), high-density isotropic carbon (IPyC layer), silicon carbide (SiC layer), and high-density isotropic pyrolytic carbon (OPyC layer) [21]; these structures are shown in Figure 5.

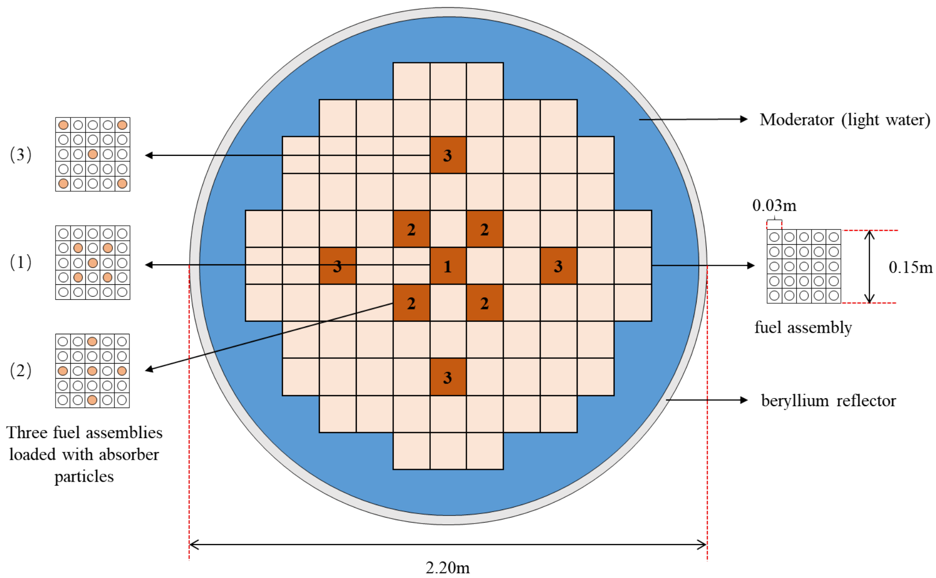

Figure 4. Schematic of SMR structures.

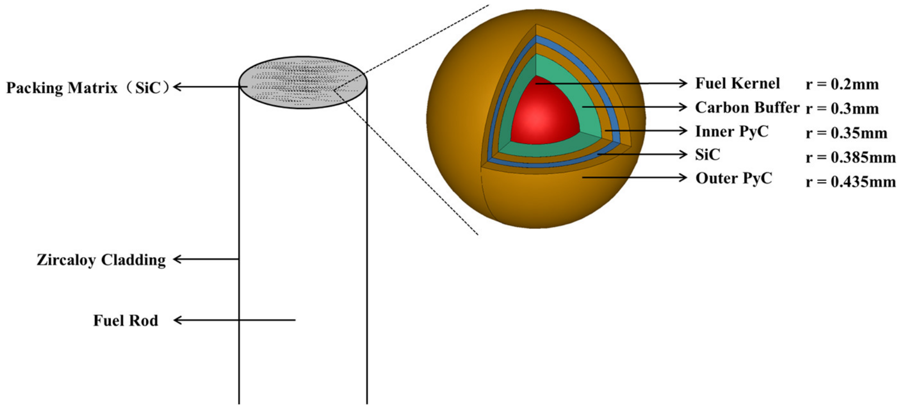

Figure 5. Schematic of TRISO-dispersed fuel particles.

Table 1. Key parameters of particulate fuel of an SMR.

Parameter	Value	Parameter	Value
Power	25 MW_{th}	Fuel type	TRISO
Height of reactor core	170 cm	^{235}U enrichment	15%
Reactor core equivalent diameter	220 cm	Number of assemblies	89
Height of active zone	150 cm	Number of assembly cells	5 × 5
Grid spacing	3 cm	Assembly without control rod	80
Diameter of fuel rod	2 cm	Assembly with control rods	9
Thickness of the cladding layer	0.15 cm	Number of control rods	45
Packing fraction	30%	Packing matrix	SiC
Moderator/coolant	Light water	Fuel	UO_2

3.2. Analysis of Variances under Different Packing Fractions

TRISO fuel particles are randomly embedded in the matrix material. Random dispersion is used to describe a distribution pattern, including the random filling of objects, events or data points in the spatial position or range, which means that the position of each point is randomly selected, and there is no obvious regularity or concentration trend. In physics, random dispersion represents the dispersion effect caused by the disordered filling of particles or particles in the medium. Hence, the random dispersion of TRISO fuel particles constitutes the first uncertainty in transport calculation [22]. Regular or random distribution models are usually adopted in the TRISO fuel particle transportation calculation. The regular distribution model refers to the model in which the fuel particles are filled sequentially according to a certain rule, and the positions and spacing of the fuel particles are regular, usually uniformly distributed, or arranged according to a specific rule, as shown in Figure 6. The deterministic spatial distribution of this model loses consideration of the random distribution, and the calculation results will deviate from the real results to a certain extent. The random distribution model refers to the model in which the fuel particles are filled according to random dispersion, and the center position and spacing of the fuel particles are generated randomly, as shown in Figure 7. This model is closer to the actual engineering–production situation and fully considers the uncertainty brought by random distribution.

During the modeling process, the random dispersion of TRISO fuel particles in a fixed fuel region mainly depends on the total number of fuel particles or the packing fraction [12], and the packing fraction significantly affects the random dispersion. The packing fraction refers to the volume fraction of all dispersed fuel particles in the matrix material. The variation in the packing fraction may lead to a regular change in the difference between the regular distribution model and the random distribution model. The randomness of the fuel particle position should increase with the increase in the number of TRISO fuel particles, but when the fuel rod is filled with fuel particles (74.048%), the fuel particle position has only one arrangement, so its randomness is close to zero [12]. Therefore, the randomness introduced by the dispersion distribution should increase first and then decrease with the increase in the packing fraction, and there exists an ideal packing fraction that maximizes the randomness introduced by the dispersion distribution of fuel particles [12] and thus, introduces the largest difference in the calculation results for the two models.

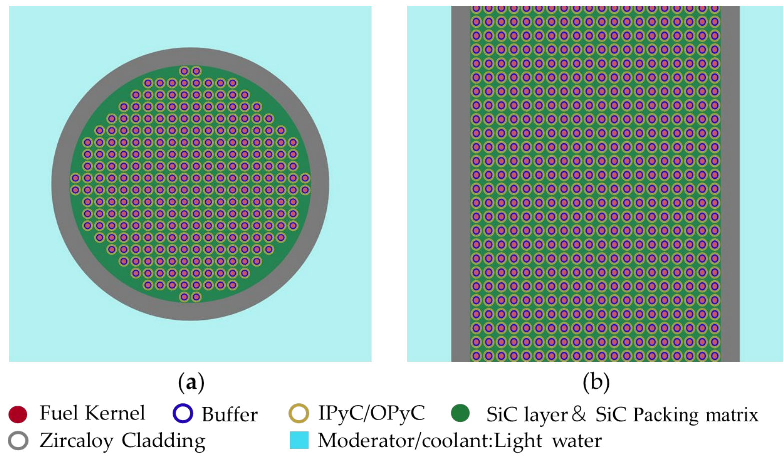

Figure 6. Schematic diagram of the regular distribution model. (**a**) radial cross section; (**b**) axial cross section.

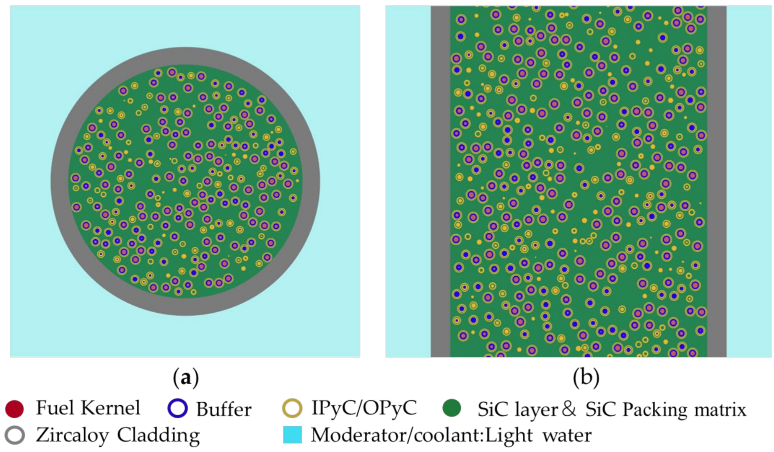

Figure 7. Schematic diagram of the random distribution model. (**a**) radial cross section; (**b**) axial cross section.

In this study, ten sets of regular distribution models and random distribution models with packing fractions of 1%, 5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, and 45% are constructed for comparison. The random distribution models construct ten different distributions to calculate their mean value and standard deviation of K_{eff}, aiming to quantify the difference in random dispersion under different packing fractions for the two models. The results are shown in Table 2.

The calculation results show a significant difference between the regular distribution model and the random distribution model in transport calculation, and the transport calculation results of the random distribution model are generally larger than those of the regular distribution model. As the packing fraction increased, the uncertainty induced by the random dispersion of fuel particles increased and then decreased; when the packing fraction was between 25 and 30%, the random distribution calculated by the random distribution model was maximized, with a standard deviation of 0.029%. The difference between the regular and random distribution models also increased and decreased; when the packing fraction is 5%, the relative difference between the regular distribution model and the random distribution model is 2.066%. The reason for the large difference between the two models is that in the regular distribution model with a small packing fraction, the distance between the fuel particles is much smaller than the average free path in the neutron fuel rod. In this case, the neutrons escaping from the fuel particles may not be slowed down or not fully enter into the adjacent fuel particles, which will increase the probability of neutron and fuel nucleus collision and resonance absorption. The interaction between adjacent fuel rods in this actual grid is usually called the mutual screening effect or Dancoff effect. The cross-screen effect leads to a large number of neutron (n, γ) reactions without fission, so the neutron utilization rate decreases. The distance between the fuel particles in the random distribution model is random, so that the spatial mutual shielding effects will not appear in large numbers, and the proportion of (n, γ) reactions will not be large. Therefore, the transportation calculation results of the random distribution model are generally larger than those of the regular distribution model.

Table 2. The regular distribution model under different packing fractions and transport calculation results were obtained by the random distribution model.

Packing Fraction	K_{eff} of Regular Model	K_{eff} Mean of Random Model	Standard Deviation of Random Model (pcm)	Relative Difference of Model (pcm)
1%	0.11842	0.12029	4.2	1554.6
5%	0.43368	0.44283	22.2	2066.3
10%	0.69283	0.70579	23.7	1836.2
15%	0.86609	0.87906	24.3	1475.4
20%	0.99748	1.00910	26.1	1151.5
25%	1.09436	1.10332	29.5	812.1
30%	1.16899	1.17629	29.0	620.5
35%	1.22304	1.22864	22.2	455.7
40%	1.27725	1.28052	28.6	255.3
45%	1.31643	1.31869	21.6	171.3

3.3. Regularity Analysis of Material Thickness

The fuel kernel and cladding layer of TRISO particles was produced by sol–gel and chemical vapor deposition methods, respectively, and the actual dimensions of the kernel and cladding layer obey the Gaussian distribution and slightly deviate from the standard design dimensions due to the manufacturing process [21]. Table 3 details the kernel radius, Buffer cladding layer, IPyC/OPyC cladding layer, and SiC cladding layer thickness [23], along with their standard deviation [21] for the TRISO-dispersed fuel particles under the existing fabrication process conditions.

Table 3. Material thickness parameters of each layer.

Material Layer	Designed Thickness (mm)	Standard Deviation of Thickness (μm)
Kernel radius	0.200	12.76
Buffer cladding layer	0.100	22.96
IPyC cladding layer	0.050	10.20
SiC cladding layer	0.035	5.10
OPyC cladding layer	0.050	10.20

The change in material thickness will directly affect the interaction between neutrons and different material layers, thus affecting the whole neutron transport calculations [24]. After reviewing the literature, among the four cladding layers of fuel particles, the loose pyrolytic carbon layer (Buffer) and the inner dense pyrolytic carbon layer (IPyC) have a greater effect on the effective multiplication factor [25]. Therefore, this study focuses on the regularity of the kernel radius, loose pyrolytic carbon layer (Buffer), and inner dense pyrolytic carbon layer (IPyC) to determine the influence of material thickness on neutron transport calculation.

The material thickness of each layer is constructed in 0.5σ increments with five layers, and the total loading of UO_2 is guaranteed to be constant. Table 4 shows the transport calculation results and Figure 8 depicts their regularity.

Table 4. Material thickness variation transport calculation results.

	Designed Thickness (mm)	Number of Fuel Particles	Transport Calculation Results (K_{eff})
Kernel	0.018724	60,993	1.17990 ± 0.00029
	0.019362	55,160	1.17826 ± 0.00029
	0.02	50,048	1.17684 ± 0.00030
	0.020638	45,548	1.17622 ± 0.00027
	0.021276	41,573	1.17470 ± 0.00030
Buffer cladding layer	0.007704	50,048	1.17325 ± 0.00027
	0.008852	50,048	1.17526 ± 0.00028
	0.01	50,048	1.17699 ± 0.00028
	0.011148	50,048	1.17879 ± 0.00027
	0.012296	50,048	1.18145 ± 0.00030
IPyC cladding layer	0.00398	50,048	1.17539 ± 0.00029
	0.00449	50,048	1.17653 ± 0.00029
	0.005	50,048	1.17723 ± 0.00029
	0.00551	50,048	1.17812 ± 0.00029
	0.00602	50,048	1.17889 ± 0.00028

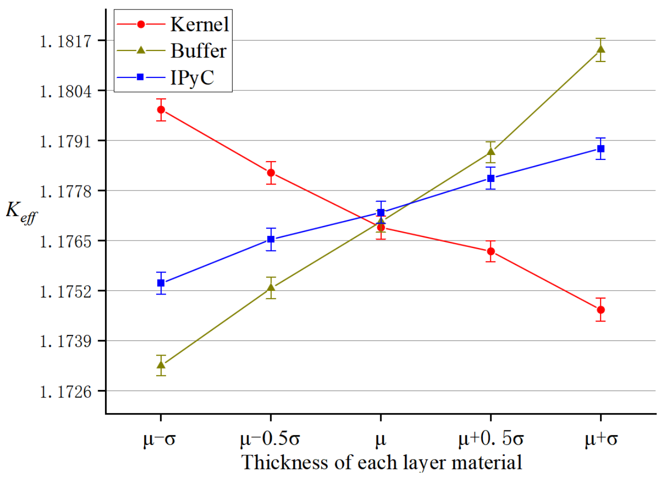

Figure 8. Effect of material thickness on transport calculation.

It is demonstrated that with the increase in UO_2 kernel radius, the K_{eff} becomes smaller with the constant UO_2 loading, and the reason is related to the spatial self-shielding effect of fuel and the fuel utilization rate. A smaller kernel size reduces the spatial self-shielding effect of the UO_2 kernel [26] and improves the fuel utilization rate but also increases the packing fraction under the same total amount of fuel. In comparison, a larger kernel size leads to an increase in the spatial self-shielding effect of the UO_2 kernel and a lower fuel utilization rate. For the Buffer and IPyC cladding layers, as the thickness increases, the K_{eff} gradually increases; the reason is related to the moderating ability and scattering probability. The thinner cladding layer reduces the moderating effect of the cladding material on the neutron and the scattering probability of the neutron to the fuel kernel, which reduces the possibility of the neutron being absorbed by the fuel. The thicker layer increases the moderating ability and scattering probability of the cladding material for neutrons and increases the probability that neutrons will be scattered back to the UO_2 kernel to undergo a fission reaction. In order to confirm the specific mathematical relationship between the material thickness and K_{eff}, the stats module in the Scipy library is used to complete the regression analysis. The mathematical model is used to determine the specific relationship form, and then the influence of the three is analyzed. The results of regression analysis are shown in Table 5. As shown in Table 5, the material thickness of each layer is close to a linear relationship with the effective multiplication coefficient, the fuel core is negatively correlated, and the cladding layer is positively correlated. From the slope of the regression line, the influence of the outer coating material on transport calculation gradually decreases.

Table 5. Results of regression analysis.

Regression Analysis Parameters	Kernel	Buffer Cladding Layer	IPyC Cladding Layer
Slope	−1.94984	1.73606	1.68431
Intercept	1.21618	1.15979	1.16881
Coefficient of determination (R^2)	0.98241	0.99333	0.99400
p value	0.00010	0.00023	0.00019
Standard error	0.15060	0.08215	0.07549

3.4. Multi-Engineering Parameter Quantitative Analysis of Overall Uncertainty

The core of TRISO fuel particles is usually a spherical core composed of UO_2 fuel. Due to variations in the chemical and isotopic composition of the uranium feedstock from different sources, suppliers, and enrichment processes, nuclear fuel enrichment uncertainty is introduced. Nuclear fuel enrichment is critical to transport calculations, and this uncertainty directly impacts the amount of ^{235}U in the nuclear fuel and thus, the overall calculations of the reactor core. Therefore, the combination of enrichment uncertainty, including random distribution of material thickness and random distribution of spatial position in the multi-engineering parameter, is essential for assessing the uncertainty of fuel particles' performance and behavior.

Sampling tools extract the enrichment sample space, and the enrichment samples are converted into nuclide density one by one. The nuclide density is imported into the OpenMC Monte Carlo transport program for transport calculation using random particle sizes. This study uses a Gaussian distribution for enrichment, with a mean of 15% and a standard deviation of 0.3333%, consistent with engineering applications. Valid intervals of (14%, 16%) covering 99.74% of the overall intervals are selected, and the sampling results are shown in Figure 9. The material thickness is modeled by constructing a sampling function in the geometry module of the OpenMC program. This involves setting the mean μ, and variance σ, of the Gaussian distribution for the material thickness of each layer and establishing the distribution interval ($\mu - \sigma$, $\mu + \sigma$) for the material thickness of each layer. Then, the samples are drawn from the distribution of each layer's thickness, and the TRISO fuel particles are constructed by cyclically superimposing the thicknesses until all the TRISO fuel particles are modeled with random thicknesses. Considering the accuracy of the transport calculation and the reasonableness of the calculation time, only 100 samples are set for the transport calculation, and the distribution of the obtained results is shown in Figure 10.

As shown in Figure 10, the transport calculation results are similar to a normal distribution, but the fitting curve is distorted. Figures 8 and 9 show that the effect of enrichment on transport calculation is much larger than that of material thickness and random dispersion, and the uncertainty of material thickness and random dispersion leads to a large distortion of the results.

The transport calculation results are first examined for their distribution using the K–S test method to determine the type of distribution. It compares the cumulative probability density function (CDF) of the calculation results with specific distributions (e.g., normal, uniform, and triangular) [12]. Table 6 summarizes the enrichment sample's K–S test and transport calculation results. As indicated, both the enrichment sample and the transport calculation results are normally distributed.

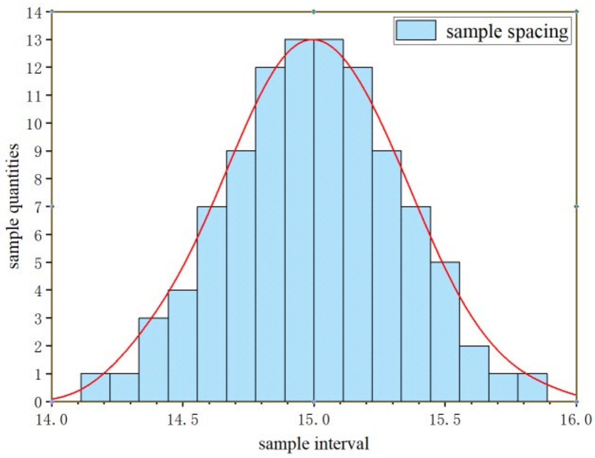

Figure 9. Distribution of enrichment samples.

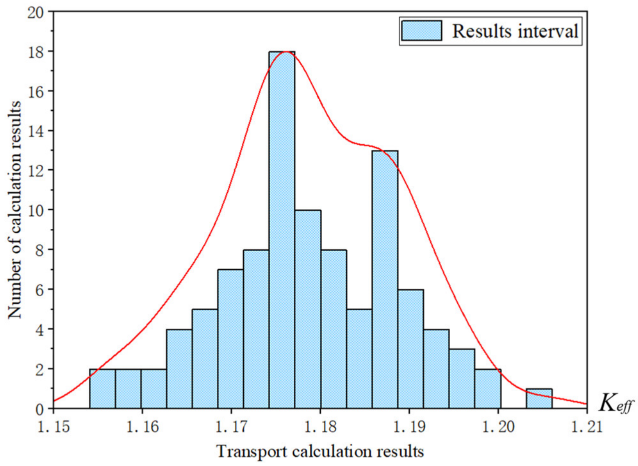

Figure 10. Distribution of multi-engineering parameter transport calculation results.

Table 6. K–S test results of enrichment sample and transport calculation.

Calculation Data	Mean	Extreme Difference	Significance Level (*p*-Value)		
			Uniform Distribution	Normal Distribution	Triangular Distribution
Enrichment sample	14.998%	1.7728%	5.9257×10^{-4}	1.00000	0
Transport calculation results	1.17862	0.04996	6.4101×10^{-4}	0.85763	0

After determining the distribution type of transport calculation results, we can use mathematical and statistical methods to obtain the mean, standard deviation, and other statistical parameters to quantify the uncertainty associated with the distribution type. The results are shown in Table 7. The enrichment sample and transport calculation results are shown in Figure 11. The 95% CI indicates that the overall parameter has a 95% probability of being within the confidence interval. The correlation coefficient is a statistic used to measure the strength of the linear relationship between two variables [10]. These include the Pearson correlation coefficient, Spearman's rank correlation, and Kendall's rank correlation coefficient. The Pearson correlation coefficient measures the strength and direction of the linear relationship between two continuous variables, with values ranging from −1 to 1 [10].

Spearman's rank correlation coefficient and Kendall's rank correlation coefficient are used to measure the rank relationship between two variables. They are similar to the Pearson correlation coefficient but are more suitable for non-linear relationships or outliers. All three correlation coefficients are close to 1, indicating a strong positive correlation between transport calculation results and the enrichment sample [10].

Table 7. Multi-engineering parameter quantitative results of overall uncertainty.

Parameter	Calculation Result
Mean	1.17862 ± 0.00028
Extreme difference	0.04996
Standard deviation	0.01003
Relative standard deviation	0.851%
95% confidence interval of mean	1.15896/1.19828
Pearson correlation coefficient	0.91443
Spearman's rank correlation coefficient	0.90890
Kendall's rank correlation coefficient	0.74088

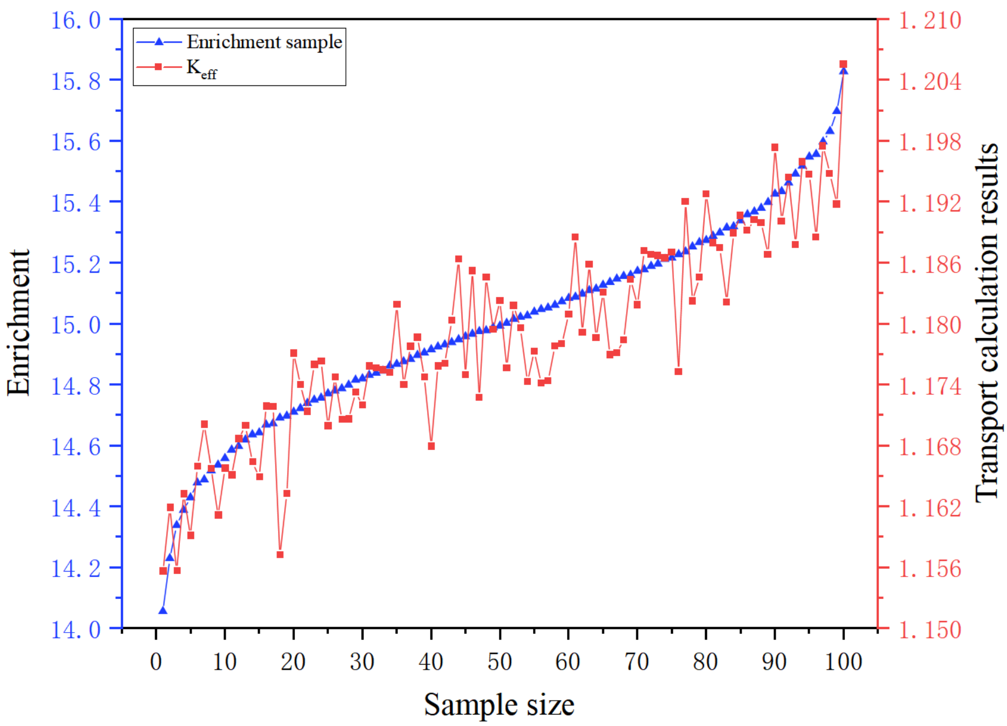

Figure 11. Distribution of enrichment sample and transport calculation results.

3.5. Multi-Engineering Parameter Quantitative Analysis of Uncertainty in the Power Distribution

Uncertainty of engineering parameters also greatly influences the reactor power distribution [27]. First, the spatial dispersion of fuel particles impacts the power distribution, and the homogeneous spatial distribution may lead to changes in the compactness of the fuel stack, which in turn affects the fuel's heat transfer and combustion efficiency. Then, the uncertainty of fuel particle size affects the power distribution, and different sizes of fuel particles lead to different heat conduction paths and combustion characteristics, which in turn affects the spatial distribution of the power distribution and peak power. Finally, different enrichments of fuel particles lead to a different neutron absorption and scattering cross-sections, affecting the shape of the power distribution and peak power. Therefore, in this study, a mesh tally is used to count the deposition energy of each reactor core assembly. Each assembly's deposition energy is normalized by the power distribution to accurately assess the range of the power distribution uncertainty, and its normalized power distribution is shown in Figure 12.

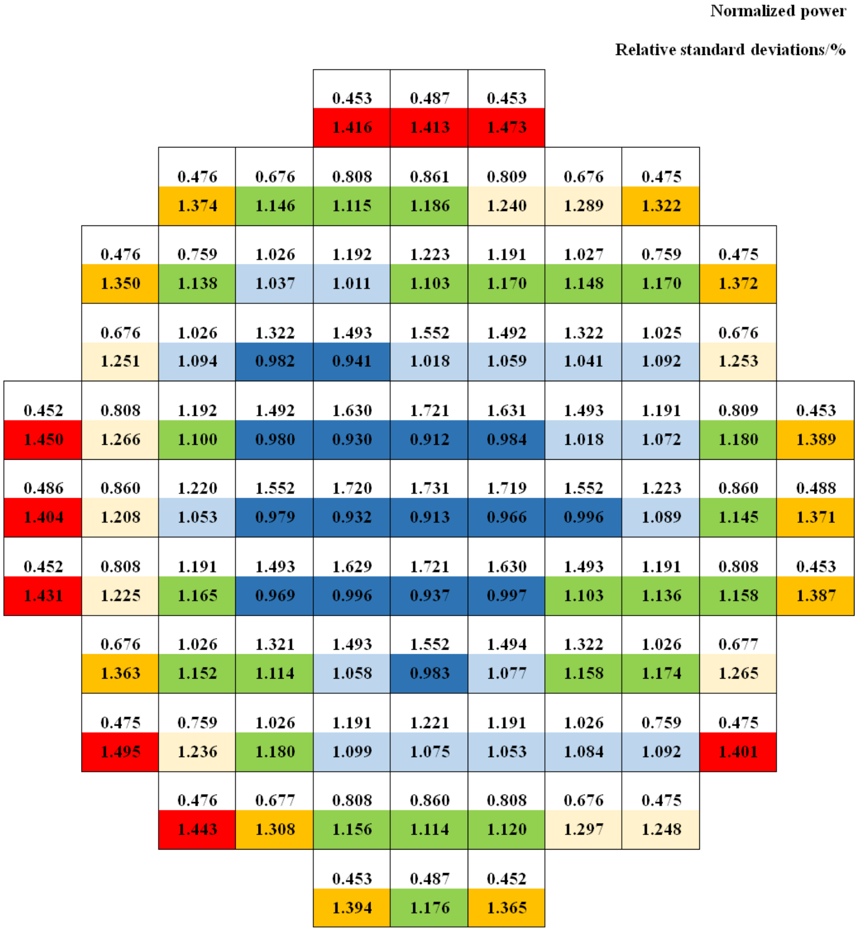

Figure 12. Distribution of the normalized power uncertainty.

As shown in Figure 12, in the power distribution, the uncertainty in the core region of the reactor core is small and gradually increases towards the periphery of the reactor core, and the maximum uncertainty in the edge region of the reactor core is 1.495%. The reasons for this are as follows:

(1) Neutron transport behaviors in the edge region of the reactor core are affected by boundary effects, and geometric and material boundaries increase uncertainty induced by engineering parameters.
(2) The flow paths of neutrons in the edge region of the reactor core are more complex, thus increasing the uncertainty induced by engineering parameters.
(3) The magnitude of the neutron flux in the core region is large, and uncertainty induced by engineering parameters has a small effect on it. In contrast, the magnitude of the deposition energy in the edge region is small, and uncertainty induced by engineering parameters has a large effect on it.

Therefore, in the reactor loaded with dispersed fuel particles, more attention should be paid to the uncertainty of the edge region or the power level of the edge region should be increased to make the power distribution of the core as flat as possible in the radial direction [28] so that the power distribution of the whole reactor is more uniform and the influence of engineering parameters on the edge region is reduced.

4. Conclusions

In this study, uncertainty quantification of engineering parameters of TRISO-dispersed fuel particles was conducted, and significant results were obtained. Firstly, the differences between the regular distribution model of the TRISO-dispersed fuel particles and the random distribution model at different packing fractions were analyzed due to the uncertainty introduced by the random distribution and the differences between the two models. Secondly, the effect of the thickness of TRISO-dispersed fuel particles on the transport calculation was investigated. Additionally, quantitative uncertainty analysis was performed by sampling the enrichment sample space, combined with a high-fidelity random model of spatial location random dispersion and multilayer material randomness.

As demonstrated, there is a difference between the regular and random distribution models in transportation calculation, but the difference is not obvious. As the packing fraction increased, the uncertainty induced by the random dispersion of fuel particles increased and then decreased; when the packing fraction was between 25 and 30%, the uncertainty induced by random distribution was maximized (0.029%). The maximum relative difference between the regular distribution model and the random distribution model is 2.066% when the packing fraction is 5%. Under constant UO_2 loading, as the radius of the UO_2 kernel increases, K_{eff} becomes smaller due to the spatial self-shielding effect and the decrease in fuel utilization. As the thicknesses of Buffer and IPyC cladding layers gradually increase, K_{eff} increases due to the enhancement of moderating ability and increased scattering probability. The quantitative uncertainty induced analysis of uncertainty on engineering parameters such as enrichment, random dispersion, and thickness using the Sampling Statistics Theory showed that the extreme difference is 0.04996, the standard deviation is 0.01003, the relative standard deviation is 0.851%, the 95% confidence interval is (1.15896, 1.19828), and there is a strong positive correlation between the transport calculation results and enrichment samples. In the power distribution, the uncertainty induced by engineering parameters is small in the center region of the reactor core and gradually increases to the periphery of the reactor core, and the maximum is 1.495% in the edge region of the reactor core.

The results of this study show that the transport calculation of TRISO-dispersed fuel particles is affected by several uncertainty factors, the most important of which is fuel enrichment. At the same time, fuel enrichment will be coupled with other engineering parameters to form overall uncertainty. These results provide an important reference for the engineering design and optimization analysis of the TRISO-dispersed fuel particle reactor.

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