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Original Article

Radiation shielding optimization design research based on bare-bones particle swarm optimization algorithm

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A B S T R A C T

In order to further meet the requirements of weight, volume, and dose minimization for new nuclear energy devices, the bare-bones multi-objective particle swarm optimization algorithm is used to automatically and iteratively optimize the design parameters of radiation shielding system material, thickness, and structure. The radiation shielding optimization program based on the bare-bones particle swarm optimization algorithm is developed and coupled into the reactor radiation shielding multi-objective intelligent optimization platform, and the code is verified by using the Savannah benchmark model. The material type and thickness of Savannah model were optimized by using the BBMOPSO algorithm to call the dose calculation code, the integrated optimized data showed that the weight decreased by 78.77%, the volume decreased by 23.10% and the dose rate decreased by 72.41% compared with the initial solution. The results show that the method can get the best radiation shielding solution that meets a lot of different goals. This shows that the method is both effective and feasible, and it makes up for the lack of manual optimization.

1. Introduction

With their high energy density, significant power coverage, and good environmental adaptability, nuclear reactors have been highly valued worldwide since the 1950s. They have been successfully applied in civil and military fields such as nuclear power generation and nuclear power propulsion [1]. Since the beginning of the 21st century, with the demand for deep space exploration, deep-sea operation, marine research, uncrewed area operation, disaster area emergency response, and other particular fields, the development of new nuclear energy devices such as space nuclear power, deep sea space stations, floating nuclear power plants, and movable land-based nuclear power sources with reactors as the primary power source has been flourishing [2,3]. Meanwhile, the rapid development of supercomputing, artificial intelligence, materials science, and other technologies has led to the development of new nuclear energy devices with long life, digitalization, and miniaturization. The United States, Russia, and other significant countries consider new nuclear energy devices for "sea, land, air, and space" as a disruptive innovation in the field of traditional nuclear energy technology and an inevitable choice to form asymmetric technology and strategic advantage [4,5,6] and put forward higher requirements for existing technologies [7].

In order to protect the safety of personnel and the reliability of reactor-related systems and equipment components, the neutron and gamma radiation levels outside the reactor must be reduced to as low as reasonably achievable (ALARA) levels through effective radiation shielding. Compared with land-based stationary nuclear power plant reactors, new nuclear energy devices for "sea, land, air and sky" have new requirements for reactor miniaturization and light weight in terms of mobility, maneuverability and payload. The weight and volume of the reactor radiation shielding system are the most important factors affecting miniaturization and light-weighting [8,9]. The traditional design methods for nuclear reactor

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radiation shielding optimization are often based on expert experience, which may consume a lot of time and effort and may not necessarily lead to a better result. Moreover, the multi-objective to single-objective screening process requires human intervention, from which all human subjective experience is introduced, and this multi-objective to single-objective optimization process can be calculated only one final solution at a time, and the final selection is limited. There are several studies applying intelligent optimization algorithms to shield optimization. A genetic algorithm-based metaheuristic optimization technique for radiation shielding design is presented by the University of South China [10]. A compact shield that is organized radially is the goal of this effort. A multi-objective optimization technique employing the PSO algorithm and the shielding calculation code ANISN is proposed in the work of the Chinese Academy of Sciences. This method is integrated with verification calculations for optimized systems using MCNP [11], etc..

This paper is based on the Bare-bones multi-objective particle swarm optimization algorithm (BBMOPSO) to automatically optimize the material, thickness, and structural parameters of a radiation shielding system and quickly obtain the optimized radiation shielding solution under the dose-volume-weight multi-objective constraints, which can provide technical support for the design of radiation shielding solutions for new nuclear energy devices.

2. Radiation shielding multi-objective optimization problem

The difficulty of dose-volume-weight multi-objective optimization in radiation shielding schemes is that their various objectives are often in conflict with each other, and the optimization of some design objectives will cause deterioration of other design objectives. For example, the dose will decrease when increasing the thickness of radiation shielding material or replacing the heavier radiation shielding material. However, simultaneously, the volume or weight will increase, so to a certain extent, the optimization of multiple objectives simultaneously is unlikely to occur. Radiation shielding solution optimization aims to have each target meet a criterion as low as possible while meeting certain limits. The following multi-objective optimization model was developed with the mathematical definition of the design variables and constraints, considering the practical needs of new radiation shielding designs for high performance [12].

$$\begin{cases} \min F(X) = (F_R(X), F_W(X), F_V(X))^T \\ s.t. \begin{cases} F_R(X) = R_N(X) + R_P(X) \le R_0 \\ F_W(X) = \sum_{m=1}^{M} V_m \cdot \rho_m \le W_0 \\ F_V(X) = \sum_{m=1}^{M} V_m \le V_0 \\ s.t. \begin{cases} X = (x_1, x_2, x_3, ..., x_{n-1}, x_n), X \in \Re \\ L_j \le x_j \le U_j (j = 1, 2, ..., n) \\ h_k(x_j) \le 0 (k = 1, 2, ..., q) \\ g_l(x_j) = 0 (l = 1, 2, ..., p) \end{cases} \end{cases} \end{cases} \tag{1}$$

In the above multi-objective optimization model, x_j is the design variable corresponding to a set of shielding optimization design solutions; L_j and U_j are the upper and lower limits of the corresponding design parameters, respectively; X is the vector of design parameters of a radiation shielding solution; R is the value space of the vector X; g_l and h_k denote the parameter constraints considering engineering conditions and economy. The radiation dose, total weight, and total volume of the shielding scheme are denoted by F_R, F_W, and F_V, respectively; R_0, W_0, and V_0 are the reference constraint values for radiation dose, weight, and volume, respectively; and $F(X)$ is the objective function of the radiation shielding design optimization problem. R_N is the neutron radiation dose outside the shielding layer, and R_P is the gamma rays radiation dose outside the shielding layer. V_m is the volume of the m_{th} shielding layer in the shielding system; ρ_m is the density of the m_{th} shielding layer.

3. Principle of particle swarm algorithm

Particle Swarm Optimization (PSO) is a stochastic optimization method proposed by Eberhart and Kennedy in 1995, which originated from the study of the predatory behavior of bird flocks [13–16]. The PSO algorithm treats the solution to the optimization problem as a bird in the search space and is abstracted as an individual with no weight and volume, hence the name "particle." Each particle has a fitness value determined by the optimized function and searches the search space at a certain speed. Similar to genetic algorithms, PSO algorithms are based on the concepts of population and fitness, except that instead of evolving through operators such as crossover and mutation, PSO finds the optimal solution through collaboration and competition among individuals. The other is the optimal solution found by the whole population so far, called the global best position, or the optimal global particle. Its basic PSO algorithm can be described as follows:

1) Initialize the position and velocity of the particle swarm.
2) Calculating the fitness of each particle in the swarm.
3) Update the optimal position p_{best} of each body of the particles.
4) Update the global best position g_{best} of all particles.
5) Update the position and velocity of each particle.
6) Determine if the number of iterations has been reached. If so, terminate the run, otherwise return to step 2).

3.1. Multi-objective particle swarm optimization algorithm

The multi-objective particle swarm optimization algorithm (MOPSO) is a method that uses the PSO optimization algorithm to solve multi-objective optimization problems. Its underlying theory is still based on the PSO algorithm, but the difference is that it deals with more than one object [17]. In the PSO algorithm, the individual optimal position p_{best} and the global optimal position g_{best} jointly lead the flight direction of each particle. However, for optimizing a single objective, the optimal solution is often just a position in space. The superiority of each particle solution can be compared by directly comparing its fitness. However, for the optimization of multiple objectives, there is no relationship between the superiority of particle solutions in this case because of the possible mutual non-domination between their particle solutions. Therefore, when using MOPSO to solve multi-objective problems, it is often necessary to construct an external storage set to keep the non-dominated solutions searched for during the optimization process and to update them. The algorithm description of MOPSO is shown in Fig. 1 and can be described as follows:

1) Determine the dimension of the target, generate a population containing several particles in the intra-dimensional search space, and initialize the velocity and position of each particle in the population as well as the external storage set.

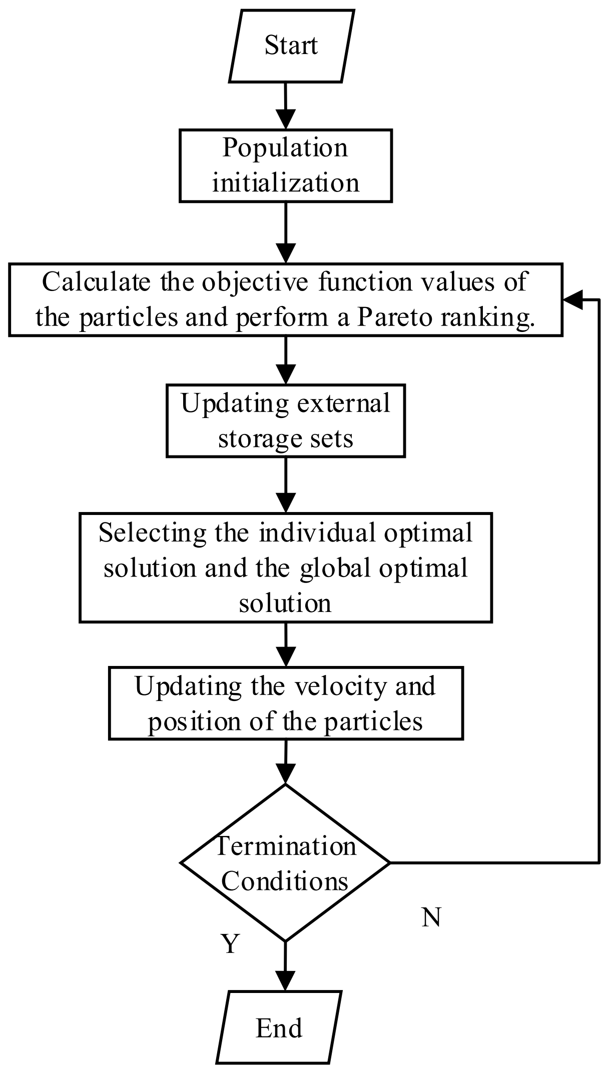


Fig. 1. Optimization iteration strategy based on multi-objective particle swarm optimization algorithm.

2) Calculate the objective function value of each particle in the population and save the non-inferior solution to the external storage set according to the dominance relation; initialize the individual optimal position p_{best} and the global optimal position g_{best} of the particles, p_{best} being the initial position of the particle and g_{best} being the best position of the initial population.
3) Change the positions of the particles based on the formulas for updating their positions and speeds.
4) Calculating the target fitness value of the particle and comparing it with the p_{best} of the previous iteration to readjust the p_{best}.
5) Update the external storage set and determine the current global optimal g_{best}.
6) Check to see if the number of iterations has been reached. If so, output all the best solutions in an external file. Otherwise, go to step 3.

Compared with other intelligent optimization algorithms, MOPSO algorithm has the following advantages: 1. Without crossover and mutation operation, MOPSO algorithm relies on particle speed to complete the search, and only the optimal particle can transmit information to other particles in iterative evolution, so the search speed is fast; 2.MOPSO algorithm has memory, and the best historical position of particle population can be remembered and transmitted to other particles; 3. Fewer parameters need to be adjusted, simple structure, easy to achieve engineering; 4. Real coding is adopted, which is directly determined by the solution of the problem, and the number of variables in the solution of the problem is directly taken as the dimension of the particle. Of course, MOPSO algorithm still has the following shortcomings: 1. Lack of dynamic adjustment of speed, easy to fall into local optimum, resulting in low convergence accuracy and difficult convergence; 2. Unable to effectively solve discrete and combinatorial optimization problems; 3. For different problems, how to choose appropriate parameters to achieve the best effect; 4. It cannot effectively solve some non-cartesian coordinate system description problems.

3.2. Bare-bones multi-objective particle swarm optimization algorithm

Bare-bones multi-objective particle swarm optimization (BBMOPSO) discards the update of particle velocity in MOPSO compared to MOPSO. It replaces it with Gaussian sampling based on the global best position g_{best} and the individual best position p_{best} [18]. Based on the existing research, the update of particle position is partially improved by using an adaptive particle update strategy, choosing the update of external storage (pareto set) based on the congestion distance and the selection of global best position g_{best}, combined with the characteristics of multi-objective optimization problems in radiation shielding design, and designing a Gaussian variational operator based on space-time, the specific process of which is as follows.

In order to better balance the “global search” and “local search” capabilities of the algorithm, an adaptive particle position update strategy is used to update the positions of the particle swarm, as shown in Equation (2-5).

$$x_{i,j}^{(t+1)} = \begin{cases} N\left(P_p \bullet r \bullet p_{i,j}^{(t)} + P_g \bullet r \bullet g_{i,j}^{(t)}, R \bullet \left|p_{i,j}^{(t)} - g_{i,j}^{(t)}\right|\right), rand < 0.5 \\ g_{i,j}^{(t)}, rand \geq 0.5 \end{cases} \tag{2}$$

$$P_p = 0.5 + \frac{0.5}{1 + \exp\left[bb(t - t_0)\right]} \tag{3}$$

$$P_g = 0.5 + \frac{0.5}{1 + \exp\left[-bb(t - t_0)\right]} \tag{4}$$

$$R = \frac{1}{1 + \exp\left[bb(t - t_0)\right]} \tag{5}$$

$x_{i,j}^{(t+1)}$ is the spatial position of the i_{th} particle in the j_{th} dimension at the moment $t+1$, $p_{i,j}^{(t)}$ is the value of p_{best}t of the i_{th} particle in the j_{th} dimension, $g_{i,j}^{(t)}$ is the value of g_{best} of the i_{th} particle in the j_{th} dimension, P_p and P_g indicates the probability of searching around the area around p_{best} and g_{best}. R is used to adjust the size of the search radius, t_0 is the turning point of the algorithm “global search” and “local search” mode, take $t_0 = t_{max}/2$. t indicates the current number of iterations, bb indicates the rate of change. Take $bb = 20/t_{max}$, t_{max} is the maximum number of iterations. The change curves of P_p and P_g are shown in Fig. 2.

In order to ensure the population diversity of the Pareto non-dominated solution set in the radiation shielding genetic search

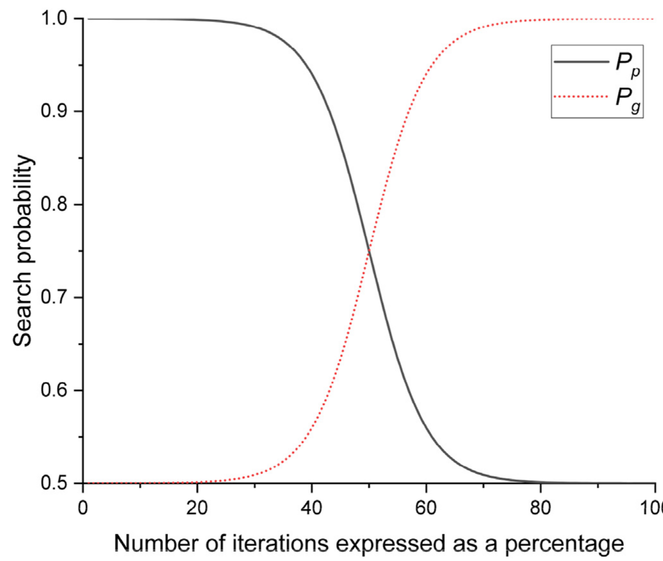


Fig. 2. Search probability in the vicinity of p_{best} and g_{best}.

process, the individual crowding distance is used for the selection process. The basic idea is that by calculating the sum of distance gaps between two individuals adjacent to each design objective in the same non-dominated hierarchy and ranking them, the formula is shown in equation (6).

$$I_i = \left|\frac{F_{i+1,1} - F_{i-1,1}}{F_{max,1} - F_{min,1}}\right| + \left|\frac{F_{i+1,2} - F_{i-1,2}}{F_{max,2} - F_{min,2}}\right| \tag{6}$$

where i-1, i, and i+1 denote the three adjacent radiation shielding solutions in the population, F is the corresponding radiation shielding design objective such as dose, weight, volume, etc., $F_{\max}$ is the maximum value corresponding to a radiation shielding design objective in the current population, and $F_{\min}$ is the minimum value corresponding to a radiation shielding design objective in the current population.

In order to avoid the premature aggregation of the population in some better solution or a certain area and the loss of population diversity, which leads the algorithm into the dilemma of local optimum, an operator based on spatio-temporal variation is designed. When the variation probability is greater than some random number, the variation range with Gaussian distribution as the variable value is selected at the current position of the particle, and if the variation probability is lower than this value, the spatial position of the particle remains unchanged, and the variation formula is shown in equation (7-9).

$$x(i,k) = \begin{cases} (x(i,k) + r_g{*}mut\_range, P_m \geq rand \\ x(i,k), P_m < rand \end{cases} \tag{7}$$

$$P_m = (1 - t/t\_max)^{5/M} \tag{8}$$

$$mut\_range = (ub(k) - lb(k)){*}\, P_m \tag{9}$$

P_m is the probability of variation, r_g follows a (0,1) normal distribution, mut_range is the range of variation, $ub(k)$ and $lb(k)$ are the upper and lower bounds of the k_{th} dimensional decision variable, respectively, and M is the variation parameter.

On the basis of the MOPSO algorithm, the BBMOPSO algorithm updates the particle velocity update formula in the MOPSO algorithm, and uses Gaussian sampling based on the global best position and the individual best position of the particle. Compared with the standard MOPSO optimization algorithm, the BBMOPSO algorithm is more compact and does not need to set control parameters such as inertia weight and learning factor. Therefore, it is easier to implement and apply to solve practical problems.

4. Benchmark validation

In this paper, the BBMOPSO radiation shielding optimization design procedure was developed based on the Multi-Objective modeling and Simulation platform for Radiation Transport system (MORST) developed by University of South China, and the application validation of the procedure was carried out using the Savannah reactor core model as the radiation shielding reference model [19].

4.1. Benchmarking model as a reference

This paper is based on the radiation shielding design problem of the Savannah reactor as a reference model. The structure of the core, primary shielding layer and the position of the detector are shown in Fig. 3. According to the literature reference, it is known that the total height of the Savannah reactor core is 229.2 cm, of which the active fuel zone is 167.6 cm, and the core diameter is 157.6 cm. In the validation process, the initial shielding of the reactor is set at 10 layers. The initial shielding material, thickness, and geometric structure design parameters are shown in Table 1, and the selection of shielding material is shown in Table 2. Based on the multi-objective intelligent optimization platform, the shielding material, thickness, and geometric structure of the reference model are optimized according to the initial shielding scheme, and then find the optimized shielding scheme with integrated dose-volume-weight multi-objective optimization.

There are two optimization objects selected in the optimization process of axial radiation protection shielding. One is the radiation shielding material, and the other is the thickness of each layer of radiation shielding material. In this calculation, the coding method of radiation materials is 1–23, a total of 23 numbers represents 23 kinds of materials, and the selected thickness range is 5–20 cm. There are two different variables for the material and thickness of each layer. Since BBMOPSO optimization method can only be optimized in the real number range, it is a discrete variable for material type, but it is very friendly for material thickness optimization. In view of the discrete problem of material types, Monte Carlo method is adopted to take the idea of rounding in real numbers, and random numbers are selected in (0,23]. If the random number is greater than 0 and less than or equal to 1, the first material is selected, and so on. The Gaussian sampling for the material type and thickness variables is the Gaussian sampling corresponding to the volume and weight.

In the optimization process, the reactor model is simplified to a certain extent in this paper, and the reactor core is simplified to a cylindrical, various homogeneous neutron source model, in which the ^{235}U fission energy spectrum is used. Using the MCX software by Xi'an Jiaotong University, the count of particles injected into the outer shield face is done with the corresponding count card. The count of particles injected into the outer shield face is then converted to the dose equivalent of the outer shield face using the conversion factor of injection rate-dose rate given by NCRP-38 and ANSI/ANS, and the shielding material is extracted from the MCX software [20].

4.2. Radiation shielding optimization results

Based on the multi-objective intelligent optimization platform,

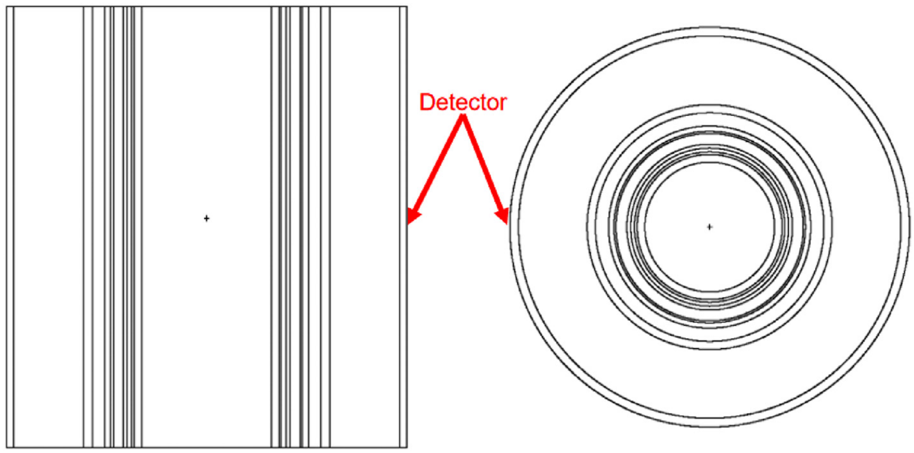


Fig. 3. Structural geometry of the core and primary shielding layer.

Table 1
Initial shielding design parameters for the reference model.

Shield number	Outer radius/cm	Material type	Density/g·cm^{-3}
1	88.3	H_2O	1.00
2	98.8	Stainless Steel 307	7.92
3	108.5	H_2O	1.00
4	118.6	Stainless Steel 307	7.92
5	128.5	H_2O	1.00
6	138.0	Stainless Steel 307	7.92
7	148.6	Lead	8.43
8	158.8	Stainless Steel 307	7.92
9	168.8	Lead	8.43
10	178.8	Stainless Steel 307	7.92

the material and structure modeling of the reference model using the shielding design scheme in Table 1 is automatically transformed into the MCNP computational model. Then the MCNP computational model is transformed into the MCX computational model using a script to perform intelligent optimization of the radiation shielding design scheme based on the BBMOPSO algorithm optimization program module. The control parameters of BBMOPSO are:

1) The population size of each generation is 100, the maximum number of iterations is 100, and the variation parameter is set to 0.5.
2) The type of radiation shielding optimization is a mixture of material type, thickness, and geometry.
3) The optimization objective of the radiation shielding solution is a “dose-volume-weight” multi-constraint objective.

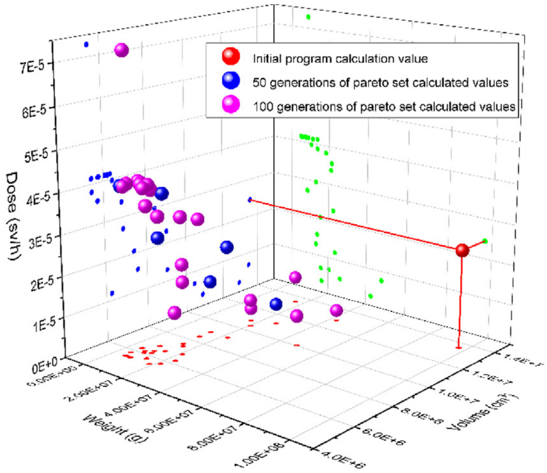
The optimization objective of the radiation shielding scheme is “dose-volume-weight” multi-constraint.

The results of the radiation shielding optimization procedure using the BBMOPSO algorithm for the baseline model are shown in Fig. 4. It can be concluded from the figure that, based on the BBMOPSO algorithm, the radiation shielding scheme gradually converges to the Pareto optimal frontier as the number of generations increases, which proves the effectiveness and feasibility of the radiation shielding optimization strategy based on the BBMOPSO algorithm proposed in this paper. In order to compare the radiation shielding design with the initial scheme, the dose rate, volume and weight target values of the initial scheme are used as the starting point, and a vertical line is set, and the area enclosed by the vertical line and the coordinate axis is the better shielding design scheme.

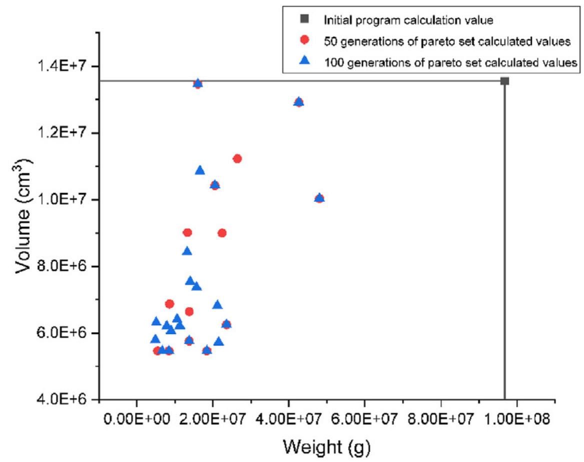
By analyzing and interpreting the Pareto front solution set, four different solutions are summarized, namely, the weight optimal solution, the volume optimal solution, and the dose optimal solution. The results are shown in Table 3 (where the dose value is the normalized dose). Since weight is equal to volume times density, there is usually a positive linear relationship between weight and volume. However, in this optimization, the material type was optimized at the same time. Table 3 shows that the optimal weight scheme and the optimal volume scheme are different, which verifies the effectiveness of this optimization process. The integrated optimized data showed that the weight decreased by 78.77%, the volume decreased by 23.10% and the dose rate decreased by 72.41%

Table 2
Material library for shielding optimization design selection.

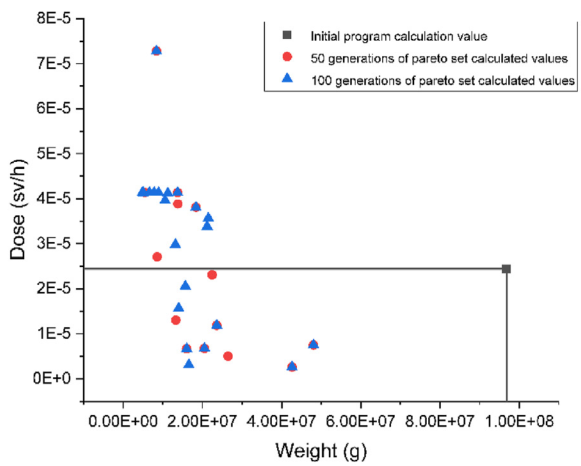
Material type	Density/g·cm^{-3}	Material type	Density/g·cm^{-3}
Water	1.00	Air	$1.205*10^{-3}$
Beryllium	1.85	Carbon Steel	7.82
Stainless Steel 307	7.92	Stainless Steel 304	7.92
Aluminum	2.70	Stainless Steel 347	7.92
Lead	11.35	Nickel-chromium-iron based solid solution strengthening alloy 1600	8.43
Tungsten	19.35	Nickel-chromium-iron based solid solution strengthening alloy 800	8.01
Gadolinium	7.90	Concrete	2.30
Polyethylene	0.93	Barite Concrete	3.35
Boron polyethylene	1.22	Calcium hydroxide stone	2.3
Lead Boron Polyethylene	3.60	Type 04 concrete	2.336
Boron steel	7.70	LS concrete	2.278
Tungsten Boron Aluminum	6.10		



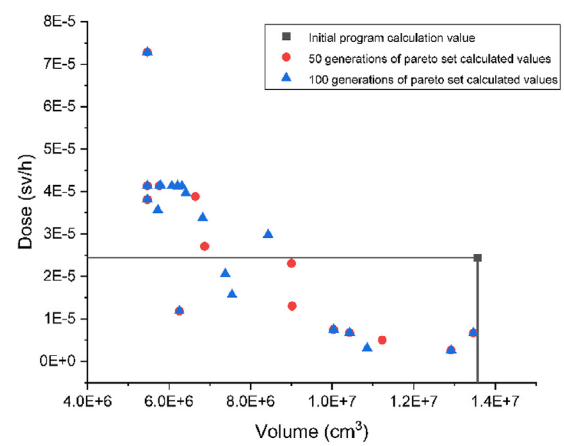
a. dose-volume-weight optimization



c. volume-weight optimization



b. dose-weight optimization



d. dose-volume optimization

Fig. 4. Results of the optimized radiation shielding scheme under the initial scheme constraints of the reference.

Table 3
Table of results calculated under different conditions.

Scheme	Weight/g	Volume/cm^3	Dose/(sv/h)
Initial shielding design	9.68015E+07	1.35634E+07	2.44405E-05
Weight optimal solution	4.87963E+06	5.79671E+06	4.13496E-05
Volume optimal solution	1.83942E+07	5.46539E+06	3.81151E-05
Dose optimal solution	4.26348E+07	1.29183E+07	2.61182E-06
Integrated optimal solution	2.05490E+07	1.04297E+07	6.74204E-06

compared with the initial solution according to Table 3. The geometry and material arrangement of the overall optimization scheme are shown in Table 4.

Table 4
Integrated optimal solution shielding design parameters for the reference model.

Shield number	Outer radius/cm	Material type	Density/g·cm^{-3}
1	93.65	Lead Boron Polyethylene	3.60
2	108.65	LS concrete	2.278
3	138.65	H_2O	1.00
4	161.3	LS concrete	2.278

5. Conclusion

Radiation shielding design multi-objective optimization is a complex and nonlinear multi-parameter optimization combination problem. The dose-volume-weight optimization problem in this paper in radiation shielding design is complemented by the Bare-bones multi-objective particle swarm optimization algorithm based on radiation shielding multi-objective optimization. In order to verify the effectiveness and feasibility of the BBMOPSO algorithm in radiation shielding optimization, a radiation shielding optimization design module based on BBMOPSO was developed in the reactor radiation shielding multi-objective intelligent optimization platform, and the present method was initially validated using the Savanna reactor. The material type and thickness of Savannah model were optimized by using the BBMOPSO algorithm to call the dose calculation code, the integrated optimized data showed that the weight decreased by 78.77%, the volume decreased by 23.10% and the dose rate decreased by 72.41% compared with the initial solution. The validation results show that this method and procedure can achieve iterative optimization of radiation shielding material, thickness, and geometry design parameters for new nuclear power devices and finally obtain an optimized radiation shielding design that satisfies the dose-volume-weight multi-objective constraint, which proves the effectiveness and feasibility of the radiation shielding optimization method based on the BBMOPSO algorithm in practical applications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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