Multi-objective Optimization Methods for Nuclear Reactor Shielding Structures under Complex Constraints

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Abstract

The optimization design of nuclear reactor shielding structures constitutes a typical complex constrained multi-objective global optimization problem. This study establishes an optimization design methodology that couples a global optimization algorithm with three-dimensional parallel SN codes and Monte Carlo codes, thereby implementing constraints on optimization parameters and sub-objectives throughout the optimization process, and applies this methodology to the optimization design of shielding structures for both marine reactors and space reactors. The research demonstrates that for marine reactor shielding problems, the approach of employing shielding weight and volume as optimization objectives while treating other radiation-related sub-objectives as constraints is more appropriate for the optimization design of marine reactor shielding, capable of achieving superior optimization results. For the optimization design of shadow shielding structures in space reactors, a structure distinct from traditional design approaches was obtained.

Full Text

Multi-Objective Optimization Method for Nuclear Reactor Shielding Structures with Complex Constraints

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Abstract

[**Background**] The nuclear reactor shielding structure serves as a critical barrier that encloses radioactive materials to protect personnel and equipment. Its design represents a typical multi-objective global optimization problem characterized by complex constraint relationships among various sub-objectives and shielding parameters. [**Purpose**] This study addresses the multi-objective optimization problem with complex constraints for nuclear reactor shielding structures. [**Methods**] We investigate the Adaptive Weight Genetic Algorithm, Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), Non-dominated Sorting Genetic Algorithm II (NSGA-II), and Non-dominated Sorting Genetic Algorithm III (NSGA-III). By coupling these multi-objective optimization algorithms with the three-dimensional parallel SN code HYDRA and the Monte Carlo code MCNP, we develop an innovative constraint-handling method for optimization parameters and sub-objectives, which is then applied to the optimized design of shielding structures for marine and space nuclear reactors. [**Results**] The optimization studies demonstrate that for marine reactor shielding, treating weight and volume as optimization objectives while constraining other radiation-related sub-objectives yields superior results. For space reactor shadow shield optimization, the method produces structures that differ significantly from traditional design approaches. [**Conclusion**] For marine reactor shielding problems, the approach of using shielding weight and volume as optimization objectives with radiation-related sub-objectives as constraints is more suitable and achieves excellent optimization results. The global optimization of space reactor shielding structures reveals that the optimal configuration is LiH, W-B4C, LiH, which substantially differs from the conventional heavy-light-heavy material design philosophy.

Keywords: Marine nuclear reactor; Space nuclear reactor; Radiation shielding; Multi-objective optimization; Radiation protection

1. Introduction

Nuclear reactor shielding structures are essential barriers that enclose radioactive materials to protect personnel and equipment. Shielding design must simultaneously reduce radiation levels to As Low As Reasonably Achievable (ALARA) levels while minimizing shielding weight and volume to enhance the mobility and economics of nuclear power systems. This optimization is particularly critical for marine nuclear power and space reactor applications.

The design of nuclear reactor shielding structures represents a typical multi-objective global optimization problem with complex constraint relationships among sub-objectives and shielding parameters, making it difficult for traditional optimization algorithms to solve effectively. Early researchers proposed linear weighting methods to handle multi-objective problems by converting them into single-objective formulations, but these approaches require empirically determined weights that lack adaptability. More recently, researchers have developed multi-objective optimization methods combining non-dominated sorting genetic algorithms with one-dimensional SN code ANISN and Monte Carlo code MCNP. While these methods have been successfully applied to marine nuclear power shielding optimization and effectively solve multi-objective global search problems, they lack consideration of complex constraints, particularly sub-objective constraints, limiting their applicability.

This paper addresses the complex constrained multi-objective optimization problem for nuclear reactor shielding structures by investigating the Adaptive Weight Genetic Algorithm, MOEA/D, NSGA-II, and NSGA-III. By coupling these multi-objective optimization algorithms with the three-dimensional parallel SN code HYDRA and Monte Carlo code MCNP, we innovatively develop constraint-handling methods for optimization parameters and sub-objectives, applying them to shielding structure optimization for marine and space reactors.

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2. Optimization Model

Reactor shielding structure optimization involves not only radiation-related physical quantities such as dose, particle flux, and energy flux, but also shielding weight and volume. Additionally, constraints exist between shielding components, and sub-objectives have limit requirements. The theoretical model is characterized as follows:

$$\min \quad F(x) = [f_1(x), f_2(x), \dots, f_m(x)] \tag{1}$$

$$\text{s.t.} \quad g_i(x) \le F_{i,0}, \quad i = 1, 2, \dots, m \tag{2}$$

$$h_k(x) \le 0, \quad k = 1, 2, \dots, p \tag{3}$$

$$v_l(x) = 0, \quad l = 1, 2, \dots, q \tag{4}$$

$$x_j^L \le x_j \le x_j^U, \quad j = 1, 2, \dots, n \tag{5}$$

where x is an n-dimensional variable vector in the decision space; $f_i(x)$ represents optimization sub-objectives; $F_{i,0}$ denotes sub-objective limits; x_j^L and x_j^U are lower and upper bounds for optimization variables; h_k and v_l represent inequality and equality constraints on decision variables, respectively.

For marine and space nuclear power shielding design problems, the theoretical model in Eq. (1) is specified as follows: Using the "Savannah" marine reactor as an example, the sub-objective values at various shielding locations are shown in Table 1 [8]. This study uses the original Savannah design values as constraints for optimization.

Table 1 Sub-objective values of the Savannah ship reactor

Sub-objective	Location	Physical Quantity	Limit Value
F1	Pressure vessel	Fast neutron fluence rate ($n \cdot cm^{-2} \cdot s^{-1}$)	1.06×10^{9}
F2	Primary shielding outer surface	Fast neutron fluence rate ($n \cdot cm^{-2} \cdot s^{-1}$)	5.80×10^{3}
F3	Primary shielding outer surface	γ-fluence rate ($MeV \cdot cm^{-2} \cdot s^{-1}$)	8.02×10^{12}
F4	Primary shielding outer surface	Thermal neutron fluence rate ($n \cdot cm^{-2} \cdot s^{-1}$)	7.38×10^{2}
F5	Primary shielding outer surface	Dose rate ($Sv \cdot h^{-1}$)	1.24×10^{-1}
F6	Secondary shielding outer surface	Thermal neutron fluence rate ($n \cdot cm^{-2} \cdot s^{-1}$)	6.03×10^{1}
F7	Secondary shielding outer surface	γ-fluence rate ($MeV \cdot cm^{-2} \cdot s^{-1}$)	5.65×10^{8}
F8	Secondary shielding outer surface	Dose rate ($Sv \cdot h^{-1}$)	3.60×10^{-5}
F9	Shielding weight	Weight (ton)	-
F10	Shielding volume	Volume (m^3)	-

Unlike marine reactors, space reactor shielding primarily concerns shielding weight, γ-energy deposition in Si materials at the dose plane, and equivalent fast neutron fluence rate. Based on El-Genk et al. [9], the limits for neutron fluence and γ-ray energy deposition at the dose plane are 1.0$\times 10^{12}$ nvt (fast neutron fluence >0.1 MeV) and 1.0 Mrad. Considering a 10-year operational lifetime, the limits for fast neutron fluence rate and γ-ray energy deposition rate in this study are 3.17$\times 10^{3}$ $\mathrm{n \cdot cm^{-2} \cdot s^{-1}}$ and 3.17$\times 10^{-3}$ $\mathrm{rad \cdot s^{-1}}$, respectively.

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3. Constraint Handling Methods

Optimization variable constraints can be implemented through inequality or equality constraints for most reactor shielding geometry and material requirements. For sub-objective constraints, we employ a lethal gene method, defining the sub-objective function for optimization individuals as follows:

$$f_i'(x) = \begin{cases} f_i(x), & \text{if } g_i(x) \le F_{i,0} \\ \text{lethal gene}, & \text{if } g_i(x) > F_{i,0} \end{cases}$$

Through this treatment, individuals violating constraints are eliminated during the optimization process.

For the Savannah marine reactor shielding problem, this paper investigates two optimization approaches: Method 1 treats all 10 sub-objectives from Table 1 as optimization objectives; Method 2 uses weight and volume as optimization objectives while treating other sub-objectives as constraints.

Space reactor shielding differs from marine reactors, with weight being the primary concern. Therefore, the multi-objective problem in Eq. (1) is converted to a single-objective problem, with constraint handling consistent with the Savannah marine reactor approach.

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4. Optimization Algorithms

4.1 Single-Objective Global Optimization Algorithm

Genetic algorithms achieve global optimization through evolutionary operations including selection, crossover, and mutation, effectively avoiding local optima encountered by gradient-based methods. This study employs an elitist genetic algorithm for global optimization, using binary encoding for individuals, tournament selection, and two-point crossover operators to achieve global search through evolutionary iterations [10].

4.2 Multi-Objective Global Optimization Algorithms

This study examines the performance of the Adaptive Weight Genetic Algorithm, MOEA/D, NSGA-II, and NSGA-III for nuclear reactor shielding structure optimization. The principles of these multi-objective optimization algorithms are briefly described below:

(1) Adaptive Weight Genetic Algorithm. This algorithm transforms multi-objective problems into single-objective problems using adaptive weights during solution:

$$w_i = \frac{1}{f_i^{\max} - f_i^{\min}}$$

where $f_i^{\max}$ and $f_i^{\min}$ are the maximum and minimum values of the i-th sub-objective in the current population, respectively. The optimization objective is then expressed as:

$$\min \sum_{i=1}^{m} w_i f_i(x)$$

During evolutionary search, weights are iteratively updated, and the Pareto set is continuously improved through genetic operators (selection, crossover, mutation), thereby achieving multi-objective global optimization.

(2) MOEA/D Algorithm [11]. MOEA/D solves multi-objective optimization problems by decomposing them into a series of single-objective sub-problems. Three main transformation methods exist: weighted sum, boundary intersection, and Tchebycheff aggregation. This study employs the Tchebycheff approach, where sub-problems are defined as:

$$\min_{x\in\Omega} g^{te}(x|\lambda, z^*) = \max_{1\le i\le m} \{\lambda_i |f_i(x) - z_i^*|\}$$

where $\lambda = (\lambda_1, \dots, \lambda_m)$ is a weight vector with $\sum_{i=1}^{m} \lambda_i = 1$ and $\lambda_i \geq 0$; $z^* = (z_1^*, \dots, z_m^*)$ is a reference point with $z_i^* = \max\{f_i(x)|x \in \Omega\}$ for each $i = 1, \dots, m$. For each Pareto optimal solution x^* of Eq. (6), there exists a weight vector λ such that x^* is optimal for Eq. (7). Conversely, each optimal solution of Eq. (7) is a Pareto optimal solution of the original multi-objective problem. Therefore, different Pareto optimal solutions can be obtained by solving single-objective optimization problems with different weight vectors defined by the Tchebycheff decomposition method.

The optimization process proceeds as follows: First, initialize the external population EP and calculate Euclidean distances between weight vectors. Initialize the set $B(i) = \{i_1, \dots, i_T\}$ where $\lambda^{i_1}, \dots, \lambda^{i_T}$ are the T closest weight vectors to λ^i. Randomly generate an initial population $\{x^1, \dots, x^N\}$ and initialize

$z = (z_1, \dots, z_m)^T$. Update population z and neighboring solutions: randomly select indices k and l from $B(i)$, generate a new solution y from x^k and x^l through genetic operators, and apply heuristic improvement to generate y'. Update z using the rule: for each $i = 1, \dots, m$, if $z_i > f_i(y')$, set $z_i = f_i(y')$. Update neighboring solutions: for each index $j \in B(i)$, if $g^{te}(y'|\lambda^j, z) \leq g^{te}(x^j|\lambda^j, z)$, set $x^j = y'$. Finally, update EP: remove all vectors dominated by $F(y')$ from EP, and add $F(y')$ to EP if no other vector dominates it.

(3) Non-dominated Sorting Algorithms [12-13]. Non-dominated sorting assigns ranks to all solutions in a population. A solution is non-dominated if no other solution in the population has better values for all objective functions. Non-dominated solutions receive rank 1. After removing rank-1 solutions, the non-dominated solutions in the remaining population receive rank 2, and this process continues until all solutions are ranked.

This study employs NSGA-II and NSGA-III for multi-objective optimization. Both algorithms follow similar procedures: For generation t with population P_t of size N, generate offspring population Q_t through selection, crossover, and mutation. The selection operation incorporates elitist strategy to preserve superior populations. The combined population $R_t = P_t \cup Q_t$ has $2N$ individuals, from which N individuals are selected for the next generation P_{t+1}. This selection involves two steps: First, perform non-dominated sorting on R_t, denoting the set of solutions with rank i as F_i. Then, starting from F_1, select individuals from R_t into P_{t+1} in ascending order of non-domination rank until the first set F_j makes $|P_{t+1}| > N$. Second, select individuals from F_j with the lowest population density into P_{t+1} until $|P_{t+1}| = N$.

The main difference between NSGA-II and NSGA-III lies in the second step: NSGA-II uses crowding distance to maintain diversity in F_j, selecting individuals with larger crowding distances, while NSGA-III selects based on uniformly distributed reference points on a normalized hyperplane.

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5. Application and Results

5.1 Marine Reactor Shielding Optimization

5.1.1 Optimization Parameters The Savannah nuclear icebreaker employs a pressurized water reactor with low-enrichment UO_2 fuel and a design power of 69 MW. The core length is 229.2 cm, with an active fuel length of 167.6 cm and an equivalent core diameter of 157.6 cm. The reactor features 18 layers of structure surrounding the core, with an annular cavity between primary and secondary shielding, as shown in Figure 1 [Figure 1: see original paper].

The pressure vessel and air insulation layer are considered fixed structures, leaving 13 optimizable parameters in the shielding structure, with corresponding materials and parameters listed in Table 2 .

Table 2 Optimization parameters and ranges

Material	Initial value (cm)	Optimization range (cm)
Reactor core	-	-
Fe (Pressure vessel)	-	-
Air (Insulating layer)	-	-
H_2O (Shield water tank)	-	-
Fe (Vessel wall)	-	-
Thermoscreen	-	-
Primary shielding	-	-
Annular cavity	-	-
Secondary shielding	-	-
Air (Counting area)	-	-

Transport calculations employ the three-dimensional parallel SN code Hydra with S16-P3 approximation and cross-sections from the BUGLE-96 database based on ENDF/B-VI [14-15].

5.1.2 Optimization Results **(1) Method 1.** We statistically analyzed the improvement of each sub-objective for Method 1 results, using Eq. (7) for evaluation:

$$\eta_{ij} = \frac{f_{i,\text{init}} - f_{i,\text{opt}}^{j}}{f_{i,\text{init}}} \times 100\%$$

where $f_{i,\text{opt}}^{j}$ is the value of the i-th sub-objective for the j-th optimized individual, and $f_{i,\text{init}}$ is the initial value of the i-th sub-objective.

The statistical results from Eq. (7) indicate that when all 10 sub-objectives are treated as optimization objectives, MOEA/D performs best, achieving the largest improvement across sub-objectives with some individuals improving by over 80%. NSGA-III ranks second with some individuals improving by over 60%, while NSGA-II and the adaptive weight genetic algorithm show the weakest performance with some individuals improving by over 50%. This aligns with the optimization principles of these algorithms, where MOEA/D and NSGA-III exhibit advantages over NSGA-II when dealing with many objectives.

(2) Method 2. Method 2 uses shielding volume and weight as optimization objectives while treating other sub-objectives as constraints. The Pareto fronts from Method 2 are shown in Figure 2 [Figure 2: see original paper]. For the two-objective case, NSGA-II performs best, NSGA-III ranks second, while the adaptive weight genetic algorithm and MOEA/D perform worst.

For nuclear reactor shielding multi-objective optimization, when radiation-related indicators (F1-F8) satisfy their limits, design emphasis naturally shifts to weight and volume sub-objectives. Therefore, we compare the optimal weight and volume individuals from both methods in Table 3 .

Table 3 Optimal weight and volume comparison between Methods 1 and 2

Individual	Weight (t)	Volume (m^3)
(a)	-	-
(b)	-	-
(c)	-	-
(d)	-	-
(e)	-	-
(f)	-	-
(g)	-	-
(h)	-	-
(i)	-	-
(j)	-	-

Note: (a), (b): Minimum weight and volume individuals from adaptive weight genetic algorithm; (c), (d): Minimum weight and volume individuals from MOEA/D; (e), (f): Minimum weight and volume individuals from NSGA-II; (g), (h): Minimum weight and volume individuals from NSGA-III; (i), (j): Minimum weight and volume individuals from Method 2 using NSGA-II.

Table 3 shows that Method 2 yields superior results for both weight and volume sub-objectives, demonstrating that Method 2 with NSGA-II is more suitable for nuclear reactor shielding multi-objective optimization. The optimized solutions compared with initial values are shown in Figure 3 [Figure 3: see original paper].

Figure 3 Initial design and optimal designs from Method 2. (a) initial design; (b) individual i; (c) individual j

Figure 3 reveals that optimized structures show clear objective-oriented characteristics compared to the initial design. For the minimum-weight individual (i), the secondary shielding is significantly reduced, achieving a 26% weight reduction. For the minimum-volume individual (j), the structure shows noticeable contraction compared to both the initial design and the minimum-weight individual, achieving a 3.5% volume reduction.

5.2 Space Reactor Shielding Optimization

5.2.1 Optimization Parameters Unlike marine reactors, space reactor shielding aims to protect electronic components at the dose plane from core neutrons and γ-rays while minimizing shielding weight to reduce launch costs. A typical space reactor structure is shown in Figure 4 [Figure 4: see original paper], with a power level of 100 kWth, equivalent diameter of 18 cm, and height of 16 cm.

The space reactor shadow shield has a 12° inclination angle, using LiH and W-B4C composite materials with 90% enriched ^{10}B. The shielding arrangement is LiH, W-B4C, LiH, W-B4C, LiH, with thicknesses denoted as t_1, t_2, t_3, t_4, t_5. To control total shielding thickness, inequality constraints are applied during optimization: $\sum_i t_i \leq$ limit.

Due to the inability of deterministic codes to describe the complex geometry of space reactors, transport calculations employ the Monte Carlo code MCNP using DE/DF cards to tally equivalent neutron fluence in Si materials [16-18]. The single-objective genetic algorithm uses a population size of 50 and 100 generations, with convergence achieved by generation 70 based on fitness function evolution.

5.2.2 Optimization Results The initial individuals generated by the genetic algorithm and the optimized shielding weight and parameters are shown in Table 4 , demonstrating significant weight reduction through algorithmic optimization.

Table 4 Optimization parameters and results

Parameter	Initial value	Optimization result	Parameter range (cm)
Weight (kg)	-	-	-
t_1 (cm)	-	-	-
t_2 (cm)	-	-	-
t_3 (cm)	-	-	-
t_4 (cm)	-	-	-
t_5 (cm)	-	-	-

The initial and optimized shielding structures are shown in Figure 5 [Figure 5: see original paper]. The global optimization reveals that the optimal shielding structure for space reactors is LiH, W-B4C, LiH, which differs substantially from the traditional design approach of using heavy-light-heavy material configurations [1].

Figure 5 Optimization of space reactor shielding structure

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6. Conclusion

This study establishes a nuclear reactor shielding structure optimization method coupling global optimization algorithms with three-dimensional parallel SN and Monte Carlo codes, applying it to marine (Savannah) and space reactor shielding optimization. The research demonstrates that: (1) When optimizing many sub-objectives, MOEA/D performs best, NSGA-III ranks second, while NSGA-II and adaptive weight genetic algorithm perform worst; (2) When optimizing few objectives, NSGA-II performs best; (3) For marine reactor shielding, treating weight and volume as objectives with radiation sub-objectives as constraints is most suitable, yielding excellent results; (4) Global optimization of space reactor shadow shield structures reveals an optimal configuration of LiH, W-B4C, LiH, significantly different from traditional heavy-light-heavy material design philosophies.

Author Contributions

Qianqian Chu: Developed research methodology and approach, drafted manuscript.
Bin Liu: Responsible for shielding structure optimization design and data analysis, critically reviewed intellectual content.
Cheng Huang: Provided guidance on shielding structure optimization methods.
Ming Zhang: Provided guidance on research methodology and theoretical direction.

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Note: Figure translations are in progress. See original paper for figures.