

Monte Carlo-Based Fuzzy TOPSIS and CFD Thermal Modeling for Inert Gas Selection in TN-32B Dry Cask Storage

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Abstract: - The type of inert gas utilised for spent fuel storage at the Rooppur Nuclear Power Plant (RNPP) has a significant impact on the thermal performance and safety of the TN-32B dry cask storage system. To determine the suitable gas, this study used fuzzy TOPSIS decision-making, Monte Carlo sensitivity analysis, and CFD simulations with ANSYS Fluent. Under a 34 kW decay heat load, the effects of air, nitrogen, argon, and helium were assessed for a single fuel assembly. The estimated peak temperatures were below the 649 K statutory safety limit: 635 K for helium, 621 K for argon, 591 K for nitrogen, and 589 K for air. For estimating uncertainties in decision-making criteria, fuzzy TOPSIS was applied using 10,000 Monte Carlo simulations, which accounted for a $\pm 20\%$ variation in criteria weights. The outcomes consistently pointed to argon as the most favorable option, showing the highest mean closeness coefficient of 0.681 and ranking first in 79.6% of the simulations. Nitrogen was identified as a strong alternative, with a mean closeness coefficient of 0.647 and securing a second-place position in 20.4% of the simulations. However, neither helium nor air reached the top rank in any simulation, and their mean closeness factors were 0.418 and 0.582, respectively, making them less advantageous. Our combined CFD-MCDM framework offers a methodical and useful approach to choosing dry cask fill gases, enhancing the security and dependability of SNF storage for new NPP projects.

Key-Words: - Dry cask, storage cask, fuzzy TOPSIS, spent nuclear fuel, safety assessment, multi-criteria decision-making, CFD, Monte-carlo, inert gas.

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1 Introduction

A reliable and low-carbon source of electricity, nuclear power is becoming more and more crucial to supplying the growing need for energy. The 2.4 GW RNPP, which will be outfitted with VVER-1200/523 reactors, is Bangladesh's first nuclear facility [1]. Spent nuclear fuel (SNF) generated at RNPP will be temporarily stored on-site before repatriation to Russia. Before being transferred to dry storage systems (DSSs), the fuel is first cooled in spent fuel pools for roughly five to six years after being removed from the reactor. To ensure safety, these systems rely on hermetic containment, radiation shielding, and passive heat removal. For the long-term handling of spent nuclear material, it is therefore essential to ensure adequate thermal performance in dry cask storage [2].

Detailed CFD-based thermal studies under realistic operating conditions are still scarce, despite the widespread use of TN-32B dry casks. In order to assess temperature distributions and confirm adherence to safety regulations, this work creates a numerical thermal model of the TN-32B dry cask using ANSYS. The impact of several inert backfill gases—argon, nitrogen, and helium—on heat transfer efficiency is specifically examined. Although helium is frequently used as the standard backfill gas, there are few rigorous comparisons with other gases. In addition, inert gas selection is often treated qualitatively, without structured consideration of safety, cost, and operational factors. To address this limitation, the present study combines CFD-based thermal analysis with a fuzzy TOPSIS multi-criteria decision-making framework, enabling an uncertainty-

aware and transparent evaluation of backfill gas options for TN-32B dry cask storage at RNPP.

1.1 Spent Nuclear Fuel

Radionuclides found in spent nuclear fuel, a type of radioactive waste produced during reactor operation, need to be handled and stored carefully. SNF management is subject to both national and international safety standards because of its thermal and radioactive properties. International agreements place a strong emphasis on reducing radiation exposure, averting mishaps, and guaranteeing environmental and public safety throughout the spent fuel management lifetime.

1.2 Dry Cask Storage Systems

Before being transferred to dry storage systems, which consist of concrete-shielded metal canisters filled with inert gas, SNF is first cooled in spent fuel pools. These devices, which were developed to get around pool storage restrictions, are now a commonly used temporary storage option. Thermal control is still necessary to preserve the integrity of the fuel cladding even when decay heat diminishes with time. Dry cask systems are suitable for long-term interim SNF storage because they are a passive, dependable, and low-maintenance substitute for pool storage [3].

Compared to wet storage, dry cask systems (DCS) provide a more dependable and secure solution for managing lost fuel over an extended period of time. Even with improved criticality management techniques like boron-10 absorbers, waste fuel pools are susceptible to overheating and radioactive leakage if water inventory is lost. They also need active cooling all the time. However, because dry storage systems rely on passive heat removal, strong shielding, and hermetic isolation, they are less susceptible to external events, natural disasters, and operational failures. Dry casks also produce little secondary waste, need little maintenance, and provide a variety of deployment options. These characteristics make dry storage a reliable and reasonably priced short-term alternative, particularly for countries like Bangladesh where permanent disposal infrastructure is still being developed.

1.3 Background of the TN-32 Dry Cask

The TN-32 dry cask is a vertically orientated, multi-layer cylindrical structure designed for storing spent nuclear fuel for the short term. It has the capacity to hold up to 32 pressurized water reactor FAs, including burnable poison rods or thimble plugs. The system uses several shielding layers to provide structural integrity and radiation protection, using a welded steel canister as the main confinement border.

For radiation attenuation, the cask has a carbon steel gamma shield, an interior confinement with a welded top for containment, and a fuel basket for spacing. Although the outer shield protects important components from exposure to the environment, neutron shielding materials are placed externally to lower neutron dose rates. An overpressure system is used to monitor pressure variations between two lid seals, and it helps with the early detection of any leaks and maintains containment integrity over the long term [4].

The typical TN32-B dry cask utilised in this investigation is depicted in Figure 1. The square-lattice fuel basket is housed inside a substantial steel canister that is encased in a concrete overpack for radiation and mechanical protection. Natural convection is made possible by top and bottom vents, which remove decay heat passively without the need for active cooling.

Because of its extensive operational history, well-established license, and regular usage in thermal benchmark studies, the TN32-B was selected as the reference cask. Despite being first created for square-lattice PWR fuel, it is a good fit for comparative thermal evaluations due to its standardised design and verified thermal data.

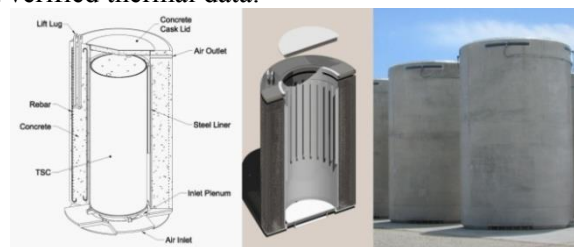


Fig. 1: Vertical dry cask system
Source: [4]

Effective fuel cycle management requires the establishment of trustworthy dry spent fuel storage techniques, particularly as the RNPP in Bangladesh is ready to start up. Even though the VVER-1200 fuel assembly geometry is different from the TN32-B design, this study uses the TN32-B cask as a

reference model to systematically evaluate thermal performance with various inert backfill gases and representative decay heat levels to support the future design and adaptation of dry storage systems at RNPP.

1.4 Thermal Analysis

The thermal behaviour of the TN32-B dry storage cask is investigated in this article, with an emphasis on the effects of various inert gases on the temperatures of spent nuclear fuel (SNF). An inert gas, usually helium, serves as the cask's interior heat transfer medium. It transmits heat from the fuel rods to the cask boundaries in conduction, convection, and radiation heat transmission processes but also keeps a chemically inert environment. Natural convection is the primary method of heat removal, and the thermal characteristics of the selected filled gas have a significant impact on how well it works. To avoid structural degradation, fuel cladding temperatures must stay below 649.1 K per regulatory safety criteria [5].

As a dry cask only uses passive methods to remove decay heat, it is crucial to accurately calculate buoyancy-driven flow, and conductive and radiative heat transfer of the structural materials. Temperature distributions within the fuel and cask are analysed by thermal analyses that allow evaluation of hotspot formation, axial and radial temperature distribution, and cooling efficiency. As high temperatures make fuel deterioration faster, these assessments are essential for long-term storage safety.

ANSYS CFD is used to create a steady-state thermal (SST) model of the vertical DCS to assess the thermal distribution inside the cask. The model solves the coupled conservation equations of momentum, mass, and energy. It is solved by using the buoyancy effects with the Boussinesq approximation and radiative heat transfer using the discrete ordinates method. These governing equations constitute the physical basis of the analysis. The equations are detailed in Section 3.1 for reproducibility. The resulting thermal outputs form the basis of the subsequent multi-criteria decision-making analysis.

1.5 Multi-Criteria Decision Making (MCDM)

Making decisions helps choose the best option from a given range of options based on predetermined standards. MCDM offers an organised method for

methodically assessing and ranking solutions when multiple often contradictory criteria must be taken into account. TOPSIS is a popular MCDM technique for finding the option that is furthest from the worst-case (negative ideal) solution and closest to the ideal solution [6].

MCDM is helpful in nuclear engineering for making a balance between operational, financial, and safety goals. For choosing an inert canister-filled gas for dry cask storage, we must take availability, cost, chemical inertness, and thermal performance into account. This study took air, nitrogen, argon, and helium as alternatives. The first step in MCDM is to build a decision matrix that shows how well each alternative performs in relation to the criteria.

In practice, data and preferences often contain uncertainty due to subjective judgment, variability in material properties, or modeling assumptions. Standard deterministic MCDM may fail under such conditions. Decision-making under uncertainty is made possible by methods such as fuzzy set theory, interval data, and linguistic variables. In this work, weighted criteria, and uncertainty in weights are explicitly handled using Monte Carlo simulation, as described in Section 3.2.

1.6 Fuzzy TOPSIS

A popular multi-criteria decision-making method called TOPSIS finds the option that is most similar to the perfect solution that is positive and the one that is most dissimilar to the ideal solution that is negative. The best and worst values across all criteria are represented by the ideal solutions, respectively [7]. In engineering situations containing uncertainty or subjective judgment, it is frequently impractical to assume that criteria values and weights are precisely known, as conventional TOPSIS does. By adding input uncertainty, fuzzy TOPSIS expands on the traditional method and makes assessments more adaptable and practical. In this study, fuzzy TOPSIS integrates CFD-derived thermal performance with non-thermal criteria to assess inert gas alternatives. We used a Monte Carlo-based sensitivity analysis to account for variability in criteria weights which allows statistical evaluation of rankings rather than a single deterministic outcome. All the mathematical formulation including the process of normalization, weighted decision matrices, ideal solutions, and closeness coefficients is described in detail in Section 3.2.

2 Literature Review

The thermal behaviour of spent nuclear fuel dry casks has been extensively studied through numerical and experimental methods. Although 3D CFD studies offered great insights into the interaction of convection and conduction [8], [9], [10], [11], early work revealed relationships between Nusselt and Rayleigh numbers for rod arrays in vertical and horizontal canisters. To reliably predict peak fuel temperatures and flow patterns under various conditions, ANSYS FLUENT has often been used to simulate helium as a filled gas in casks from the emergence of commercial CFD tools [12], [13], [14], [15], [16]. More recent research, such as coupled thermal, mechanical, and transient simulations has emphasized how different surface radiation, emissivity, and accident scenarios affect thermal performance [17], [18].

In nuclear engineering, structured decision-making techniques have also been used. Techniques including AHP, TOPSIS, and fuzzy-based frameworks have been used for site assessment, technology selection, and safety evaluation under uncertainty. Fuzzy logic addition has enabled handling of subjective judgment and ambiguous data in nuclear safety and energy systems [19], [20], [21], [22]. In thermal applications, authors [23] analyzed accident-tolerant fuels using thermal-hydraulic simulations, and other author [24] applied fuzzy MCDM for insulation material selection.

Other studies have emphasized model simplification, validation strategies, and long-term performance. Authors [13] experimentally investigated welded-top concrete casks. Authors [25] proposed a two-step CFD methodology separating external airflow and internal heat transfer to improve accuracy. In a study [26] authors evaluated axial and radial temperature distributions and ensured compliance with regulatory limits.

Despite this progress, most studies focus on helium as a filled gas, with limited systematic evaluation of alternative options such as argon, nitrogen, and air. Also, a few ANSYS based studies integrate gas dependent thermal performance with decision making frameworks. The present study addresses these gaps by combining CFD thermal analysis with fuzzy TOPSIS and Monte Carlo sensitivity analysis to identify a suitable filled gas for TN-32B dry cask storage.

3 Methodology

3.1 CFD Modeling

A three-dimensional model of a single TN-32B fuel assembly (FA) was developed in SOLIDWORKS 2020, including the internal fluid domain within the basket to study thermal-hydraulic behavior [27], [28]. The effects of four inert backfill gases—air, nitrogen, argon, and helium—on heat transmission were assessed. With ANSYS FLUENT 2025 R1, thermal simulations were carried out. Figure 2 illustrates the overall workflow, encompassing geometry creation, CFD simulation, and post-processing of thermal results. To improve computational efficiency and capture the important heat transfer process between the fuel rods, and canister filled, a simplified single fuel assembly (FA) model (Figure 3) was used. As the 34 kW of decay heat was evenly distributed among 32 assembly (1.0525 kW per FA), with boundary conditions designed to reflect the exterior cask environment. The model makes the assumptions of geometric symmetry and homogenous material qualities for all FAs. This simplification still makes it possible to compare various filled gases effectively and to estimate peak cladding temperatures with accuracy.

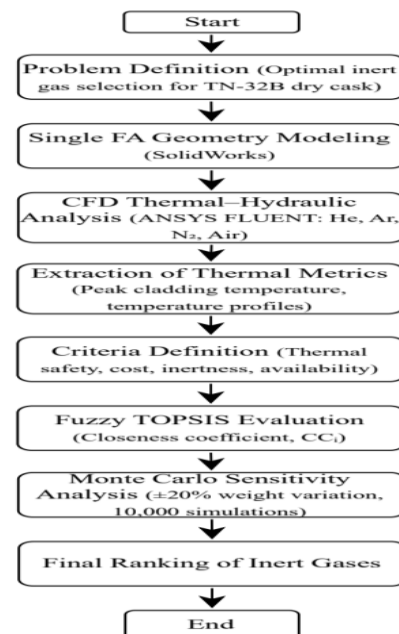


Fig. 2: Thermal hydraulic workflow of a single TN-32B FA in ANSYS FLUENT.

Source: created by the authors

3.1.1 Mesh Sensitivity Analysis

Figure 3 shows a high-quality mesh generated for the full domain, illustrating element distribution and mesh quality to ensure accurate CFD simulation results.

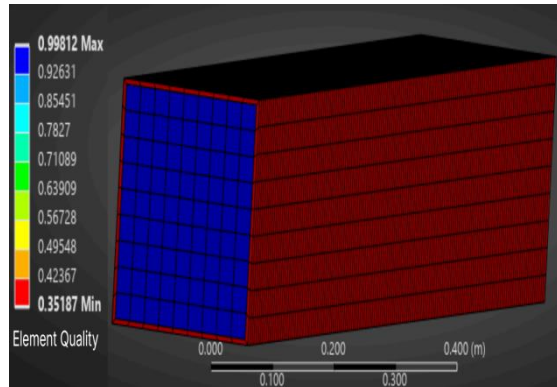


Fig. 3: Mesh quality of the single fuel assembly model for various backfill gases.

Source: created by the authors

For numerical accuracy and minimizing meshing errors, a mesh independence study was conducted. We have applied three mesh sizes: fine (0.008 m), medium (0.025 m), and coarse (0.05 m). We have taken maximum fuel temperature convergence as the primary criterion in the simulation of four filled gases. Table 1 provides a summary of the mesh specifications and matching maximum fuel temperatures (in K).

Table 1. Mesh properties. (Temperature in K)

Element Size (m)	Nodes	Elements	He	N ₂	Ar	Air	% Δ (Medium to Fine)
Coarse (0.05)	3,939	12,417	617	590	619	588	–
Medium (0.025)	19,992	17,082	635	591	621	589	0.17–2.86
Fine (0.008)	411,264	384,262	635	592	622	590	0.09–0.23

Source: created by the authors

Temperatures increased noticeably from coarse to medium mesh, with helium having the biggest difference of 2.86%. Very slight variations were seen in temperature when the mesh was refined further beyond the fine level, which suggests that the solution had successfully converged at the medium meshing. Thus, the medium mesh size was selected for subsequent simulations as it balances accuracy and computational efficiency. Figure 4 shows the

maximum fuel temperature variation with mesh size and highlights helium's higher sensitivity compared to other gases.

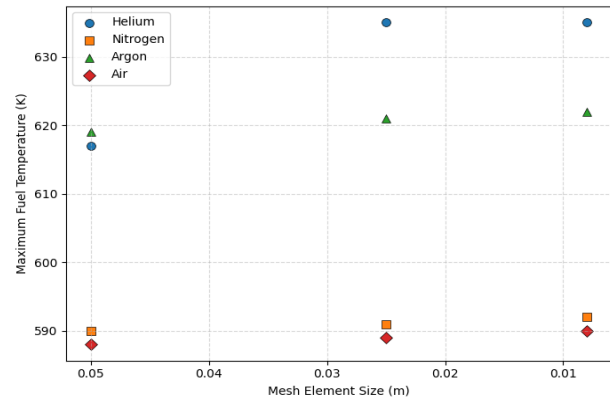


Fig. 4: Maximum fuel temperature for different fill gases versus mesh size.

Source: created by the authors

3.1.2 Mathematical and Physical Models

Surface-to-surface radiation, heat conduction through the materials, and buoyancy-driven natural convection determine the thermal-hydraulic behaviour of the filled gases. For temperature changes below 70 K, the Boussinesq approximation is used to account for density variations in the gas, which is assumed as Newtonian and incompressible.

The flow region is represented by the effective Reynolds number,

$$Re_{eff} = \frac{\rho v D_h}{\mu} \quad (1)$$

Here, the dynamic viscosity is denoted by μ , the gas density by ρ , the hydraulic diameter by D_h , and the characteristic buoyancy-driven velocity by v .

The Reynolds number ranges from 1.7×10^4 to 1.9×10^4 for argon, air, and nitrogen, indicating transitional or weakly turbulent flow, and is roughly 2×10^3 for helium, indicating near-laminar flow, according to the converged CFD data.

The governing equations are: The following describes steady-state flow:

Continuity:

$$\nabla \cdot \mathbf{u} = 0 \quad (2)$$

The velocity vector is denoted by $\mathbf{u}$.

Momentum:

The equation for momentum is written as follows:

$$\rho(\mathbf{u} \cdot \nabla) \mathbf{u} = -\nabla p + \mu \nabla^2 \mathbf{u} + \rho \mathbf{g} \quad (3)$$

Here, μ stands for dynamic viscosity, g for gravitational acceleration, and p for pressure.

Energy:

$$\rho c_p (u \cdot \nabla T) = k \nabla^2 T + q' \cdot v + S_{\text{rad}} \quad (4)$$

Here, c_p = specific heat, T = temperature, k = thermal conductivity, $q' \cdot v$ = volumetric decay heat source, and S_{rad} = radiative heat source.

Turbulence: The SST $k-\omega$ model is used to solve transport equations for the turbulent kinetic energy (k) and the specific dissipation rate (ω) in order to account for buoyancy-driven turbulence. The air, nitrogen, and argon fluxes are simulated using this method. Helium stays close to laminar. The relation denotes the Boussinesq approximation for buoyancy-driven flow:

$$\rho = \rho_0 [1 - \beta(T - T_0)] \quad (5)$$

Here, the local fluid density is denoted by ρ , the density at the reference temperature T_0 by ρ_0 , and the thermal expansion coefficient by β .

Decay Heat: A volumetric source of 34 kW of decay heat (1.0525 kW per assembly) is added to the fuel. Only verification is done using equivalent surface fluxes (lateral: $1.36 \text{ kW} \cdot \text{m}^{-2}$; top/bottom: $23.2 \text{ kW} \cdot \text{m}^{-2}$).

Radiation: The Discrete Ordinates approach is used to treat thermal radiation. With emissivities of UO_2 fuel = 1.0, aluminum basket = 0.77, and gas = 0.8, the surfaces are opaque and grey.

3.1.3 Inert Gas Properties, Boundary Conditions, and Numerical Solution

The simulations were carried out in ANSYS Fluent 2025 R1 using a pressure-based segregated solver with SIMPLE pressure-velocity coupling. To guarantee greater numerical accuracy, second-order discretization techniques were used for the momentum, energy, and turbulence equations; radiation is solved with a first-order scheme. Gravity is $9.8 \text{ m} \cdot \text{s}^{-2}$ in $-y$, pressure is 101,325 Pa, and reference temperature is 298 K for the Boussinesq approximation. Thermal and physical properties of materials are temperature-dependent. Convergence is reached when continuity, momentum, and turbulence residuals fall below 10^{-3} and energy residuals below 10^{-6} . It is confirmed by the stabilization of maximum fuel temperature and heat flux.

3.2 Multi-Criteria Decision-Making Framework: Fuzzy TOPSIS

To identify the most suitable gas for dry cask storage, a fuzzy TOPSIS methodology is used. This approach is favored for its simplicity, efficiency, and capacity to handle several conflicting criteria under uncertainty. The alternatives are denoted as $B_1, B_2, \dots, B_m$. These are assessed against evaluation criteria $D_1, D_2, \dots, D_n$ using a decision matrix, where each entry y_{ij} represents the performance of alternative i with respect to criterion j [29].

In this investigation, the options B_i correlate to the four inert gases—air, argon, nitrogen, and helium—that are taken into consideration during dry cask backfilling. The requirements for D_j are selected to combine CFD-based thermal performance with qualitative operational considerations in order to capture thermal safety, heat removal efficiency, and the practical viability of dry storage operations.

Key word definitions:

Features: All of the criteria D_j symbolises a quality that is used to assess options. Features can be either cost-type (lower is better, such as maximum fuel temperature, economic cost) or benefit-type (greater is better, such as inertness, availability). Other options include the candidates B_i are inert gas alternatives for cask backfilling that are mutually exclusive.

Weights: Every criterion has a weight w_j that corresponds to its relative importance:

$$w_j = W_1, W_2, \dots, W_n \quad (6)$$

The weights are assigned based on literature guidance, with greater emphasis placed on safety-related thermal criteria. To accommodate uncertainty in expert opinion, fuzzy weighting is employed rather than fixed scalar values.

Normalization: To compare criteria on a common scale, vector normalization is used:

$$t_{i,j} = y_{i,j} / \sqrt{\sum_{i=1}^m y_{i,j}^2} \text{ for } i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (7)$$

In an article the author [29] describes the official TOPSIS procedure as follows, using the language already defined:

1. To enable equitable comparisons across all criteria, normalise the decision matrix by converting each attribute into a dimensionless quantity.

2. Create the normalised weighted matrix: Based on their respective relevance, give each criterion $w_j = 1, \dots, j=1, \dots, n$ a weight w_j . The weighted normalised matrix is then created by multiplying each column of the normalised decision matrix by its associated weight. Every component of this matrix is computed as follows:

$$u_{ij} = w_j * t_{ij} \text{ for } i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (8)$$

3. Determine the best options: Using the weighted normalised matrix, find the positive ideal solution (PIS), B^+ , and the negative ideal solution (NIS), B^- . The worst-case performance is represented by the negative ideal, while the best performance attainable across all criteria is represented by the positive ideal. These solutions are formally described as follows using the weighted normalised values:
PIS:

$$B^+ = \{u_1, u_2, u_3, \dots, u_n\}$$

Here

$$u_j^+ = \{\max(u_{ij}) \text{ if } j \in J; \min(u_{ij}) \text{ if } j \in J'\} \quad (9)$$

NIS:

$$B^- = \{u_1, u_2, u_3, \dots, u_n\}$$

Here

$$u_j^- = \{\min(u_{ij}) \text{ if } j \in J; \max(u_{ij}) \text{ if } j \in J'\} \quad (10)$$

where the set of cost characteristics (where lower values are better) is represented by (J') and the set of benefit attributes (where higher values are better) by (J).

4. Determine separation measures: Determine how far each option is from the optimum solutions, both positive and negative. An alternative's distance from the optimal choice is measured by its separation from the positive ideal solution, which can be found using the following formula:

$$P_i^+ = \sqrt{\sum_{j=1}^n (u_{ij} - u_j^+)^2}, i = 1, 2, \dots, m \quad (11)$$

In a similar vein, how each alternative differs from the negative ideal alternative is:

$$P_i^- = \sqrt{\sum_{j=1}^n (u_{ij} - u_j^-)^2}, i = 1, 2, \dots, m \quad (12)$$

5. Determine the degree to which CC_i^* is similar to or close to the optimal answer.

$$C_i^* = P_i^- / (P_i^+ + P_i^-), 0 < C_i^* < 1 \quad (13)$$

Note that when $B_i = B^+$ where $C_i^* = 1$

When $B_i = B^-$ where $C_i^* = 0$

6. Rank the alternatives: The ranking is determined by taking each option's closeness coefficient (CC_i). The inert gas with the greatest value is determined to be the most appropriate for dry cask storage under RNPP operating circumstances. The alternatives are arranged in descending order of CC_i .

This method offers an organised and transparent way to assess inert gas choices while taking uncertainty and conflicting design goals into consideration by fusing temperature data from CFDs with a fuzzy MCDM framework.

4 Results and Interpretation

4.1 CFD Results Analysis

The heat and flow pattern in a single FA was analyzed after the momentum, energy, continuity, and turbulence (k and ω) equations had converged. Pressure, velocity, and temperature contour and vector demonstrate axial heat distribution, turbulence, and buoyancy-driven circulation. According to the SST $k-\omega$ model, the maximum fuel temperatures for argon, nitrogen, and air are 621 K, 591 K, and 589 K, respectively.

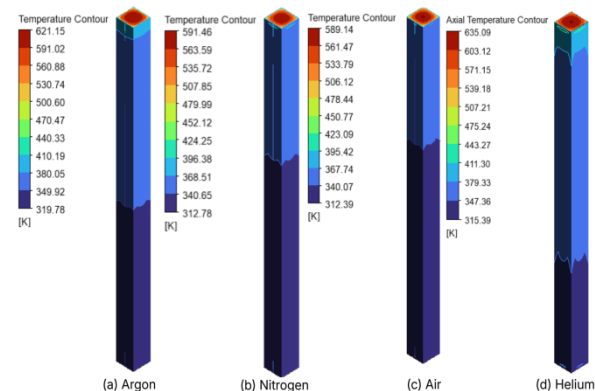


Fig. 5: Axial temperature contours of a single FA for different fill gases under the same operating conditions: (a) argon, (b) nitrogen, (c) air (SST $k-\omega$), and (d) helium (laminar).

Source: created by the authors

Because of limited heat distribution, the temperatures are greater toward the top and bottom axial boundaries (Figure 5a–c). With the laminar flow model, helium reaches 635 K (Figure 5d), and displays a similar axial hotspot pattern which shows

that despite variations in flow regime, thermal behaviour is similar across all four gases.

The gradient from the hot midline to the colder periphery is depicted in a 2D contour in Figure 6 together with the associated temperature variation along the x-direction for the argon as filled gas. Effective heat conduction is demonstrated by the distinct radial gradient in both figures, which also indicates that the mesh and boundary conditions correctly depict the thermal behavior.

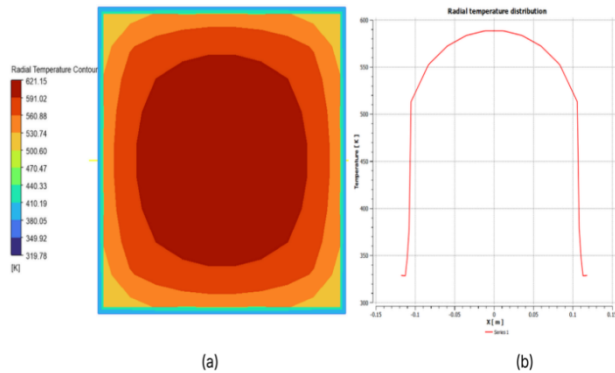


Fig. 6: Radial temperature distribution for the argon as-filled case: (a) 2D temperature contour, and (b) temperature variation along the x-direction.

Source: created by the authors

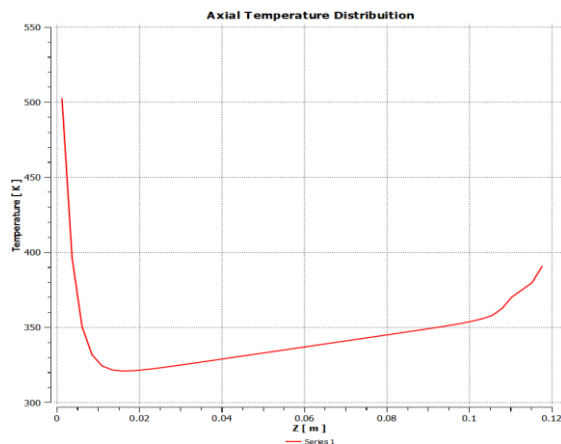


Fig. 7: Temperature profile using argon as the backfill gas along the fuel assembly's y-axis.

Source: created by the authors

The fuel's axial temperature profile is displayed in Figure 7. While the center segment remains rather constant, temperatures rise significantly near the inlet and outlet regions. The steep temperature gradients close to the surfaces show the intense thermal interactions induced by the boundary conditions. The fuel coating reaching the maximum temperatures

while the surrounding fluid stays relatively cooler indicates efficient heat transmission from the fuel to the surrounding coolant.

Figure 8 shows the highest fuel cladding temperatures under the same thermal circumstances for several fill gases (helium, air, nitrogen, and argon). Because of its low density, low Prandtl number, and less buoyancy-driven convection, helium exhibits the highest peak temperature while having a high thermal conductivity.

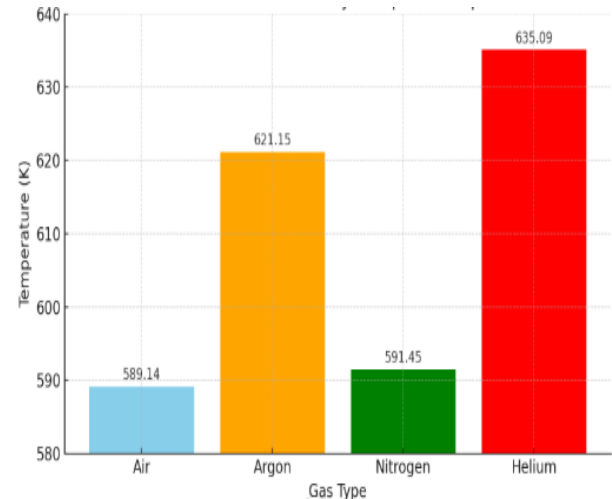


Fig. 8: Peak Cladding Temperatures for different fill gases.

Source: created by the authors

4.2 Result Analysis of Fuzzy TOPSIS Method

Table 2. Decision matrix

Material	Max Temp	Cost/litre	Inertness	Availability
Air	589	1.66	1	5
Helium	635	11.92	5	1
Argon	621	4.72	4	2
Nitrogen	591	1.67	2	4

Source: created by the authors

Using Equation 7, a normalized decision matrix was constructed (Table 2) for all alternatives across the evaluation criteria. Here, maximum fuel temperature and cost per litre are treated as *cost criteria* (lower values preferred), while inertness and availability are *benefit criteria* (higher values preferred). Table 3 provides a summary of the normalized values that were obtained for each possibility and were necessary for the TOPSIS computation.

Table 3. Each criterion's normalized matrix.

Material	Max Temp	Cost/litre	Inertness	Availability
Air	0.4834	0.1277	0.1475	0.7377
Helium	0.5214	0.9163	0.7377	0.1475
Argon	0.5097	0.3631	0.5902	0.2949
Nitrogen	0.4854	0.1285	0.2949	0.5902

Source: created by the authors

Safety was given top importance when choosing the selection of criteria weights (Table 4). The maximum temperature was assigned a weight of 0.40, indicating its crucial significance in upholding thermal limitations and guaranteeing the integrity of the dry cask storage system. Both inertness and fuel cost per litre were given moderate weights of 0.25 in order to balance economic considerations with chemical stability. While cost affects the project budget overall, inertness helps lower the risk of chemical reactions in the storage environment. Availability was assigned a lower weight of 0.10 since it is crucial for supply logistics and practical implementation. This weighing strategy supports a sensible and well-balanced multi-criteria decision-making process by giving safety top priority while preserving operational and financial viability.

Table 4. Weight of all criteria

Criterion	Baseline Weight
Max Temp (K) (cost)	0.40
Cost per litre (cost)	0.25
Inertness (benefit)	0.25
Availability (benefit)	0.10

Source: created by the authors

In the next step, each normalized value is multiplied by its corresponding weight to create the weighted normalized matrix. Table 5 presents this matrix for all alternative options.

Table 5. Weighted normalized matrix

Filled Gas	Max Temp	Cost/litre	Inertness
Air	0.1934	0.0319	0.0369
Helium	0.2086	0.2291	0.1844
Argon	0.2039	0.0908	0.1476
Nitrogen	0.1942	0.0321	0.0737

Source: created by the authors

Figure 9 visualization clearly conveys the decision logic from the fuzzy TOPSIS analysis: the radar chart displays each gas's weighted normalized

performance across the four criteria (maximum fuel temperature, fuel cost, inertness, and availability). The radar chart reveals where each gas gains or loses relative strength.

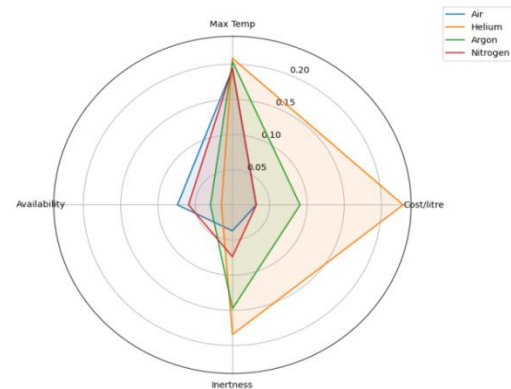


Fig. 9: Radar Chart of Weighted Normalized Performance

Source: created by the authors

Next, equations 9, 10 are used to determine the negative and positive ideal solutions (NIS, PIS). For determining PIS highest values for each criterion is used and to determine the NIS lowest value for every alternative with respect to the criteria is taken.

In the next step, we used equation 11 and 12 to calculate the deviation between each alternative with the NIS and PIS values for every criterion.

In the last steps Equation 13 was used to calculate the closeness coefficient for every criterion and by comparing the closeness coefficient for all alternative gases. The best canister-filled gas is determined and ranking can be done among all the gases. Equation 13 is used to determine each logistics service provider's closeness coefficient. The results are used to rank the options, as indicated in Table 6.

Table 6. TOPSIS analysis results.

Filled Gas	P ⁺	P ⁻	Closeness (CCi)	Rank
Air	0.1475	0.2106	0.588	3
Helium	0.2106	0.1475	0.412	4
Argon	0.086	0.162	0.653	2
Nitrogen	0.111	0.215	0.659	1

Source: created by the authors

Based on the fuzzy TOPSIS evaluation, nitrogen emerges as the most suitable inert gas for the TN-32B dry cask application, achieving the highest closeness coefficient ($C_i^+ =$

0.659). Its well-balanced performance in terms of availability, price, inertness, and thermal behaviour is reflected in this result. Argon ranks second ($C_i^+ = 0.653$), offering strong inertness and moderate cost, making it a competitive alternative. Air comes third ($C_i^+ = 0.588$), benefiting from excellent availability and low cost, though with lower chemical stability. Because of its high price and restricted supply, helium comes in last ($C_i^+ = 0.412$) despite having higher thermal conductivity and inertness. Overall, the decision matrix identifies nitrogen as the most viable inert gas option for TN-32B dry cask storage, with argon and air serving as practical alternatives depending on operational and economic priorities.

The bar chart in Figure 10 shows that Argon and nitrogen have almost the same highest closeness coefficient 0.653 and 0.659, respectively, making it difficult to choose the best overall choice. Air is on rank third while Helium ranks lowest. Thus probabilistic Monte Carlo analysis was conducted to see the robustness of the ranking.

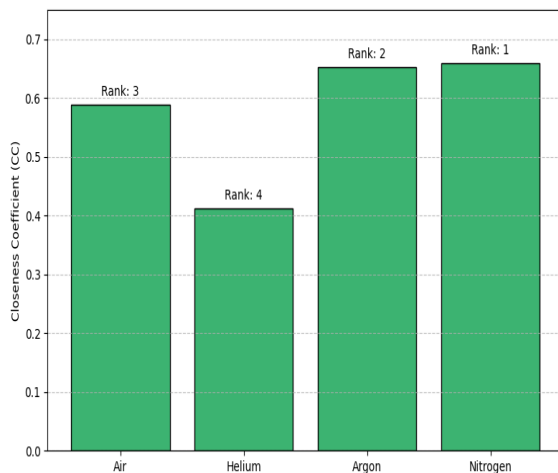


Fig. 10: Deterministic TOPSIS Closeness Coefficients Ranking.

Source: created by the authors

4.2.1 Stochastic Analysis of Weight Uncertainty

To evaluate the robustness of the MCDM rankings under uncertainty, a Monte Carlo simulation was conducted in which the decision criteria weights were randomly perturbed within $\pm 20\%$ of their baseline values (Table 7). A total of 10,000 realizations were performed to ensure statistical stability. The $\pm 20\%$ variation range was selected in accordance with established practice in Monte

Carlo-based MCDM sensitivity analyses, as it represents realistic uncertainty in stakeholder preferences while preserving the relative dominance of the criteria [18], [20].

Table 7. Baseline weights and $\pm 20\%$ perturbation bounds used in the Monte Carlo sensitivity for 10000 simulation.

Gas	Mean CCi	Std. CCi	95% CI (Lower)	95% CI (Upper)
Air	0.583	0.038	0.511	0.653
He	0.417	0.038	0.347	0.489
Ar	0.681	0.009	0.662	0.696
N2	0.648	0.034	0.581	0.712

Source: created by the authors

Table 7 presents the baseline weights for four criteria used in the fuzzy TOPSIS analysis along with their $\pm 20\%$ perturbation bounds applied during a 10,000-run Monte Carlo sensitivity simulation. The criteria include two cost factors—Maximum Fuel Temperature and Cost per litre—and two benefit factors—Inertness and availability.

The results show that Argon consistently ranks as the best material, achieving the highest mean closeness coefficient (Mean CCi = 0.6812) with low variability (Std CCi = 0.0090) and topping the ranking in 7,960 simulations. Nitrogen follows as a strong candidate with a mean CCi of 0.6471 and 2,040 first-place rankings. Air and Helium perform less favorably, with lower mean CCi scores (0.5825 and 0.4175 respectively) and never achieving the top rank in any simulation (Figure 11).

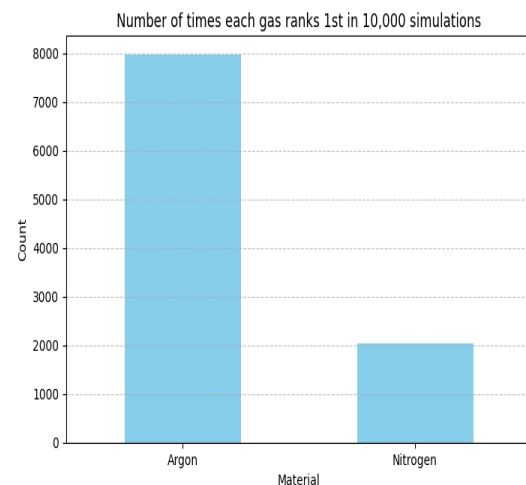


Fig. 11: Percentages of time each material ranked 1st.

Source: created by the authors

Although deterministic TOPSIS suggests nitrogen as the top-ranked option, this ranking is sensitive to small perturbations in criteria weights. The following Monte Carlo study shows that argon exhibits higher robustness, consistently dominating across a broad range of probable preference configurations.

4.2.2 Robustness Analysis of Monte Carlo TOPSIS Results under Weight Uncertainty

A Monte Carlo-based TOPSIS technique with 10,000 realizations that took criteria weight uncertainty into account was used to assess the robustness of inert gas selection. With a tight 95% confidence range of 0.662–0.696 and the greatest mean closeness coefficient (0.681), Argon demonstrated both strong performance and resilience to changes in stakeholder preferences. With a mean value of 0.648, nitrogen came in second, but its broader confidence range (0.581–0.712) suggested that it was more sensitive to weight uncertainty. Despite its advantageous thermal characteristics, helium continuously ranked lowest, whereas air and helium performed worse overall. Together with argon's distinct separation from air and helium, the small overlap between the argon and nitrogen confidence intervals statistically supports argon as the most reliable option in the simulated decision space.

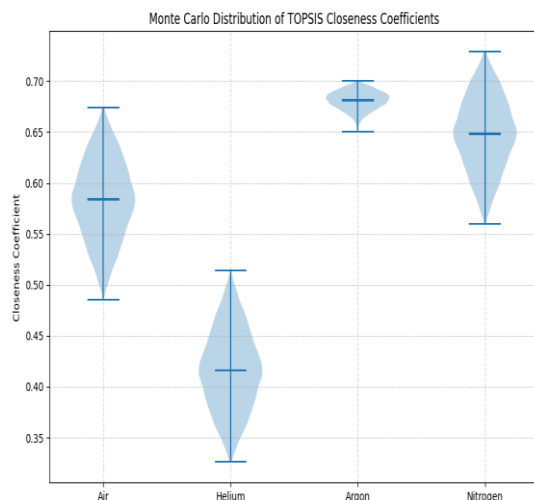


Fig. 12: Monte Carlo Distributions of TOPSIS Closeness Coefficients for Candidate Inert Gases.
Source: created by the authors

The probability distributions of the TOPSIS coefficients obtained from the 10,000 Monte Carlo simulations are shown in Figure 12. Argon shows the highest median value and the smallest distribution

which means superior performance as well as stability. Whereas nitrogen shows competitive but more unpredictable outcomes. Air and helium have lower median values but helium performs the worst throughout the simulations.

4.2.3 Rank Acceptability and Dominance Analysis

Pairwise dominance probabilities measure the chance that one option will perform better than another across all Monte Carlo simulations. It was calculated to further evaluate robustness. Table 8 displays the calculated dominance probability matrix.

Argon demonstrates near complete dominance over air and helium, outperforming them in 100% of simulations. But Argon dominates nitrogen in approximately 79.6% of simulations. Nitrogen consistently dominates air and helium but is outperformed by argon in the majority of cases. Air and helium do not dominate any alternative under the given uncertainty limit. These dominance relationships confirm that argon is not only the highest performing option on average, but also the most robust across a wide range of stakeholder preference's data.

Pairwise dominance probabilities derived from Monte Carlo TOPSIS simulations. Here, values greater than 0.5 indicate dominance of the row alternative over the column alternative.

Table 8. Pairwise dominance probability matrix showing the likelihood of alternative i outperforming alternative j ($P(i > j)$).

Dominating gas ↓ / Compared gas →	Air	Helium	Argon	Nitrogen
Air	—	0.992	0	0
Helium	0.008	—	0	0
Argon	1	1	—	0.796
Nitrogen	1	1	0.204	—

Source: created by the authors

4.2.4 Monte Carlo Convergence Assessment

Figure 13 shows the convergence behavior of the Monte Carlo simulations by showing the running mean of the TOPSIS closeness coefficient for each filled gas as a function of the number of simulations. All alternatives show rapid stabilization of the running mean within approximately 1,000–2,000 simulations, after which only negligible fluctuations are observed. The convergence trends confirm that a total of 10,000 simulations is sufficient to ensure

statistical stability. Argon's durability is further reinforced by its limited variability as it converges to the maximum stable mean value. On the other hand, as indicated by their broader confidence ranges and higher standard deviations, air, nitrogen, and helium converge to lower mean values with bigger variations.

4.2.5 Overall Interpretation

Argon is the most reliable inerting gas when considering combined thermal, economic, inertness, and availability factors. This is supported by the convergence behaviour, confidence intervals, rank acceptance, and dominance probability. Although nitrogen is a good secondary option, it is less resilient than argon due to its increased susceptibility to preference ambiguity. Throughout the investigated decision space, air and helium constantly perform better.

5 Result Validation

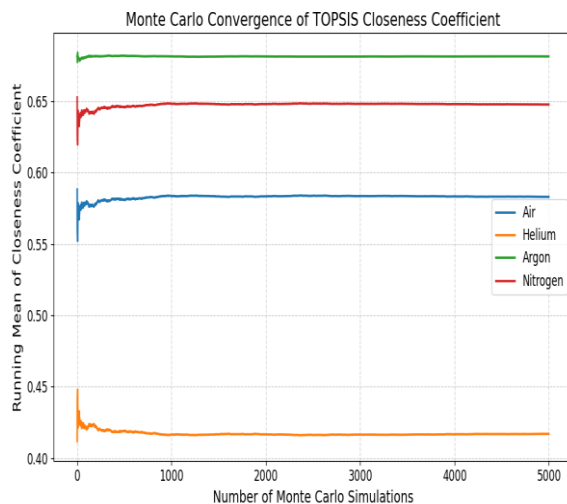


Fig. 13: Monte Carlo convergence of TOPSIS closeness coefficients.

Source: created by the authors

The consistency of anticipated fuel assembly (FA) temperatures with previous experimental results, previous CFD analyses, and relevant licensing criteria was examined in order to evaluate the numerical approach's dependability. ANSYS Fluent was used to perform steady-state simulations with a fuel assembly-level decay heat of 34 kW. Peak temperatures for the fuel assembly were predicted for air to be 589 K, 621 K for argon, 591 K for nitrogen,

and 635 K for helium. This pattern appears to be consistent with the expected physical behaviour of the fill gases, which is impacted by differences in their thermophysical properties. Helium has the highest temperature for its low density and the buoyancy driven flow characteristics.

Instead of precisely following the reference simulation, our evaluation emphasizes agreement in general trends and thermal boundaries. The expected peak temperature for helium was contrasted with [30], which showed that a complete TN32 system with 32 FAs and a 38.44 kW decay heat could reach a maximum temperature of 617 K. The observed difference is primarily due to the differences simplification of geometry and heat distribution of a full cask-scale.

Further comparison with the CFD study [31], which investigated a helium-filled dry cask containing 21 PWR assemblies under a 20–25 kW heat load, shows close similarity for decay heat scaling. Similarly, in NUREG/CR-7260 for a TN32-B cask, provide an additional reference envelope within which the present predictions reasonably fall when differences in geometry, modeling scope, and boundary conditions are considered [32].

Table 9. Predicted temperature limitations for fuel assemblies compared to typical references

Type of Comparison	Fill Gas	Conditions	Benchmark Temp (K)	This Study (K)	Difference (%)
Literature comparison	Helium	32 FAs, 38.44 kW	617	576	-7
Experimental reference	Helium	TN32-B, 30.5 kW	481	576	+20
CFD benchmark	Helium	21 PWR FAs	590	576	-2
Licensing limit	Helium	FSAR design limit	649	576	-11
	Air			589	-9
	Argon			621	-4
	Nitrogen			591	-9

Source: [30], [31], [32], [33], [34].

Every calculated temperature stays below the Holtec FSAR's 649 K design limit [33]. For all gas studied, the resulting safety margins vary from around 2% for helium to roughly 9% for air indicating regulatory compliance. A mesh sensitivity

analysis revealed that the maximum temperature differed by just under 0.3 percent between the medium and fine mesh sizes, which further confirms the numerical correctness. Table 9 summarizes a comparison with benchmark studies and licensing limits. For examples with significantly different setups, the anticipated temperatures vary within 20%. For conditions that are nearly identical, they change by less than 7%. Overall, these findings support the stability and physical consistency of the numerical framework, offering a solid foundation for additional parametric research and multi-criteria decision analysis.

6 Limitation

Several simplifying assumptions are included in this study:

- Heat transfer between assemblies and full three-dimensional effects were not taken into account because the CFD simulation was conducted on a single fuel assembly rather than the entire 32-unit cask.
- The thermal analysis was restricted to steady-state settings; it did not take into account seasonal variations in ambient temperature or transient factors that can have an impact on long-term storage behavior.
- A small number of criteria with defined weights were utilized in the fuzzy TOPSIS evaluation; these weights could vary depending on operational, safety, or financial priorities.

7 Conclusion

This study used a fuzzy TOPSIS decision-making approach in conjunction with CFD simulations to assess the optimal inert gas for storage and investigate the thermal performance of the TN-32B dry cask. Maximum fuel temperatures for air were found to be of 689 K, 635 K for helium, 621 K for argon inert gas, and 591 K for nitrogen were found in simulations of a single FA with a 34 kW decay heat load. The cask's thermal safety under the investigated conditions was confirmed by the fact that all readings were below the 649 K regulation limit.

Argon was the most reliable option when using fuzzy TOPSIS with Monte Carlo sensitivity analysis on four criteria: maximum fuel temperature, petrol

cost, inertness, and availability. It ranked first in around 80% of the 10,000 simulations and also had the highest mean closeness coefficient of 0.681. Whereas in 20% of cases, nitrogen ranked first with a mean CCI of 0.647. With mean CCI values of 0.582 and 0.418, respectively, air and helium were less favorable and never reached the top rank. Thus, argon and nitrogen provide the best overall balance of thermal performance, affordability, inertness, and availability.

The CFD–MCDM framework created here can assist future fuel management at RNPP and similar facilities by offering a methodical approach to find the suitable conditions for dry cask storage. To further extend this study, future research should incorporate full 32 FAs simulations, transient thermal analysis, and experimental validation.

This study has some limitations as a single fuel assembly operating in steady-state settings served as the basis for the investigation. It might not have adequately captured 3D thermal interactions in an entire cask. Realism would be increased by extending the model to a full 32 FAs configuration. Material properties, more intricate radiation exchange, and transient thermal effects can also be included. Lastly, to facilitate automatic weight learning and improved stakeholder preference adaption, machine learning or bio-inspired optimization methods, like neural networks or genetic algorithms, into fuzzy MCDM frameworks can be applied.

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