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An improved TOPSIS-ANP composite shielding material performance evaluation method based on gray relational projection algorithm

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The performance of shielding materials directly affects the radiation protection effect and plays a very important role in the process of ensuring the safety of nuclear energy. Therefore, this paper introduces the performance evaluation of composite shielding materials, which firstly points out the disadvantages of the traditional TOPSIS method, proposes a weighted projection model of composite shielding materials under extended TOPSIS theory, and clarifies the principle of projection dimensional reduction and algorithm implementation. Secondly, this paper also introduces the basic assumption of non-linear mapping relationship between index dimensions, and scientifically determines the weight of index system based on ANP structural model, so as to form an improved TOPSIS-ANP composite shielding material performance evaluation method based on gray relational projection algorithm with coupling characteristics. The empirical results show that the improved TOPSIS-ANP composite shielding material evaluation method proposed in this paper is consistent with the conclusion of the ratio of lead-boron-polyethylene shielding materials optimized based on genetic algorithm, which proves the effectiveness of the evaluation method proposed in this paper. Meanwhile, the evaluation index system of this method is more comprehensive, and the evaluation method is more efficient and scientific as well, which has a good promotion prospects and application advantages.

KEYWORDS

composite shielding material, nuclear radiation protection, TOPSIS, grey relational projection algorithm, network hierarchy analysis

1 Introduction

In the process of nuclear fission, reactor may produce various radiation rays, including particle α and β, X-ray and γ-ray, as well as neutrons of various energies. Therefore, nuclear reactor shielding (Lacey, 2021; Wang et al., 2021; Zeng and Li, 2013) shall be a key method to ensure nuclear energy safety. In practice, people also put forward higher requirements for other properties of shielding materials in

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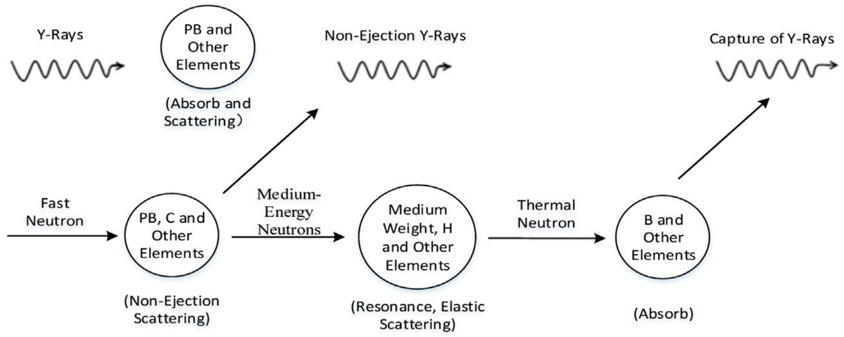

FIGURE 1
Schematic diagram of shielding principle for common shielding materials.

addition to shielding performance. For example, the shielding materials need to have mechanical structure function, which has good heat resistance under the condition of water loss accident, and good radiation aging resistance, wet heat aging or flame retardant performance. Materials science and technology are changing with each passing day, and are generally developing towards composite shielding materials (Sun et al., 2021), typically represented by polyethylene based, polymer based, ceramic, metal hydride materials, etc (Lu and Chen, 1994; Koichi, 2005; Celli et al., 2006; Courtney, 2008; Hayashi et al., 2009;). In the early days, the design of these composite shielding materials was mainly based on experience judgment and test, and the design efficiency was low, and there was no theoretical design for specific radiation field, specific performance requirements, etc., which led to that the distribution ratio of the developed composite shielding materials was not optimal, and the performance of all aspects was not fully guaranteed. With the rapid development of computing methods, the optimization design of composite shielding material composition based on genetic algorithm has been widely used in many fields and achieved good results (Liao, 2010). However, its objective function is limited, which is generally dominated by radiation dose. Complex ones will increase comprehensive objectives such as thermal conductivity and mechanical properties. Other important performance indicators such as uniformity and radiation aging properties are not considered, and there are still limited methods for comprehensive evaluation of composite shielding materials. Therefore, how to design a scientific method to evaluate the comprehensive performance of these various shielding materials, and then determine the optimal scheme is the main purpose of the author.

The basic principle of radiation shielding protection is shown as Figure 1.

2 Defects and improvement ideas of traditional TOPSIS evaluation methods

In 1981, C.L. Hwang and K. Yoon first proposed the concept of ideal solution (Hwang and Yoon, 1981) (Technique for Order Preference by Similarity, TOPSIS), which examines the closeness between the scheme to be decided and the ideal scheme by constructing positive and negative ideal solutions to multi-index decision-making problems, so as to take the result as a basis for judging the advantages and disadvantages of the evaluation scheme. However, as the research continues, the disadvantages of the traditional TOPSIS method are becoming more and more obvious. Literature (Li et al., 2015a) believes that the traditional TOPSIS ideal solution is unstable, and the evaluation efficiency is defined and limited by the influence of multi-dimensional spatial distance change, literature (Huang and Zheng, 2001) points out that due to the existence of relative ideal points, the use of TOPSIS method will produce reverse order problems, and must be eliminated by constructing GTOPSIS method.

On the basis of the studies above, the traditional TOPSIS method is difficult to adapt to the complex evaluation environment, so effective improvement of the traditional TOPSIS method shall be an important way to improve the scientific evaluation effect. By introducing the interval number theory, reference (Jahanshahloo et al., 2005) and reference (Jahanshahloo et al., 2008) solve the uncertainty of data index observation when TOPSIS is applied to multi-index decision-making problem to a certain extent. Reference (Li et al., 2021a) pointed out that since the ideal solution concept of interval number proposed by Jahanshahlo in reference (Jahanshahloo et al., 2005) and reference (Jahanshahloo et al., 2008) is a virtual exact solution, there exists a risk of error ordering. In order to solve this problem, it is necessary to use the direct interval number ideal solution method to evaluate and improve. Reference (Opricovic and Tzeng, 2004) and (Opricovic and

Tzeng, 2007) has applied the extended VIKOR method on multi-index decision-making problems with interval number, extending the effective application scope of TOPSIS.

For this reason, this paper defines a basic problem of performance evaluation of composite shielding materials in line with the real environment, takes the feasibility study of TOPSIS extension method (Chen and Zhang, 2015; Ke and Wang, 2020) as the premise, puts forward the concept of gray correlation projection angle based on gray correlation theory, and establishes a TOPSIS performance evaluation model based on gray correlation projection algorithm. On this basis, this paper takes the basic assumption that there is a multivariate non-linear interaction between each index. Analytic Network Process (ANP) has the advantage in the construction of non-linear network (Yu et al., 2020; Li et al., 2021b; Li, Zhou), and the non-linear weighting of index set is realized by taking multiple non-linear interaction effects among indicators as the basic assumption. Finally, an improved TOPSIS-ANP material performance evaluation model based on gray relational projection algorithm was formed.

3 Improved TOPSIS-ANP material performance evaluation principle of grey correlation projection algorithm

3.1 Mathematical description of the weighting problem of composite shielding materials

The so-called weighting problem of composite shielding materials refers to the establishment of performance evaluation index system panel data on the basis of the establishment of performance evaluation indicators of composite shielding materials, together with the formation of composite two-dimensional plane data composed of evaluation objects and multi-level performance evaluation index systems. Based on this, the weight determination research problem is carried out under the comprehensive action of the object and the multi-level performance evaluation composite index.

Definition 1: The vector formed by a given set of evaluation objects is I, noted as $I = (1, 2, \cdots, m)$ and $i \in I$, the vector formed by the corresponding evaluation index set is J, noted as $J = (1, 2, \cdots, n)$ and $j \in J$, and the corresponding evaluation time is t.

Definition 2: Given that $x_{ij}(t)$ represents the evaluation value of the number i evaluated object in object set I and the evaluation value of the number j evaluated index in indicator set J at time t in time sequence set T, the initial decision matrix $X(t)$ is formulated as follows:

$$X(t) = \left\{x_{ij}(t)\right\}_{m\times n} = \begin{pmatrix} x_{11}(t) & \cdots & x_{1n}(t) \\ \vdots & \ddots & \vdots \\ x_{m1}(t) & \cdots & x_{mn}(t) \end{pmatrix} \tag{1}$$

In this case, the metric set weight is $\beta_j(t)$, and the modified weighted decision matrix is $X'(t)$

$$X'(t) = \left\{x_{ij}(t)\right\}_{m\times n} = \begin{pmatrix} \beta_1(t)\cdot x_{11}(t) & \cdots & \beta_1(t)\cdot x_{1n}(t) \\ \vdots & \ddots & \vdots \\ \beta_n(t)\cdot x_{m1}(t) & \cdots & \beta_n(t)\cdot x_{mn}(t) \end{pmatrix} \tag{2}$$

In the above equation, finding a reasonable weight $\beta_j(t)$ is the key to solve the weight determination problem of composite shielding materials.

3.2 Complete algorithm design

The improved TOPSIS-ANP evaluation method based on gray relational projection algorithm is derived from the extension of the classical TOPSIS method. By normalizing the decision matrix, this method finds out the positive ideal solution and the negative ideal solution of the problem to be evaluated. Then, with the help of the mathematical projection relation, calculates the projection closeness between the feasible solution and the positive and negative ideal solution under the influence of non-linear weight, and transforms the complex weighting problem into dimension reduction (Yu, 2020), so as to evaluate the advantages and disadvantages of each feasible scheme. The algorithm implementation steps are as follows:

STEP 1: Evaluation object data preprocessing. Using the 0–1 extreme value treatment method (Xu and Li, 2020), the dimensional and order of magnitude influence between indicators are eliminated to ensure comparability between indicators. The basic formulas are as follows:

$$y_{ij}(t) = \frac{x_{ij}(t) - \min x_j(t)}{\max x_j(t) - \min x_j(t)} \tag{3}$$

$$y_{ij}(t) = \frac{\max x_j(t) - x_{ij}(t)}{\max x_j(t) - \min x_j(t)} \tag{4}$$

$$y_{ij}(t) = \begin{cases} \dfrac{2\left[x_{ij}(t) - \min x_j(t)\right]}{\max x_j(t) - \min x_j(t)}, \\ \min x_j(t) \le x_{ij}(t) \le \dfrac{\max x_j(t) + \min x_j(t)}{2} \\ \dfrac{\max x_j(t) - x_{ij}(t)}{\max x_j(t) - \min x_j(t)}, \\ \dfrac{\max x_j(t) + \min x_j(t)}{2} \le x_{ij}(t) \le \max x_j(t) \end{cases} \tag{5}$$

$$y_{ij}(t) = \begin{cases} x_1,\ 0 \le x_{ij}(t) \le a_1 \text{ or} x_{ij}(t) \textit{ shall be level } 1 \\ x_2,\ a_1 \le x_{ij}(t) \le a_2 \text{ or } x_{ij}(t) \textit{ shall be level } 2 \\ \cdots \\ x_n,\ a_{n-1} \le x_{ij}(t) \le 1\ x_{ij}(t) \textit{ shall be level } \text{n} \end{cases} \quad (6)$$

In the (Eqs 3–6) equation above, the 0-1 extreme value conversion formula of positive indicators, negative indicators, intermediate indicators and comment (interval) indicators are represented in order. Where, $y_{ij}(t)$ represents the data after normalization processing, and there is $y_{ij}(t) \in [0,1]$; $\max x_j(t)$ and $\min x_j(t)$ respectively represent the upper and lower bounds that the index j is allowed to change when the observation is made at time t. The complete matrix form after considering ANP weighting is as follows:

$$Y(t) = \left\{y_{ij}(t)\right\}_{m\times n} = \begin{pmatrix} y_{11}(t) & \cdots & y_{1n}(t) \\ \vdots & \ddots & \vdots \\ y_{m1}(t) & \cdots & y_{mn}(t) \end{pmatrix} \quad (7)$$

$$Y'(t) = \left\{y'_{ij}(t)\right\}_{m\times n} = \begin{pmatrix} \beta_1(t)\cdot y_{11}(t) & \cdots & \beta_1(t)\cdot y_{1n}(t) \\ \vdots & \ddots & \vdots \\ \beta_n(t)\cdot y_{m1}(t) & \cdots & \beta_n(t)\cdot y_{mn}(t) \end{pmatrix} \quad (8)$$

STEP 2: Define the ideal solution. With reference to time t, the maximum value of the evaluation result of the number j index in object set I is positive ideal scheme, and the minimum value is negative ideal scheme, which is taken as the benchmark scheme of evaluation. The calculation formula of positive and negative ideal schemes is:

$$\begin{cases} Y^+(t) = \{y_{01}^+(t), y_{02}^+(t), \cdots, y_{0n}^+(t)\},\ y_{0j}^+(t) = \max_i(y_{ij}(t)) \\ Y^-(t) = \{y_{01}^-(t), y_{01}^-(t), \cdots, y_{0n}^-(t)\},\ y_{0j}^-(t) = \min_i(y_{ij}(t)) \end{cases} \quad (9)$$

STEP 3: Establish an ideal gray correlation coefficient matrix. Referring to the grey correlation analysis principle, taking the positive ideal scheme $Y^+(t)$ and the negative ideal scheme $Y^-(t)$ as the reference sequence, then the gray correlation coefficient $\xi_{ij}^+(t)$ for the number i evaluated object in the object set I, which ranges at the moment t corresponding to the number j indicator in the evaluation set J shall be:

$$\xi_{ij}^+(t) = \frac{\min_i \min_j \left|y_{0j}^+(t) - y_{ij}(t)\right| + \rho \max_i \max_j \left|y_{0j}^+(t) - y_{ij}(t)\right|}{\left|y_{0j}^+(t) - y_{ij}(t)\right| + \rho \max_i \max_j \left|y_{0j}^+(t) - y_{ij}(t)\right|} \quad (10)$$

$$\xi_{ij}^-(t) = \frac{\min_i \min_j \left|y_{0j}^-(t) - y_{ij}(t)\right| + \rho \max_i \max_j \left|y_{0j}^-(t) - y_{ij}(t)\right|}{\left|y_{0j}^-(t) - y_{ij}(t)\right| + \rho \max_i \max_j \left|y_{0j}^-(t) - y_{ij}(t)\right|} \quad (11)$$

Where, ρ is the resolving coefficient, and the value range is $\rho \in [0,1]$, resulting in a matrix of positive and negative ideal gray correlation coefficients, which are denoted as:

$$E^+(t) = \left\{\xi_{ij}^+(t)\right\}_{m\times n} = \begin{pmatrix} \xi_{01}^+(t) & \cdots & \xi_{0n}^+(t) \\ \xi_{11}^+(t) & \cdots & \xi_{1n}^+(t) \\ \vdots & \ddots & \vdots \\ \xi_{m1}^+(t) & \cdots & \xi_{mn}^+(t) \end{pmatrix} \quad (12)$$

$$E^-(t) = \left\{\xi_{ij}^-(t)\right\}_{m\times n} = \begin{pmatrix} \xi_{01}^-(t) & \cdots & \xi_{0n}^-(t) \\ \xi_{11}^-(t) & \cdots & \xi_{1n}^-(t) \\ \vdots & \ddots & \vdots \\ \xi_{m1}^-(t) & \cdots & \xi_{mn}^-(t) \end{pmatrix} \quad (13)$$

Where, $E^+(t)$ and $E^-(t)$ represent positive ideal gray correlation coefficient matrix and negative ideal grey correlation coefficient matrix respectively, and satisfy $\xi_{01}^+(t) = \xi_{02}^+(t) = \cdots = \xi_{0n}^+(t) = \xi_{01}^-(t) = \xi_{02}^-(t) = \cdots = \xi_{0n}^-(t) = 1$.

STEP 4: DETERMINE THE INDICATOR SET. The use of ANP to determine the index set requires the establishment of an ANP structure model, including the control layer and the network layer. Then, the index weight $\beta_j(t)$ is determined. The principle of the ANP weighted structure model (Sun et al., 2011) is shown in Figure 2.

STEP 5: Calculate gray projection closeness. Considering the influence of the index set weights on the original coefficient matrix, let $G^+(t) = \beta_j(t)E^+(t)$, $G^-(t) = \beta_j(t)E^-(t)$, expand to obtain the two benchmark-weighted gray correlation coefficient matrices, denoted as:

$$G^+(t) = \begin{pmatrix} \beta_1(t) & \cdots & \beta_n(t) \\ \xi_{11}^+(t)\beta_1(t) & \cdots & \xi_{1n}^+(t)\beta_n(t) \\ \vdots & \ddots & \vdots \\ \xi_{m1}^+(t)\beta_1(t) & \cdots & \xi_{mn}^+(t)\beta_n(t) \end{pmatrix} \quad (14)$$

$$G^-(t) = \begin{pmatrix} \beta_1(t) & \cdots & \beta_n(t) \\ \xi_{11}^-(t)\beta_1(t) & \cdots & \xi_{1n}^-(t)\beta_n(t) \\ \vdots & \ddots & \vdots \\ \xi_{m1}^-(t)\beta_1(t) & \cdots & \xi_{mn}^-(t)\beta_n(t) \end{pmatrix} \quad (15)$$

Where $G^+(t)$ and $G^-(t)$ respectively represent positive ideal weighted gray correlation coefficient matrix and negative ideal weighted gray correlation coefficient matrix. Generally, the feasible scheme is denoted as $z_i(t)$, the ideal scheme as $z_i^*(t)$ and the row vector is denoted as:

$$z_i(t) = \left(\xi_{i1}(t)\beta_1(t), \xi_{i2}(t)\beta_2(t), \cdots, \xi_{in}(t)\beta_n(t)\right) \quad (16)$$

$$z_i^*(t) = \left(\beta_1(t), \beta_2(t), \cdots, \beta_n(t)\right) \quad (17)$$

Let the angle between the two row vectors $z_i(t)$ and $z_i^*(t)$ be $\theta_i(t)$, call $\theta_i(t)$ the gray associative projection angle, and the rest of the string functions are:

$$\cos\theta_i(t) = \cos\left(z_i(t), z_i^*(t)\right) = \frac{z_i(t)\cdot z_i^*(t)}{\|z_i(t)\| \bullet \left\|z_i^*(t)\right\|} \quad (18)$$

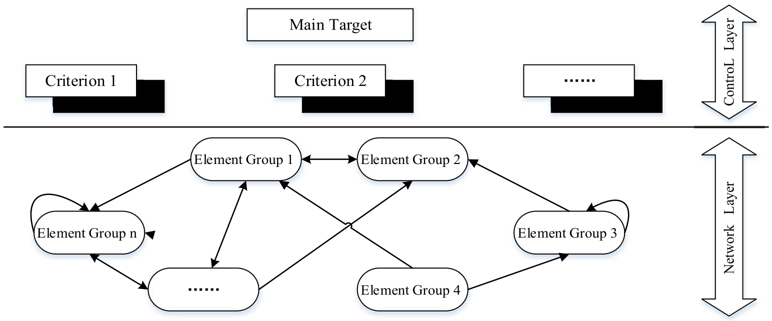

FIGURE 2
ANP network structure principle.

The projected value of $z_i(t)$ on $z_i^*(t)$ is:

$$B_i(t) = \|z_i(t)\| \cdot \cos\theta_i(t) = \frac{z_i(t)\cdot z_i^*(t)}{\|z_i^*(t)\|} = \sum_{j=1}^{n}\xi_{ij}(t)\frac{\beta_j^2(t)}{\sqrt{\sum_{j=1}^{n}\beta_j^2(t)}} \tag{19}$$

Based on this, the positive and negative ideal gray correlation projection values are obtained and simply written as:

$$B_i^+(t) = \sum_{j=1}^{n}\xi_{ij}^+(t)\bar{\beta}_j(t), B_i^-(t) = \sum_{j=1}^{n}\xi_{ij}^-(t)\bar{\beta}_j(t)$$

In equation

$$\bar{\beta}_j(t) = \frac{\beta_j^2(t)}{\sqrt{\sum_{j=1}^{n}\beta_j^2(t)}} \tag{20}$$

Therefore, the closeness degree of gray relation projection is:

$$R_i(t) = \frac{B_i^{+2}(t)}{B_i^{+2}(t) + B_i^{-2}(t)} \tag{21}$$

Where, the value of $R_i(t)$ reflects the quality of the final evaluation result.

3.3 Establishment of performance evaluation index system for composite shielding materials

The comprehensive performance of composite shielding materials shall include a number of quantifiable evaluation indexes, which can be divided into level 1 indexes, level 2 indexes and level 3 indexes according to the level of influence. The level 1 indexes include basic properties, physical properties and chemical properties. The level 2 indexes are further divided into seven evaluation dimensions: density properties, process properties, shielding properties, mechanical properties, thermal properties, flame retardant properties and tolerance. The level 3 indicators select the most representative one to three observable quantitative indicators of each dimension for quantitative evaluation and focus on reflecting the comprehensive performance of composite shielding materials. The specific indicator system is shown in Table 1.

4 Numerical example analysis

4.1 Numerical example background and index system establishment

This section uses a lead-boron polyethylene composite shielding material as an example to verify the applicability of the improved TOPSIS-ANP evaluation model of the gray correlation projection algorithm. In order to ensure the comparability of the research, five domestic suppliers A, B, C, D and E with the production capacity of lead-boron-polyethylene composite shielding materials in 2022 are selected as the research objects. The performance characteristics of their lead-boron-polyethylene shielding materials are investigated, and the advantages and disadvantages are compared. According to the basic idea of composite shielding material performance evaluation index system established in Table 1, some indexes were refined to design the performance evaluation index system of marine lead-boron-polyethylene composite shielding material, which completely covered the specific content of all aspects of the performance of the composite shielding material, and defined the reference value range of each indexe in level 3. According to the source term characteristics of PWR reactor, based on theoretical design and engineering application experience, a

TABLE 1 Composite shielding material performance evaluation index system and index description.

Level 1 index	Level 2 index	Level 3 index	Index description	Index type
Basic Features	Density Performance	Density	Control within the tolerance range of theoretical values, reflecting the accuracy of raw material ratio control and ensuring material shielding performance	Intermediate Value
		Density Uniformity	Indicate the degree of material mixing uniformity, reflect the level of processing technology, ensure the material shielding performance	Backward
	Process Performance	Appearance Feature	Reflect the shape quality of forming shielding material, whether there are bubbles, slag, cracks and other reflect the processing technology level, to ensure the quality of material processing	Comment
		Dimensional Tolerance	Reflect the size tolerance of molding shielding material, reflect the level of processing technology, to ensure the accuracy of material processing	Backward
Physical Properties	Mechanical Properties	Tensile Strength	Indicate whether the mechanical tensile property of the material is superior	Forward
		Bending Strength	Indicate whether the mechanical bending property of the material is superior	Forward
		Compression Strength	Indicate whether the mechanical compression property of the material is superior	Forward
	Thermal Performance	Thermal Deformation Temperature of Load	Indicate whether the heat resistance of the material is superior	Forward
		Linear Expansion Coefficient	Indicate whether the deformation performance of the material is superior	Backward
	Shielding Performance	γ-ray Shielding Coefficient	Indicate whether the material has superior shielding ability for γ-rays	Forward
		Thermal Neutron Shielding Factor	Indicate whether the material has superior thermal neutron shielding capability	Forward
		Fast Neutron Shielding Factor	Indicate whether the material is superior to fast neutron shielding	Forward
Chemical Properties	Flame Retardant Properties	Oxygen Index	Indicate whether the material has superior anti-flame ability	Forward
	Resistant Performance	Mechanical Property Retention Rate after Damp and Heat Aging	Indicate whether the irradiating ability of the material is superior, that is, whether the mechanical properties such as tensile strength decrease significantly after a certain cumulative irradiation during the life period	Forward
		Mechanical Property Retention Rate after Irradiation	Indicate whether the irradiating ability of the material is superior, that is, whether the mechanical properties such as tensile strength decrease significantly after a certain cumulative irradiation during the life period	Forward

comprehensive optimization index of lead boron polyethylene composite shielding material is proposed. See Table 2 for details.

4.2 Modeling and empirical analysis process

In 2022, the shielding material products provided by 5 domestic lead-boron polyethylene composite shielding material suppliers were sampled and tested, the original data was collected, sorted out and summarized, and the data was processed in advance according to the 0-1 extreme value treatment method given in Eqs 3–6, and the original data and processed results in advance are detailed in Table 3.

Therefore, the ideal scheme and the correlation coefficient matrix of the scheme to be evaluated were determined, and the positive, negative ideal scheme and the ideal gray correlation coefficient matrix were calculated.

The ANP network structure model for performance evaluation of composite shielding materials with the core architecture of "Control Layer—Network Layer" is established by using ANP for index weighting. The basic structure is described as follows: the control layer is a first-level indicator,

TABLE 2 Performance evaluation index system and numerical reference standard of PB-PE composite shielding materials.

Level 1 index	Level 2 index	Level 3 index	Index type	Index code	References value	Note
Basic Features	Density Performance	Lead Boron Polyethylene Density	Intermediate Value	J_1	1.8–2.4	Unit g/cm^3
		Density Uniformity	Backward	J_2	0–0.1	Unit g/cm^3
	Process Performance	Appearance Feature	Comment	J_3	Level 1:1.0 Level 2:0.8 Level 3:0.6	Level 1: no bubbles, slag inclusions, cracks; Level 2: No slag inclusion, significant cracks, the number of bubbles in any 100 mm × 100 mm area does not exceed 5 and the diameter is not more than 2 mm; Grade 3: No slag inclusion, significant cracks, the number of bubbles in any 100 mm × 100 mm area does not exceed 10 or the diameter is not more than 4 mm
		Dimensional Tolerance	Backward	J_4	Length and width tolerance 0–2, thickness tolerance 0–0.5	Unit mm, The length and width tolerances and thickness tolerances shall be averaged according to the 0-1 extreme value method
Physical Properties	Mechanical Properties	Tensile Strength	Forward	J_5	8–20	Unit MPa
		Bending Strength	Forward	J_6	10–20	Unit MPa
		Compression Strength	Forward	J_7	15–50	Unit MPa
	Thermal Performance	Thermal Deformation Temperature of Load	Forward	J_8	100–170	Unit ^{0}C
		Linear Expansion Coefficient	Backward	J_9	1.0×10^{-4} –3.0×10^{-4}	Unit m/(m●^{0}C)
	Shielding Performance	γ-ray Shielding Coefficient	Forward	J_{10}	1.5–2.5	Dose rate ratio before and after shielding, shielding material 4 cm thick,^{60}Co source
		Thermal Neutron Shielding Factor	Forward	J_{11}	96%–100%	The share of thermal neutrons that are absorbed, shielding material 2 cm thick, thermal neutron source
		Fast Neutron Shielding Factor	Forward	J_{12}	3.0–4.0	Dose rate ratio before and after shielding, shielding material 4 cm thick,^{252}Cf source
Chemical Properties	Flame Retardant Properties	Oxygen Index	Forward	J_{13}	18%–25%	The value is calculated in percentage
	Resistant Performance	Mechanical Property Retention Rate after Damp and Heat Aging	Forward	J_{14}	90%–100%	The ratio of measured values after and before moisture-heat aging test at 70°C for 30 days and 95% humidity
		Mechanical Property Retention Rate after Irradiation	Forward	J_{15}	80%–100%	Ratio of measured values after and before cumulative irradiation test with 10^5Gy

the network layer is a binary structure, the second-level indicator is set as a group, and the third-level indicator is set as a node. Each group and node is an internal network relationship that influences each other and is controlled by the control layer. The ANP network was constructed under the main interface of the Super Decision software, the connection direction and dominance relationship between each group and node were established, and the index weight was determined after the ultimate super matrix was calculated. The visualization interface of related processes was shown in Figures 3, 4. Using the principle of gray projection Angle, the positive and negative ideal gray correlation projection values are calculated, and then the gray correlation projection closeness is obtained. The specific values are shown in Table 4.

According to the data shown in Table 4, B^+ (2022) represents the positive ideal gray correlation projection value of the performance of five kinds of lead-boron polyethylene composite radiation shielding materials, B^- (2022) represents

TABLE 3 Data collection and processing of lead-boron polyethylene composite shielding material products provided by five suppliers.

Supplier code	Original data					Processing data				
	1	2	3	4	5	1	2	3	4	5
J_1	1.92	1.98	2.11	2.02	1.86	0.400	0.600	0.967	0.733	0.200
J_2	0.065	0.037	0.010	0.041	0.029	0.350	0.630	0.900	0.590	0.710
J_3	Level 1	Level 1	Level 2	Level 1	Level 2	1.000	1.000	0.800	1.000	0.800
J_4	1.19, 0.013	0.32, 0.027	0.41, 0.013	0.66, 0.048	0.19, 0.022	0.638	0.785	0.833	0.595	0.843
J_5	13.5	16.6	19.2	14	15.1	0.458	0.717	0.933	0.500	0.592
J_6	18.9	19.6	20.1	20.1	19.5	0.742	0.960	1.000	1.000	0.950
J_7	52	45	49	47	44	1.000	0.857	0.971	0.914	0.829
J_8	140	170	168	160	126	0.571	1.000	0.971	0.857	0.371
J_9	1.31	1.62	1.2	2.01	1.74	0.845	0.690	0.900	0.495	0.630
J_{10}	2.16	2.1	2.49	2.52	2.55	0.660	0.600	0.990	1.000	1.000
J_{11}	99.10%	98.60%	99.70%	99.40%	100%	0.775	0.650	0.925	0.850	1.000
J_{12}	3.95	3.75	3.95	3.91	3.88	0.950	0.750	0.950	0.910	0.880
J_{13}	25%	26%	25%	23%	22.50%	1.000	1.000	1.000	0.714	0.643
J_{14}	95.70%	96.90%	98.50%	98.10%	98.30%	0.570	0.690	0.850	0.810	0.830
J_{15}	96.80%	95.50%	94.90%	96.20%	97.70%	0.840	0.775	0.745	0.810	0.885

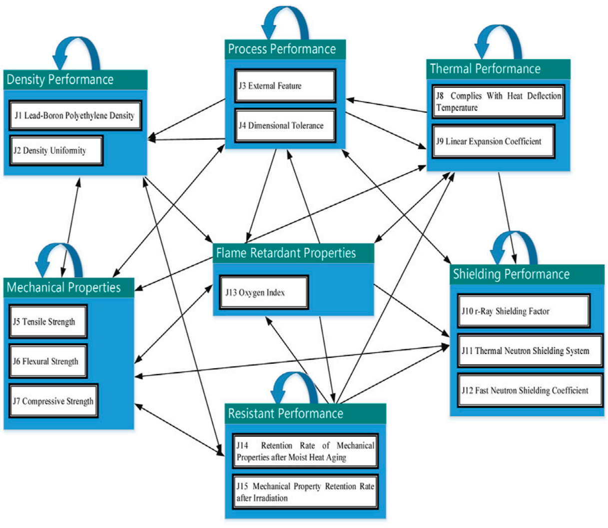

FIGURE 3
ANP network structure of composite shielding material performance evaluation.

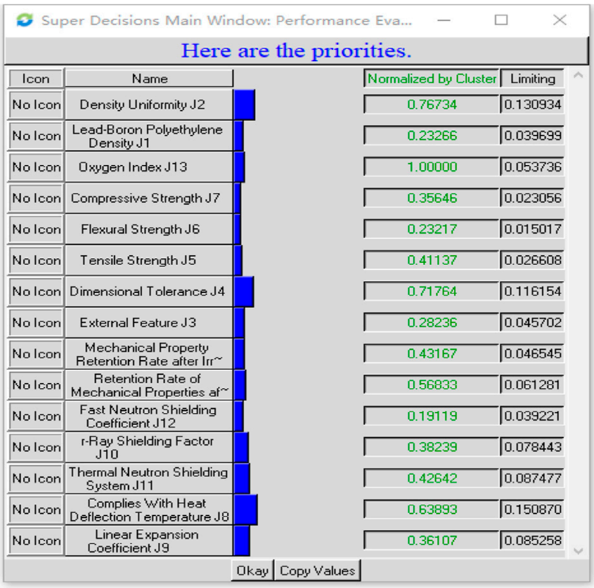

FIGURE 4
Priority level of indicators under limit super-matrix (centralized weight of indicators).

the negative ideal gray correlation projection value of the performance of five kinds of lead-boron polyethylene composite radiation shielding materials, and $r(2022)$ represents the gray correlation projection closeness of the properties of the five composite radiation shielding materials.

The greater the value of the gray correlation projection closeness, the closer the performance of the composite radiation shielding material from the corresponding

TABLE 4 Comparison of TOPSIS-ANP grey relational projection values and closeness.

Index parameters	Alternative supplier of lead-boron-polyethylene composite radiation shielding material				
	1	2	3	4	5
B^{+} (2022)	0.141	0.195	0.272	0.170	0.191
B^{-} (2022)	0.207	0.158	0.112	0.173	0.180
R(2022)	0.318	0.605	0.854	0.490	0.530

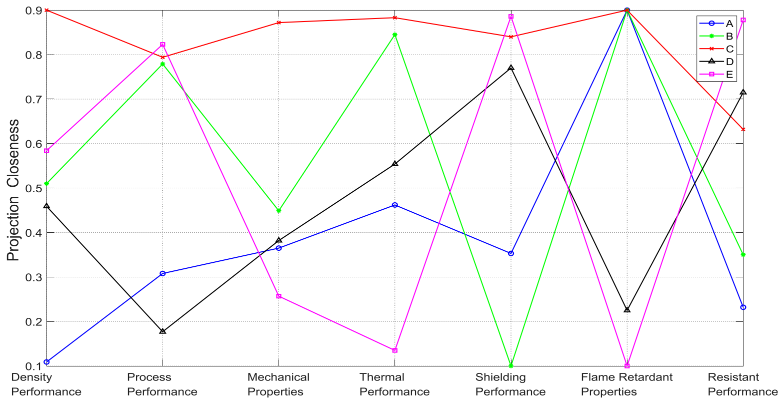

FIGURE 5
Performance Comparison of Five Lead-Boron Polyethylene Composite Radiation Shielding Materials (as seven dimensions).

supplier is to the optimal solution. Obviously, the proximity of the gray correlation projection is 0.854 > 0.605 > 0.530 > 0.490 > 0.318 from largest to smallest. Therefore, the performance of shielding materials (supplier selection priority) is determined from superior to inferior C, B, E, D and A. Furthermore, by examining the distribution of grey correlation projections in the dimensions of seven secondary indicators, more meaningful conclusions can be obtained. The specific results are shown in Figure 5.

Figure 5 shows the differences in the performance of five lead-boron-polyethylene composite radiation shielding materials in seven dimensions. Although the shielding material provided by supplier C is the best solution, from the perspective of sub-indexes, supplier C still has a large room for improvement in the two indexes of process performance and tolerance of the shielding material.

5 Comparative validity test of algorithms

The basic idea of validity test is to compare the results of the traditional composite shielding material performance evaluation method with the proposed algorithm, so as to prove the superiority of the proposed algorithm. The matching design of composite shielding materials is a multi-objective optimization problem with constraints. As an effective random search method, genetic algorithm has the characteristics of global optimum, good consistency and convergence, etc, which has good adaptability to solve the multi-objective optimization problem with constraints, and has been widely used in many fields with better results. Some achievements have been achieved in the design of lead-boron-polyethylene composite shielding materials with this method (Li et al., 2015b). Therefore, this section adopts the optimization design of shielding materials based on genetic algorithm for example verification, and compares the results with those of the improved TOPSIS-ANP algorithm to demonstrate the rationality and reliability of this method.

5.1 Basic information introduction

Genetic algorithm (Holland, 1975) is a computer random global search and optimization method developed by imitating the biological evolution mechanism in nature. In the process of implementing genetic algorithm, the commonly used tools for optimizing the design of lead-boron-polyethylene composite shielding materials are GENOCOP program (Michalewicz and

Nazhiyath, 1995; Michalewicz and JanikowGENOCOP, 1996) and MCNP program (X-5 Monte Carlo Team, 2003).

In this case, GENOCOPⅢ is used, which combines the feasible solution search method with the genetic algorithm to solve the optimization problem of the composition ratio of constrained composite shielding materials based on the repair of the infeasible solution, improving the computational efficiency and accuracy of the calculation results of the genetic algorithm. Also in this case, MCNP five is used to calculate the equivalent dose rate of neutron and γ-rays after passing through lead-boron-polyethylene composite shielding material.

According to the characteristics of PWR reactor source, the shielding thickness and the composition ratio of Pb/BPE composite shielding material were optimized for the combination of Pb/BPE composite shielding material.

5.2 Modeling and design

In the input file of MCNP software, the flux-dose conversion factor of rays is added to make the results in the output file output with the dose value, and the dose value is extracted as the objective function of the genetic algorithm. The shielding design is to minimize the dose generated after the rays pass through the material through the optimal design of the components and structure of the shielding material, which can be expressed by Eq. 24. In the formula, the thermal conductivity of the material, the mechanical properties of the material and the weight of the whole multi-layer shield are considered, namely:

$$\min f(X) = \left[f_D, \frac{1}{f_\lambda}, f_\alpha, f_p \right]^T \tag{22}$$

In equation: $f_D(X)$——the radiation dose sub-target after penetrating the material; $f_\lambda(X)$——thermal conductivity sub-target of the material; $f_\alpha(X)$——sub-target of mechanical properties of materials; $f_p(X, Z)$——the density sub-target of the material. X is the vector composed of the mass fractions of each component, $X = [x_1, x_2, \cdots, x_p]^T$, where $x_i\,(i = 1, 2, \cdots, p)$ is the mass fraction of each component in the shielding material. Z is the thickness vector of each layer of the shield, $Z = [z_1, z_2, \cdots, z_p]^T$, $z_i\,(i = 1, 2, \cdots, p)$ is the thickness of the material of each layer of the shield, z_{all} is the total thickness of the shield, x and z meet the following conditions.

Equation 23 through Eq.26 are the constraint conditions:

$$\sum\nolimits_{i=1}^{n} x_i = 1 \tag{23}$$

$$\sum\nolimits_{i=1}^{n} \frac{z_i}{z_{all}} = 1 \tag{24}$$

$$0 \le x_i \le 1 \tag{25}$$

$$0.01 \le x_i \le 1 \tag{26}$$

Where, Eq. 23 represents that the sum of material components of each layer is 1; Eq. 24 indicates that the sum of the thickness ratio of each layer is 1; Eq. 25 indicates that the mass fraction of each material is between 0 and 1; Eq. 26 The ratio between the thickness of each layer and the total thickness is between 0.01 and 1.00.

The key of multi-objective optimization design is to make clear the relationship between each sub-objective: independent or interrelated. In the initial research, by referring to the existing research basis and reasonable assumptions, the functional relationship between the weight factor of each sub-target and the related sub-target was given. The design reference parameter selects the performance parameter of the existing radiation shielding material with excellent performance or predicts the optimal value of the single performance of the material. Finally, an optimized overall objective is determined by dimensionless and weighted summation of the sub-objectives.

After each sub-objective is dimensionless, Eq. 20 becomes:

$$f_{total1} = \alpha \frac{f_D}{f_{D\min}} + \beta \frac{f_{\lambda\max}}{f_\lambda} + \gamma \frac{f_\alpha}{f_{\alpha\min}} + (1 - \alpha - \beta - \gamma) \frac{f_p}{f_{p\min}} \tag{27}$$

The mechanical model is based on the Kerner method, which is commonly used to predict the particle reinforced composites, and the reinforced boron carbide is spherical and uniformly dispersed. The volume modulus, shear modulus, Poisson's ratio and elastic modulus are shown in Eqs 28, 29.

$$k_c = \left(\sum \frac{k_i \varphi_i}{3k_i + 4\mu_m} \right) \Big/ \left(\sum \frac{\varphi_i}{3k_i + 4\mu_m} \right) \tag{28}$$

$$\mu_c = \mu_m \frac{\sum_{i=2}^{n} \frac{\varphi_i \mu_i}{(7-5\nu_m)\mu_m + (8-10\nu_m)\mu_i} + \frac{\varphi_m}{15(1-\nu_m)}}{\sum_{i=2}^{n} \frac{\varphi_i \mu_m}{(7-5\nu_m)\mu_m + (8-10\nu_m)\mu_i} + \frac{\varphi_m}{15(1-\nu_m)}} \tag{29}$$

$$\nu_c = \frac{3k_c - 2\mu_c}{6k_c + 2\mu_c} \tag{30}$$

$$E_c = 2\mu_c (1 + \nu_c) \tag{31}$$

Where: k_i—— material volume modulus; E_i—— elastic modulus of materials; μ_i——shear modulus of material; ν_i—— Poisson's ratio of material i; φ_i—— volume fraction of reinforcement material. The different subscripts c, m, p in the formula represent composites, matrix and reinforcing materials.

Thermal conductivity indicates the thermal conductivity of a material. Materials with high thermal conductivity are easy to release heat. Generally speaking, for shielding materials, the higher the thermal conductivity, the better. In this example, the Nielsen-Lewis model was used as the sub-target to optimize the thermal conductivity, and the Nielsen model was shown in Eqs 32–34.

$$\lambda_c = \lambda_m \frac{1 + AB\varphi_p}{1 - B\Phi\varphi_p} \tag{32}$$

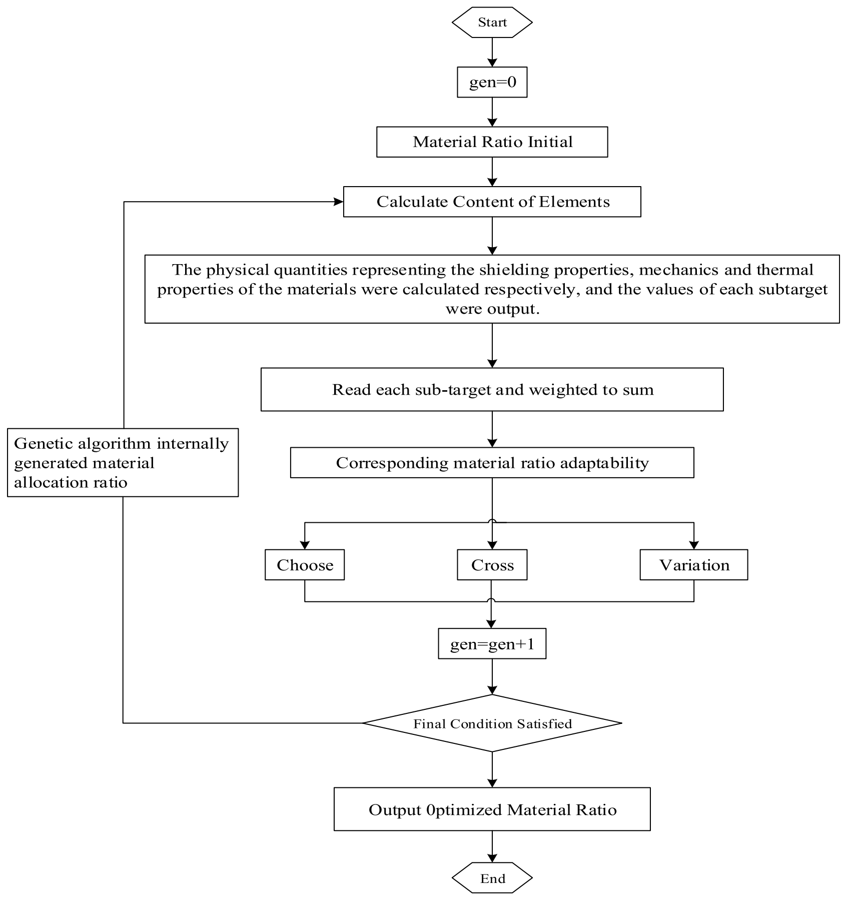

FIGURE 6
Flow chart of integrated optimization design of shielding component structure.

Where,

$$B = \frac{\lambda_p/\lambda_m - 1}{\lambda_p/\lambda_m + A} \quad (33)$$

$$\Phi = 1 + \frac{1-\varphi_{\max}}{\varphi_{\max}^2}\varphi_p \quad (34)$$

In equation: A ——correlation constant of particle shape and orientation; B —— thermal conductivity constant of each component; Φ—— the maximum bulk fraction $\varphi_{\max}$ with dispersed phase particles.

The e multi-objective optimization design process of lead-boron-polyethylene composite shielding material is shown in Figure 6.

5.3 Performance optimization results and comparison

According to the flow chart shown in Figure 6, the multi-objective optimization design of the material was carried out. Assuming that the total thickness of the Pb + Pb boron-polyethylene composite shielding material was 20 cm, when the ^{235}U induced fission energy spectrum was taken as the radiation source, the result was: thickness ratio of 0.375: 0.625, that is, the thickness of the first layer of lead plate is 7.5 cm, and the thickness of the second layer of lead-boron-polyethylene composite shielding material is 12.5 cm. Meanwhile, the mass fraction of lead and boron carbide in the lead-boron-polyethylene composite shielding material is 55.3% and 8%, respectively, and the density is 2.11 g/cm^3.

In summary, the density of a lead-boron-polyethylene composite shielding material optimized based on genetic algorithm is about 2.11 g/cm^3, which is consistent with the results of the improved TOPSIS-ANP evaluation method. However, the optimal design results based on the genetic algorithm only considered the neutron and γ-ray shielding properties, density, mechanical properties, thermal conductivity and other factors, while the composite shielding material evaluated by the TOPSIS-ANP method based on the improved gray relational projection algorithm is more comprehensive and easier to calculate.

6 Conclusion

This paper introduces an improved TOPSS-ANP evaluation method based on gray relational projection algorithm, which takes five main suppliers of lead boron-polyethylene composite shielding materials in China in 2022 as the research object, so as to conduct a comprehensive evaluation of the performance of lead boron-polyethylene composite shielding materials. From the characteristics of the method, the method is designed according to the principle of gray projection angle, and the non-linear weighting idea is used to determine the quality of indicators by examining the relationship between the projection of each indicator dimension and the target value. Because the manufacturing process and industrial technology of shielding materials are not involved in the performance evaluation process, this method is widely used and can be extended to the performance evaluation of other composite shielding materials. The evaluation index system is comprehensive and objective, the evaluation process is scientific and reasonable, and the final evaluation conclusion has strong credibility as well.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

KZ proposed a weighted projection model of composite shielding materials based on the extended TOPSIS theory, clarified the principle and algorithm implementation of projection dimension reduction, and carried out an empirical test. XL, HW, SL, KS are responsible for the collection of original data, the collation and analysis of calculation results.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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