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Validation of the neural network for 3D photon radiation field reconstruction under various source distributions

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Introduction: This paper proposes a five-layer fully connected neural network for predicting radiation parameters in a radiation space based on detector readings.

Methods: The network is trained and tested using gamma flux values from individual detector positions as input, and is used to predict the gamma radiation field in 3D space under different source term distributions. The method is evaluated using the mean percentage change error (PCT) for the test set under different source term distributions.

Results: The results show that the neural network method can accurately predict radiation parameters with an average PCT error range of 0.53% to 3.11%, within the given measurement input error range of $\pm 10\%$. The method also demonstrates its ability to directly reconstruct the 3D radiation field with some simple source terms.

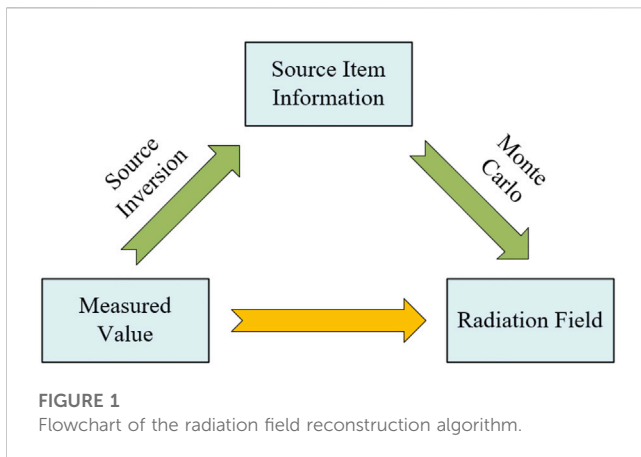
Discussion: The proposed method has practical value in real operations within radiation spaces, and can be used to improve the accuracy and efficiency of predicting radiation parameters. Further research could explore the use of more complex source term distributions and the integration of other types of sensors for improved accuracy.

KEYWORDS

3D radiation field, reconstruction method, Monte Carlo, artificial intelligence, neural network

1 Introduction

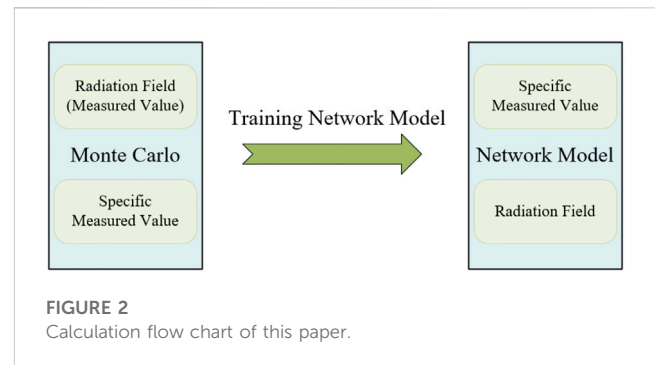
To satisfy the current and ambitious goals with respect to climate change, a complete transformation of the global energy system is required. Nuclear energy is a major source of low-carbon electricity and plays a significant role in preventing greenhouse gas emissions. Due to the radiation dose limits of personnel and the environment during the construction and operation of nuclear power facilities, traditional nuclear technology that are implemented in traditional nuclear power plants often lacks flexibility. Before workers are allowed to enter a radiation operation space, the three-dimensional (3D) radiation field in the entire work space is typically defined. The geometry model, combined with the computer-calculated simulated worker dose exposure information, can then be used to determine the radiation dose of the workers that can be quantitatively gained before the work commences (Hughes, 1996). This is pertinent for reducing the radiation damage received by the workers during the actual operation process to create a safe working environment. The



typical focus of the above process is to establish a 3D radiation field in the personnel operation area. Therefore, carrying out research on the reconstruction method of the dose distribution of a 3D radiation field can provide a more accurate and practical method for optimizing workers' protection equipment and measures against radiation. This facilitates great improvement of the safety level of the physical nuclear devices; furthermore, it can also more comprehensively ensure the health of workers. Therefore, research on the reconstruction method of radiation fields supports broad applications in the whole life cycle of the operation, including the inspection and eventual decommissioning of nuclear equipment (Zhu et al., 2010; Liu et al., 2011).

The methods for calculating radiation field parameters can be divided into two categories: Direct calculation methods and reverse reconstruction methods. By considering the geometric factors, source terms, and material information of the computing space, the direct calculation method uses a numerical basis to calculate the radiation field parameters in the geometric space. At present, the most commonly used direct calculation methods are the Monte Carlo method, discrete coordinate method and point kernel integration method. Although direct calculation methods can accurately calculate the radiation parameters within the radiation field, all three methods need to accurately describe the source term information in the radiation field. This is not always feasible; in practical application scenarios, the activity information of the source term is often unknown, while other information of the source term, such as the location of the source term and the geometric information of the entire radiation field, is often available. In practice, it is necessary to first invert the source term parameters in the space, predict the source term parameters, and then calculate the radiation field parameters for the whole space by a direct calculation method.

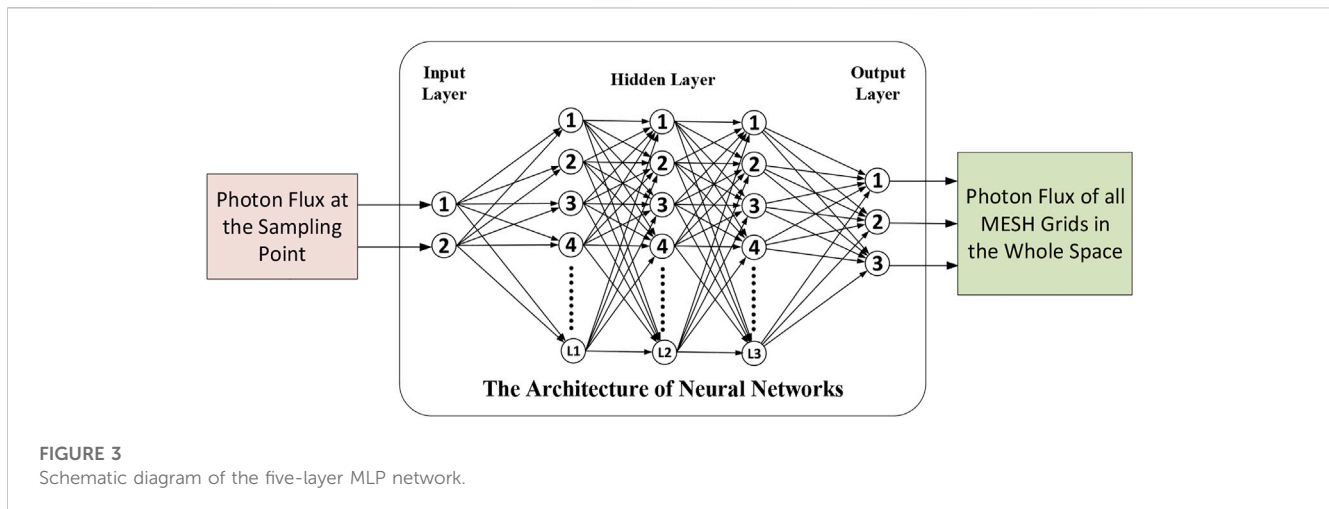
As shown in Figure 1, the reverse reconstruction method is mainly used to analyze and reconstruct the overall radiation field from finite sampling points through interpolation algorithms and artificial intelligence calculation methods. Much research has been conducted on inverse reconstruction methods based on interpolation algorithms. Wang and Cai, (2018) proposed a method based on net function interpolation to the reciprocal of the dose rate field. Sai et al. (2016) incorporated the interpolation



technique for multiple secondary scattering data into the reconstruction process, and Zhu et al. (2021) proposed a method based on the improved Cahn-Hilliard (C-H) equation to reconstruct the 3D gamma dose rate field using arbitrarily located sparse measurements. Although reverse reconstruction methods based on interpolation algorithms have been extensively studied, these methods often require a large number of uniform sampling points located throughout space, and in reality, these are often unattainable requirements.

For nuclear technology, artificial intelligence methods are mainly used in equipment fault diagnosis and have achieved good results (Zhong and Ban, 2022a; Zhong and Ban, 2022b; Zhong et al., 2022). However, few studies have been performed on artificial intelligence (AI)-based reverse reconstruction methods. In the actual radiation field, the relationship between the measured values of the radiation obtained by the scattered detector and the radiation parameters in the whole space is often difficult to describe with a determined mathematical model. Subsequently, the non-linear method represented by the neural network is likely to become an effective tool for radiation field reconstruction. Li et al. (2018) proposed using a simple radial basis function (RBF) neural network model that, when combined with the inverse distance weighting method used to calculate difference values, can be used to obtain whole space radiation parameters, as verified by a simple calculation. Zhou et al. (2021) proposed an adaptive back propagation (BP) neural network with learning rate attenuation, and its accuracy and feasibility were verified. Although the two aforementioned reconstruction methods have achieved positive results, they still exhibit some shortcomings, which include (1) these two methods have only been applied in the rapid reconstruction of the two-dimensional radiation field and have not been verified in the three-dimensional radiation field, (2) both methods require a large amount of uniform sampling performed throughout the whole space, which cannot be realized in the real radiation field environment, and (3) the two methods only include a single source term. In reality, the distribution of sources is not constant. The influence of source term parameters on the reconstruction of the radiation field needs further discussion.

In conclusion, based on the artificial intelligence method, it is very important to solve the actual radiation protection problem and study algorithms for 3D radiation field reconstruction from individual sampling points considering source term parameters. To solve the above problems, as shown in Figure 2, we propose an algorithm to reconstruct the 3D gamma radiation field based on



finite sampling values by using neural networks and then test different distribution source terms by using common complex geometric examples. The Monte Carlo method is used in this paper to calculate the distribution of the 3D radiation field to obtain a data set that is then used during the process training of the neural network. Finally, the 3D gamma radiation field is reconstructed.

2 3D Radiation field reconstruction methods and processes

Neural networks are common machine learning models within the field of artificial intelligence and are used mostly in supervised learning methods. The purpose of supervised learning is to train a model so that any input value can be used in the model, which outputs a predicted value. Ideally, the predicted value is close to the real value, reflecting the good “fit” of the mapping relationship between the input value and the output value. If a neural network method is used to reconstruct the flux distribution of the whole 3D space from the values obtained with a limited number of detectors, rapid reconstruction of the 3D radiation field can be realized, which is of great significance to actual radiation shielding (Mahdavi et al., 2019; Zhou et al., 2021).

As shown in Figure 3, we develop a five-layer multilayer perceptron (MLP) neural network to accurately reconstruct the gamma radiation field studied in this paper. An MLP, also known as a fully connected neural network, is a neural network composed of a single perceptron with full connections, which is one of the most traditional neural networks. An MLP network consists of an initial input layer, an intermediate hidden layer, and a final output layer. The nodes of the input layer correspond to the photon flux value at the detector in the radiation space. To simulate the measurement errors that may occur during the actual measurement process, the input layer data are superimposed with a certain range of fluctuation error terms. The nodes of the output layer correspond to the division of mesh grids in the X, Y, and Z directions. Then, the radiation source terms in the radiation field space are changed to obtain different data sets for neural network training and

verification of the model. The three points should be noted as follows:

- (1) The input received by the neural network is the numerical value of the detector, and the result of the fluctuation error term of the random range ($\pm 10\%$) is superimposed, which is the measurement error of the detector itself under simulated practical conditions.
- (2) Preprocessing is performed for the training data set x, y , where x represents the photon flux at finite points in the three-dimensional space detected by the detectors, which is the input of the neural network. y represents the reconstructed radiation field of the whole space, which is the ground truth. Since the value of photon flux has a small order of magnitude, roughly on the order of $10^{-5} - 10^{-7}$, to improve the convergence rate during neural network training, the network performs the normalization treatment of linear transformation for the input data to (x_i, y_i) , specifically, which artificially presets the sample mean and variance of x to be $3.38E-06$ and $3.78E-06$ and presets the sample mean and variance of y to be $2.80E-06$ and $2.75E-06$, respectively. Then, the following standardization operation is performed:

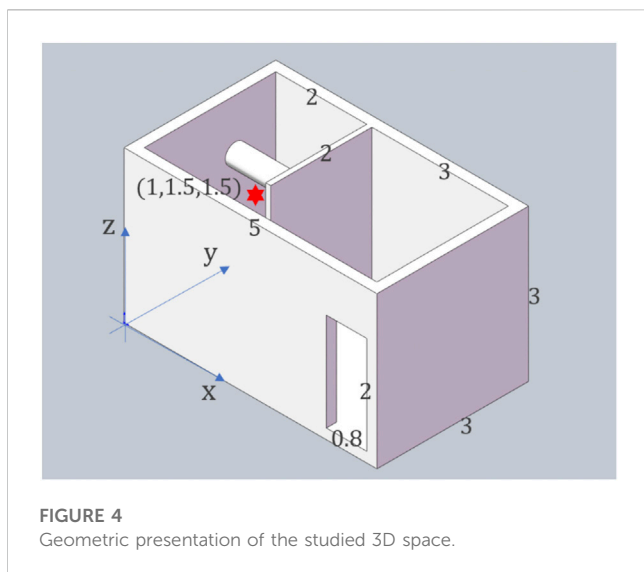
$$z'_i = (z_i - \bar{z}) / \sigma(z) \quad (1)$$

where $z_i = x_i$ or y_i .

- (3) The evaluation of the network can be divided into two steps, in which the percentage change error (PCT) is used. In the first step, we use the output value of the model o'_i to calculate the predicted value of the radiation field o using $o_i = o'_i \cdot \sigma(y) + \bar{y}$, where $\sigma(y)$ represents the preset variance of the ground truth when performing regularization, and \bar{y} represents the preset mean of the ground truth during regularization. In the second step, we calculate the PCT by the following formula:

$$\text{PCT} = |o_i - y_i| / y_i \quad (2)$$

This paper utilized a five-layer MLP neural network to reconstruct the three-dimensional dose distribution in space for different types of neutron sources with varying numbers, shapes,



and distributions. Following the principle of simplicity to complexity in exploration experiments, this study sequentially validated the calculations for five scenarios: A monoenergetic neutron point source, a neutron point source with a Maxwellian energy distribution, a dual neutron source with one discrete neutron energy spectrum and one Maxwellian continuous neutron energy spectrum, a neutron surface source, and a neutron volume source.

3 Description of calculation examples

3.1 Geometric description

The 3D model used in this paper is shown in Figure 4. A 3D model room is simulated, and the X, Y, and Z directions correspond to the three dimensions of the length, width, and height of the room, with values of 5.00 m, 3.00 m, and 3.00 m, respectively; the room is separated by a wall, with a thickness of 0.10 m; the thickness of the outer wall is 0.20 m, and a door is opened in a portion of its X-Z plane, with a width of 0.80 m and a height of 2.00 m. The position of the radiation source is located at the coordinates (1.00 m, 1.50 m, and 1.50 m) and placed in the inward space of the room. The source is used as the default radiation source. Moreover, a cylindrical beam is added to the inner room, with the beam position at $Y = 2.00$ m, $Z = 2.00$ m, radius $R = 0.20$ m, above the side of the radiation source.

3.2 Material description

In this example, the outer wall of the house is made of boron-containing concrete with a thickness of 20.00 cm; the walls inside the house consist of two layers of material: One layer is boron-containing polyethylene with a thickness of 5.00 cm, and the other layer is carbon steel with a thickness of 5.00 cm, which combined constitute the thickness of the interior wall of 10.00 cm. The cylindrical beams in the inner room are also made of carbon steel, with a radius of 0.20 m. The materials used above are the most commonly used shielding materials in nuclear facilities. The source term used in this paper is a

neutron source of 0.00253 eV–2.00 MeV; in this energy interval, the reaction cross-section of different nuclides (n, γ) varies tremendously, which greatly increases the complexity of the gamma radiation field in the room. The information on materials above is found in the dedicated manual, and the specific data are shown in Table 1:

3.3 Statistical description

As shown in Figure 5, the following is an example of an initially set single-energy neutron source radiation field. The source term is an isotropic radiation source placed in the middle of the inner room ($X = 1.00$ m, $Y = 1.50$ m, $Z = 1.50$ m), with a direction angle of 4° . The energy of monoenergetic neutrons is set from 0.00253 eV for thermal neutrons to 2.00 MeV for fast neutrons. The statistics in this example are primarily divided into the following 2 V

- (1) Neutron and photon fluxes are counted by detectors placed at 27 selected positions in the room. The upper, middle, and lower layers are placed in the room. Nine spherical detectors are placed in the same position for each layer. The default radius of the detector is 5.00 cm. The calculated flux of neutrons and photons is the flux data in the sphere with a given radius, with the detector position located at the center of the sphere.
- (2) The entire 3D space is divided into MESH grids to calculate the radiation field parameters. The specific process is to evenly divide 10 segments at 0.00 m–2.00 m and 10 segments at 2.00 m–5.00 m in the X direction, 10 segments at 0.00 m–3.00 m in the Y direction, and 10 segments at 0.00 m–3.00 m in the Z direction. Therefore, the 3D space of the whole radiation field is divided into $20 \times 10 \times 10$, equaling 2000 3D meshes, so that the neutron flux and photon flux in each mesh space can be calculated. Figure 6 shows the diagram of the mesh grid division. Figure 7 shows the typical calculation results of the photon flux distribution under a neutron source.

Both neutron and photon radiation parameters are important physical quantities to consider in radiation protection. The aim of this paper is to verify the effectiveness of neural networks in predicting radiation fields. The physical process of photon production from neutrons is an indirect process, making the prediction more complex. Therefore, this study focuses on verifying the effectiveness of neural network methods in predicting photon radiation fields.

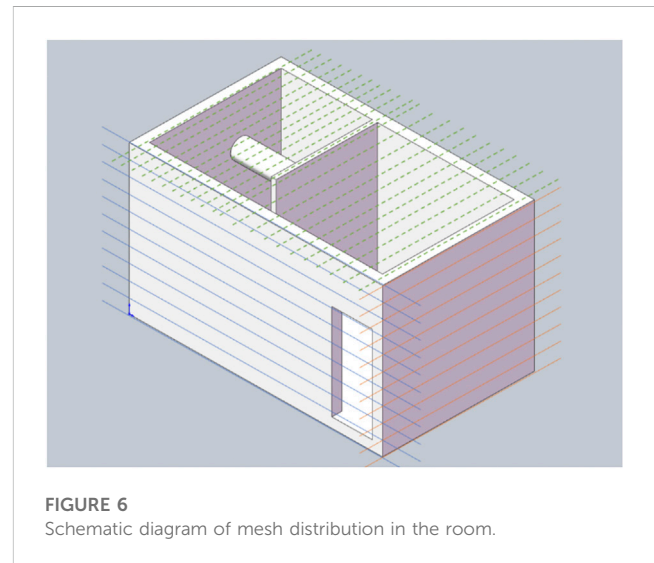
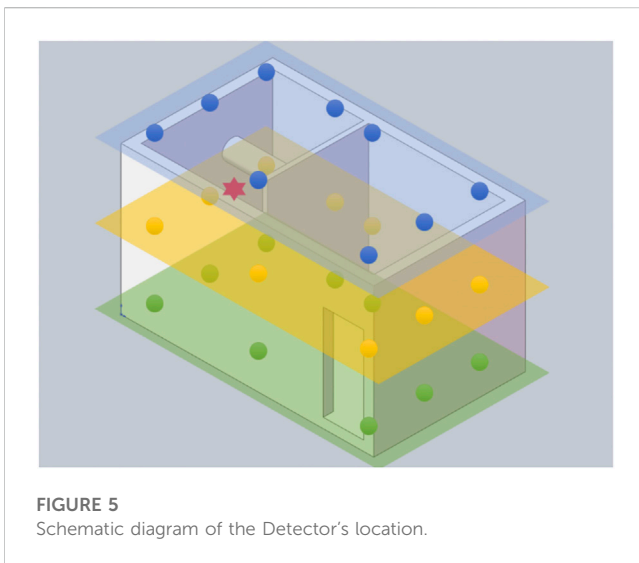
4 3D Radiation field reconstruction results and discussion

In this paper, simulation and training are carried out for five cases, resulting in new prediction examples from the obtained neural network. Figures 8, 9, Figures 10, 11, Figure 12 show the top views ($Z = 1500$) of the calculated value, predicted value, statistical error, and relative error of the 3D radiation field photon flux under these five source terms.

The neural network used in this study has an input layer with 27 nodes and an output layer with 2000 nodes, with three hidden layers of 8, 64, and 512 nodes to reduce the feature dimensions. The

TABLE 1 Nuclide and density parameter information of the studied material.

Material	Concrete (2.30 g/cm ³)									
Nuclide	H (%)	C (%)	Na (%)	Mg (%)	Al (%)	Si (%)	K (%)	Ca (%)	Fe (%)	B (%)
Mass Percentage	30.40	0.20	0.90	0.10	1.00	15.10	0.70	1.50	0.20	10.00
Material	Polyethylene (0.93 g/cm ³)			Steel (7.82 g/cm ³)			Air (0.001205 g/cm ³)			
Nuclide	H (%)	C (%)	B (%)	C (%)	Fe (%)	C (%)	N (%)	O (%)	Ar (%)	
Mass Percentage	61.70	28.30	10.00	2.30	97.70	0.01	75.50	23.20	1.30	



mean squared error (MSE) function was chosen as the loss function, and the rectified linear unit (ReLU) function was selected as the activation function, with PCT used to evaluate the training performance. The data set was divided into a training set, validation set, and testing set of 3825, 1026, and 553 samples, respectively, with a ratio of 7:2:1. The calculation results are presented below.

4.1 Reconstruction results of the five source terms

(1) Single Energy Point Source

When the radiation source is a single energy neutron point source, the neutron energy range is 0.00253 eV–2.00 MeV, the average PCT value of the test set is 0.53%, and the maximum PCT value between different batches is 1.12%. The average statistical error of the Monte Carlo calculation of the photon flux is 1.86%. The average relative deviation in the whole space MESH grid is 5.23%, and the average relative deviation in the MESH grid on the left side of the wall is 2.49%.

(2) Maxwell Fission Spectrum Point Source

When the radiation source follows the Maxwell fission spectrum distribution, the average PCT value on the test set is 3.11%, and the maximum PCT value between different batches is 3.66%. The average statistical error of the Monte Carlo calculation of the photon flux is 1.82%. The average relative deviation in the whole space MESH grid is 32.67%, and the average relative deviation in the MESH grid on the left side of the wall is 19.78%.

(3) Double-Point Source

When the radiation source is a double-point source, which uses a discrete neutron distribution, the other source utilizes a neutron distribution from the Maxwell fission spectrum. In the test set, the average PCT value was 0.80%, and the maximum PCT value between different batches was 1.43%. The average statistical error of the Monte Carlo calculation of the photon flux is 1.57%. The average relative deviation in the whole space MESH grid is 7.21%, and the average relative deviation in the MESH grid on the left side of the wall is 6.71%.

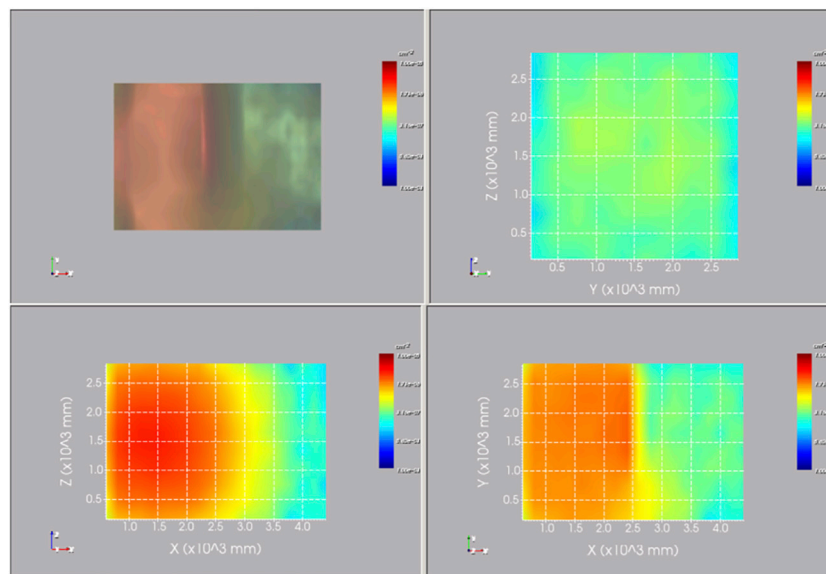


FIGURE 7
Schematic diagram of the photon flux distribution under a neutron source.

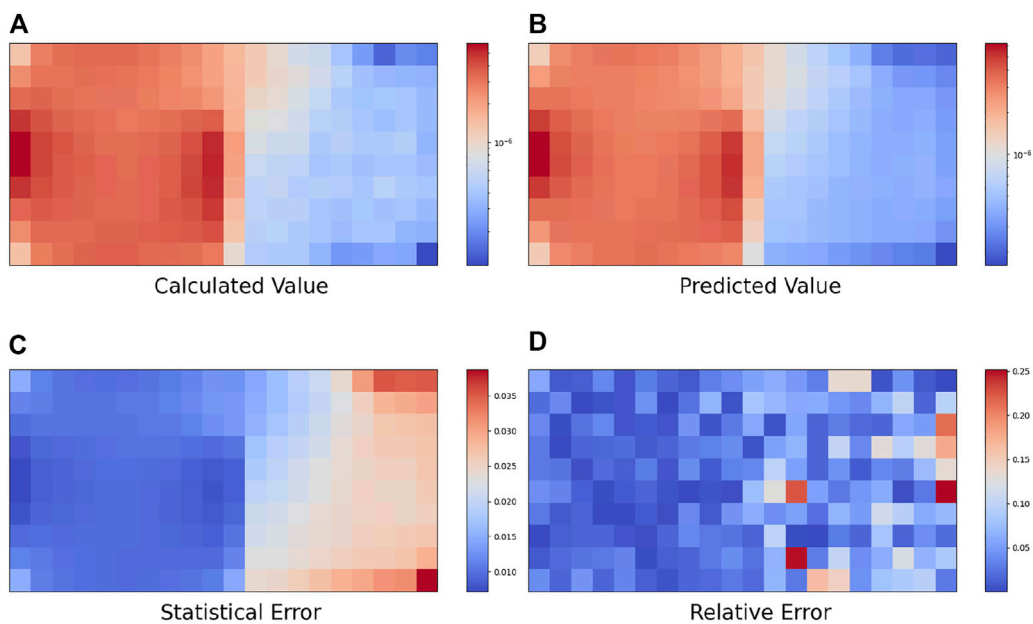


FIGURE 8
Reconstruction results of the single energy source term.

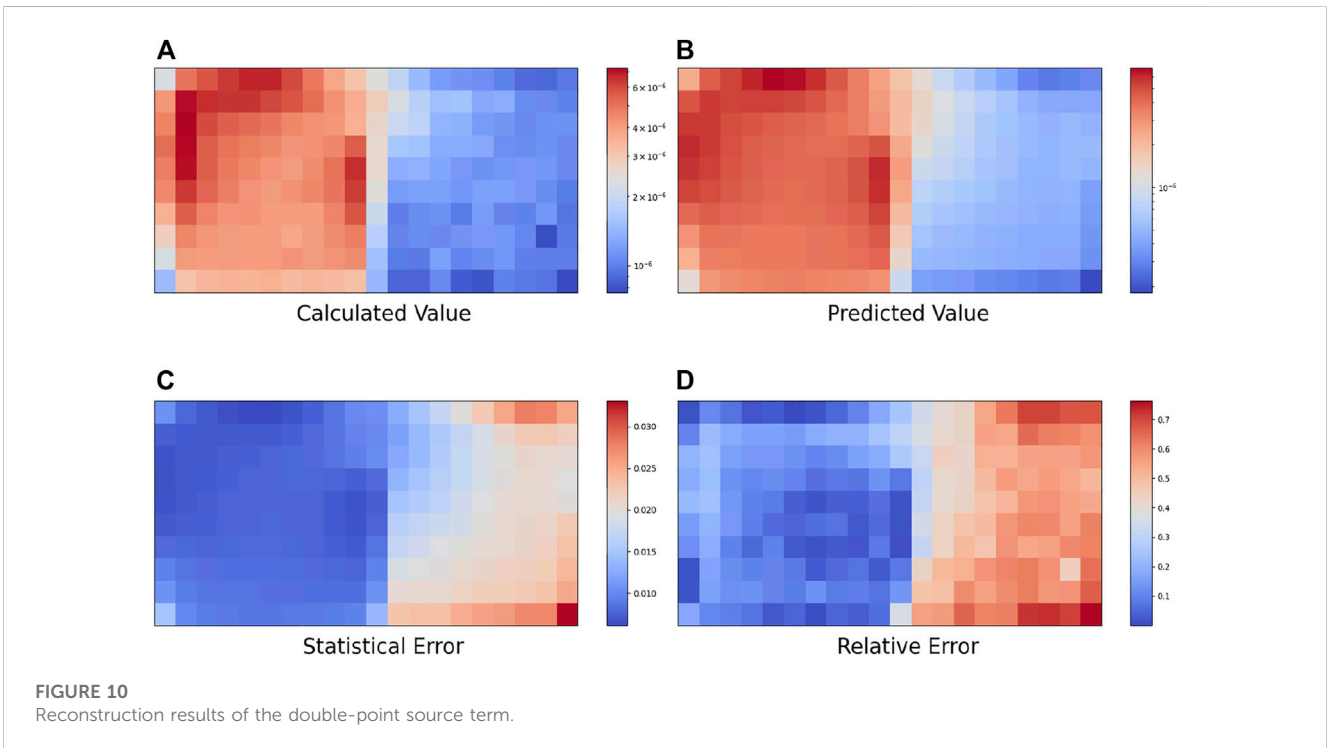
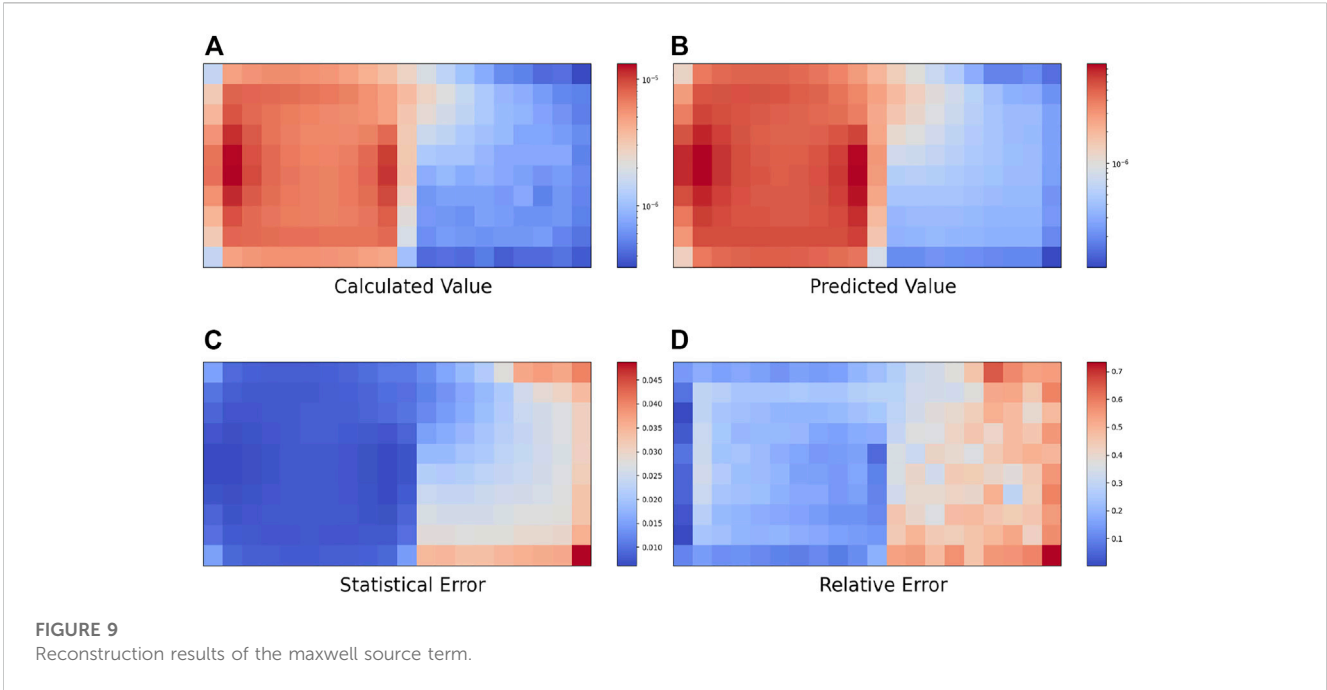
(4) 2D Surface Source

When the radiation source is in a 2D surface source distribution, the radioactive sources are distributed on the circular surface. In the test set, the average value of PCT is 0.92%, and the maximum value of PCT between different batches is 1.46%. The average statistical error of the Monte Carlo calculation of the photon flux is 1.66%. The average relative deviation in the whole space MESH grid is 36.75%,

and the average relative deviation in the MESH grid on the left side of the wall is 17.69%.

(5) 3D Cylindrical Source

When the radiation source is in a 3D cylindrical source distribution, the radioactive sources are distributed in the cylinder, with the weight related to the radius. In the test set, the average PCT value was 1.98%, and the maximum PCT value



between batches was 2.79%. The average statistical error of the Monte Carlo calculation of the photon flux is 2.02%. The average relative deviation in the whole space MESH grid is 56.22%, and the average relative deviation in the MESH grid on the left side of the wall is 42.59%.

4.2 Comparison and discussion of reconstruction results

In summary, the reconstruction results of the MLP network for photon flux distribution in radiation field space under different source

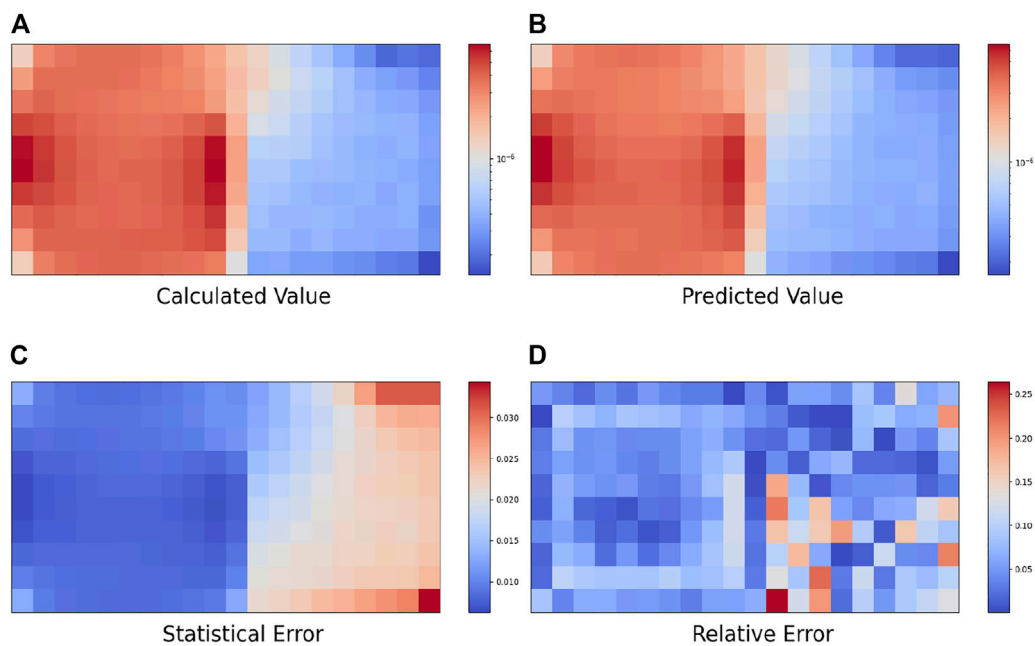


FIGURE 11
Reconstruction results of the 2D surface source term.

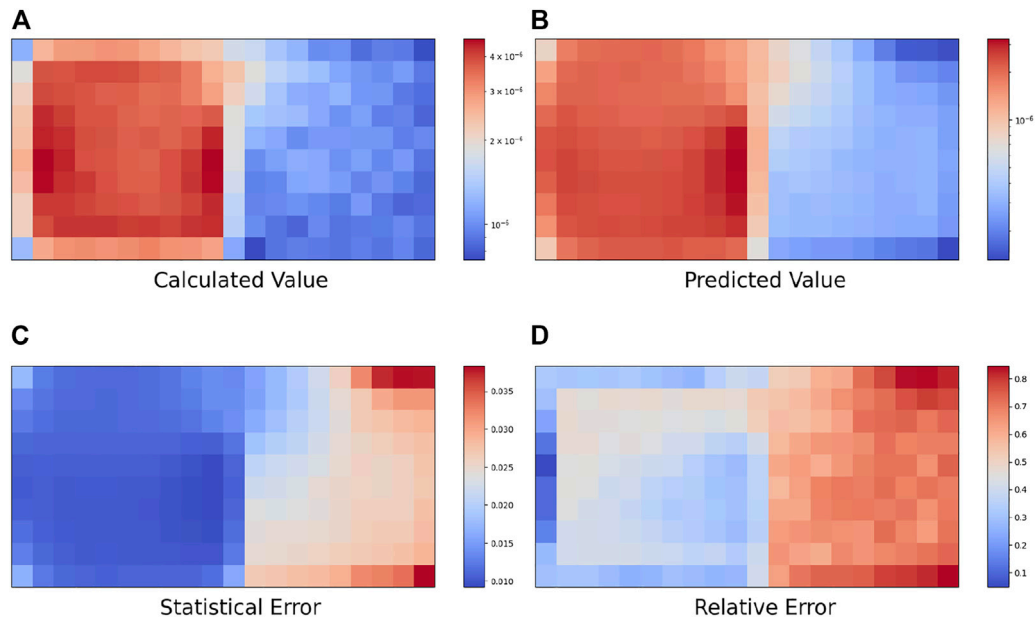


FIGURE 12
Reconstruction results of the 3D cylindrical source term.

intensities are shown in Table 2. The mean PCT of the test set ranges from 0.53%–3.11%, and the maximum value is 3.66%, which is less than the error range of the given input measured value ($\pm 10.00\%$). For simple source items, this method can obtain acceptable radiation field prediction values. However, for more complex source items, the relative deviation of

the predicted value of the radiation field is larger. This result shows that this method can be used to predict the simple gamma radiation field.

From the results summarized in Table 2, it can be found that the radiation field prediction using a single-energy neutron source and a double-point source has better performance than the other three

TABLE 2 Summary of reconstruction of radiation field by MLP neural network.

Setting of radiation source	Average PCT on test set (%)	Maximum PCT on test set (%)	Average statistical error (%)	Mean relative deviation on full space (%)	Mean relative deviation on left space (%)
Single energy point source	0.53	1.12	1.86	5.23	4.29
Maxwell fission spectrum point source	3.11	3.66	1.82	32.67	19.78
Double-point source	0.80	1.43	1.57	7.21	6.71
2D Surface source	0.92	1.46	1.66	36.75	17.69
3D Cylindrical source	1.98	2.79	2.02	56.22	42.59

methods. As the energy spectrum parameters and spatial distribution of the source term become more complex, the prediction results of the neural network become more general. The specific analyses are as follows:

- (1) The results demonstrate that when the source parameters are relatively simple, both PCT and calculated values exhibit small relative deviations from the predicted values. However, under complex source parameters, although the PCT is low, the relative error is high and does not match the predicted values. This can be attributed to the fact that the MLP neural network employed in this study is relatively simple, thereby making it difficult to adapt to the extensive spatial distribution and energy spectrum parameter changes of complex source items. Moreover, the generalization capability of the MLP neural network model is limited, and while it performs well on the training set, it does not provide satisfactory prediction results for data outside it. Furthermore, the neural network used in this study exhibits overfitting problems for complex source items, which can be mitigated by increasing the data volume and using dropout and other techniques. Thus, to improve the accuracy of the predictions, one must consider employing a more sophisticated neural network model that is capable of adapting to complex source parameters.
- (2) The single-energy neutron source term emits neutrons with equal energy, while the influence of the 3D radiation field is relatively uniform. Therefore, there is a relatively fixed relationship between the sampling value of the detector sampling point and the radiation field of the whole space. When the parameters of the source term become more complex, the neutrons emitted by the source term need to be sampled according to energy, position and angle, and the complexity is greatly increased. Therefore, the relationship between the sampling value of the detector sampling point and the whole space radiation field becomes more complicated, which eventually leads to relatively poor prediction results of the neural network.
- (3) The scattering term in the radiation field greatly increases the complexity of the radiation field. Since a wall divides the geometric space into two parts, neutrons can only reach the space on the right side of the wall through multiple scattering. The complex relationship of the sampling value and photon radiation field in the space on the right side of the wall is greatly

increased, ultimately leading to relatively poor prediction results of the neural network. Therefore, the prediction effect of the space on the left side of the wall is much better than that of the space on the right side of the wall.

In conclusion, the neural network method has a certain application in the reconstruction of 3D radiation fields, but its predictive performance is affected by factors such as the source item energy spectrum distribution, source item spatial distribution, and scattering terms. In the test scenarios of this study, satisfactory radiation field prediction results were only achieved under the conditions of a single-point source and double-point source. Due to the numerous influencing factors, there is no neural network structure that can effectively solve all radiation field reconstruction problems. Therefore, further investigation is required to explore the effectiveness of the neural network method for radiation field reconstruction under complex source item conditions. In addition, the effects of different neural network types, structures, and hyperparameters on the reconstruction of 3D radiation fields also need to be compared and verified in future studies.

5 Conclusion

In this paper, to solve the common problem of radiation field reconstruction in practice, the reconstruction algorithm of the 3D gamma radiation field from individual sampling points under the source term parameters is studied. We then propose an algorithm for reconstructing the 3D gamma radiation field based on finite sampling values using neural networks, and different distributed source terms are then tested using common complex geometric examples that exist in real use. During the process of neural network training, the Monte Carlo method is used to calculate the distribution of the 3D radiation field used in this paper. To obtain the data set required for training, a five-layer MLP neural network is trained that then identifies the reconstruction function of the 3D gamma radiation field. By testing different distribution source terms, the mean PCT is identified as 0.53%–3.11%, and the maximum value is 3.66%, which is less than the error range ($\pm 10\%$) of the given input measured value, verifying the feasibility and accuracy of the proposed method for the prediction of the gamma radiation field.

The above research results provide positive benefits, as they have broad application prospects for strengthening the radiation protection of

on-site operators of nuclear devices, reducing the radiation damage suffered by operators, more accurately evaluating the spatial dose distribution of nuclear facilities that are to be decommissioned, and reducing the collective dose absorbed throughout the life cycle of nuclear facilities. In addition, with the in-depth application of machine learning in recent years, the reconstruction of the radiation field using neural networks may become the next research focus in the field of radiation protection, which is of exploratory significance for the optimization of sites emitting radiation.

Furthermore, research can be continued from the following three aspects. (1) The neural network model used in this paper is relatively basic. Thus, it is necessary to test and study the application of other neural network models in complex radiation dose fields in the future. (2) The 3D model established in this paper is relatively simple, while the reactor geometry and source terms in practice are more complex. In the future, it is also necessary to explore the influence of the number and distribution of different sampling points on the radiation field reconstruction method. (3) In this paper, only the reconstruction of the photon radiation field is verified, and the reconstruction method of the neutron radiation field can be explored in the future.

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

HY: Data analysis, Methodology, Validation, Formal analysis, Visualization Software, Writing Original Draft, recording image data WZ: Data analysis, Methodology, recording image data,

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Conflict of interest

Author WZ was employed by Nuctech Company Limited.

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