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Original Article

An adaptive deviation-resistant neutron spectrum unfolding method based on transfer learning

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ABSTRACT

Neutron spectrum is essential to the safe operation of reactors. Traditional online neutron spectrum measurement methods still have room to improve accuracy for the application cases of wide energy range. From the application of artificial neural network (ANN) algorithm in spectrum unfolding, its accuracy is difficult to be improved for lacking of enough effective training data. In this paper, an adaptive deviation-resistant neutron spectrum unfolding method based on transfer learning was developed. The model of ANN was trained with thousands of neutron spectra generated with Monte Carlo transport calculation to construct a coarse-grained unfolded spectrum. In order to improve the accuracy of the unfolded spectrum, results of the previous ANN model combined with some specific eigenvalues of the current system were put into the dataset for training the deeper ANN model, and fine-grained unfolded spectrum could be achieved through the deeper ANN model. The method could realize accurate spectrum unfolding while maintaining universality, combined with detectors covering wide energy range, it could improve the accuracy of spectrum measurement methods for wide energy range. This method was verified with a fast neutron reactor BN-600. The mean square error (MSE), average relative deviation (ARD) and spectrum quality (Qs) were selected to evaluate the final results and they all demonstrated that the developed method was much more precise than traditional spectrum unfolding methods.

1. Introduction

Neutron spectrum plays an important role in the field of reactor design and safety, because it is a significant parameter for reactor criticality, radiation dose protection, fuel consumption analysis and plasma diagnostics, etc. Due to the complexity of the interaction of neutrons with other substances in the environment, the difficulty of spectrum measurement is further increased [1].

Most of mainstream neutron spectrum measurement methods, such as multi-sphere spectrometer, cannot directly give neutron spectrum results. They need to be incorporated with suitable spectrum unfolding program. Therefore, the spectrum unfolding program is of vital significance to improving the accuracy and efficiency of neutron spectrum measurement. There are many efficient spectrum unfolding algorithms for neutron spectrum measurements: iteration algorithm, maximum entropy algorithm, least-squares algorithm, singular value decomposition algorithm and Monte Carlo algorithm [2]. These traditional spectrum unfolding algorithms have distinct mathematical principles and relatively transparent processes [3]. However, these algorithms still have limitations in their use for online spectrum measurement. For example, the iteration algorithm requires constant optimization of the default spectrum, which is difficult to balance in accuracy and efficiency [4]. The limitation of the maximum entropy algorithm is that the number of its constraint functions is related to the samples, which leads to a huge computation time in its iterative process [5]. The least-squares algorithm would cause serious errors when the discreteness of the measured values is large and when the existing outliers are not few [6]. The method of singular value decomposition algorithm is like black-box algorithm and is not highly explanatory [7]. The Monte Carlo algorithm first converts deterministic problems into random problems; therefore, its efficiency depends on the complexity of the model. Meanwhile, the MC algorithm is highly accurate in a transient

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process; however, it is difficult to solve dynamic problems [8]. In addition to these traditional algorithms, new methods based on artificial neural networks are gradually being applied to the field of spectrum unfolding.

In recent years, researchers have been actively involved in the development of accurate and efficient spectrum unfolding methods. Carrillo applied artificial neural network spectrum unfolding algorithm to the Bonner spheres spectrometer and unfolded neutron spectrum of different radiation fields [9]. Mohammadi applied the method of artificial neural network algorithm to the Bonner spheres spectrometer based on gold foils activation and unfolded neutron spectrum of ^{241}Am–Be source whose results showed great agreement with the reference spectrum of ISO 8529-1 [10]. Shahabinejad developed a two-steps genetic algorithm spectrum unfolding method to unfold a neutron spectrum from a pulse height distribution whose results showing a better accuracy than the existing codes [11]. Hosseini applied the artificial neural network and modified least square method to liquid organic scintillators respectively, and unfolded neutron spectrum of ^{252}Cf and ^{241}Am–Be source [12]. The results also fit well with the ISO spectrum. As recent as in 2017, Alvar has applied radial basis function (RBF), multilayer perceptron, and artificial neural network to Lil detectors with Eu impurity, and the results indicated that RBF neural network can be an effective method for neutron spectrum unfolding [13].

Artificial neural networks are mathematical or computational models based on biological nervous systems, also commonly referred to as neural networks. The model consists of several artificial neurons, which could be used to simulate the complex relationship between input and output data so that the corresponding output could be obtained under the condition of known input [14]. In most cases, the ANN is an adaptive system that changes its structure by adjusting internal parameters during the learning phase to minimize errors between the calculated output and the expected output [13]. Compared with the objective fact that genetic algorithm requires a large number of iterative calculations and its limited processing data size [15], the determined ANN model has the advantages of high efficiency, high stability and high fault tolerance for noise data [16]. At present, spectrum unfolding algorithm based on artificial neural network is extensively applied, although, they also have their limitations: the accuracy of the result needs to be improved, and the training set data used for training of the ANN model is insufficient, etc. [10,12,13,17].

In view of the currently shortcomings of spectrum unfolding with ANN algorithm, for improving the accuracy and efficiency of spectrum unfolding, as well as solving the problem of spectrum measurement with wide coverage of energy domain, this work developed an adaptive deviation-resistant neutron spectrum unfolding method based on transfer learning. Traditional machine learning algorithms use previously acquired statistical models trained with or without labeled training data to predict future data [18,19], while the most prominent advantage of transfer learning is its ability to intelligently apply previously learned knowledge to solve new problems more efficiently or present better solutions [20]. This paper consists of three parts: methods, verification and conclusion. The principle and the effect of the developed method were introduced in detail below.

2. Methods

The neutron spectrum unfolding method developed in this research used Monte Carlo code to calculate thousands of neutron spectra to construct its spectra database. The database was then trained to establish the ANN model which reflected the relationship between neutron spectrum and recorded values of detectors. In that case, the neutron spectrum corresponding to the recorded values of detectors could be predicted through the ANN model. On the basis of transfer learning idea, the ANN model structure of the previous step was maintained. Then, the specific eigenvalues (such as the material information and total flux) of each unfolded spectral position were added to the output data of the previous ANN as the input data, together with the new ANN, the fluctuation of neutron flux of each energy segment was predicted and the spectrum constructed by previous ANN could be automatically optimized to achieve the final target spectrum.

The proposed method was applied to a spectrum unfolding model of a combined fission ionization chamber, according to the requirements of the online measurement of neutron spectrum for fission reactors. ^{235}U fission ionization chamber, boron-coated ionization chamber with cadmium cap and ^{238}U fission ionization chamber were chosen as the detectors. The outer layer of the boron-coated ionization chamber is covered with a layer of 1 mm cadmium. The total length of the detector is 130 mm and the outer diameter is 10 mm. The ionized gas is composed of 96% argon and 4% nitrogen [21]. The structure of detector is shown in Fig. 1. The spectrum unfolding process is shown in Fig. 2.

2.1. Construct the spectra database

Based on the idea of artificial neural network, the research used the Super Multi-functional Calculation Program for Nuclear Design and Safety Evaluation (SuperMC) [22–24] to calculate and extract neutron spectrum of several typical reactors and encapsulated all the spectra into the database.

In accordance with the reactor type, the database contained neutron spectra of CLEAR-P reactor, RBEC-M reactor and BN-600 reactor. The spectra of CLEAR-P and RBEC-M reactor were used as training set, and the spectra of BN-600 reactor were taken as test set. Each neutron spectrum was divided into 87 groups with coverage energy range of 10^{-9} MeV–20 MeV.

Furthermore, in order to increase the diversity of the training set, it added some neutron spectra of typical fast reactors from the IAEA report No. 318 [25]. The final size database was around 1500.

2.2. Adaptive deviation-resistant method based on transfer learning

For the application of spectrum unfolding, input data are a large number of recorded values of detectors, while the output is the neutron spectrum corresponding to the recorded values, and the training is mainly based on the idea of backpropagation.

The work used backpropagation algorithm for model training, taking the 3-layer ANN structure as an example (the hidden layer contains two nodes), its principle is shown in Fig. 3.

Assuming that there is an ANN model with n layers, the BP algorithm mainly includes the following steps:

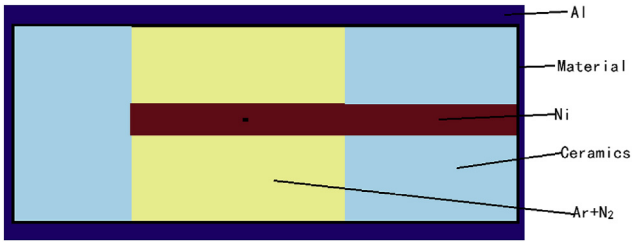

Fig. 1. Structure of detector.

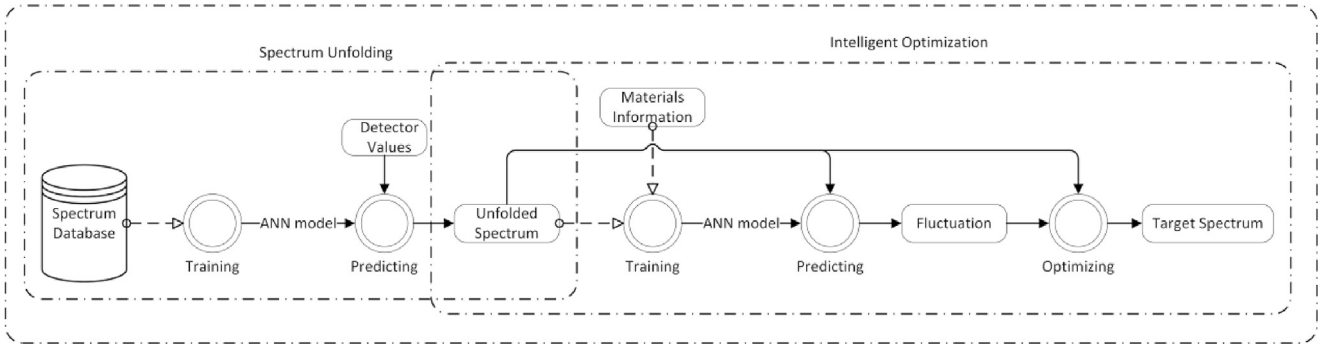

Fig. 2. Flow chart of the spectrum unfolding method.

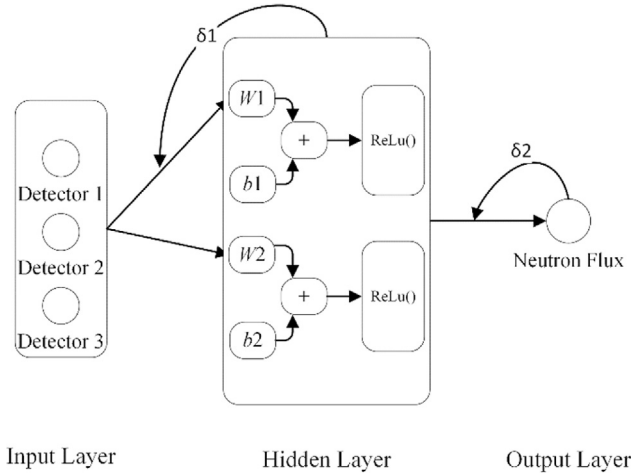

Fig. 3. BP principles applied to spectrum unfolding.

1. Carry out the feed forward conduction calculation, using the forward conduction formula to obtain the activation values of n_2 and n_3 up to the output layer n_n;
2. For the output layer (n_l layer), calculate its residual:

$$\delta(n_l) = -(y - a(n_l)) * f'(z(n_l)) \tag{1}$$

3. For each layer of $l = n_l - 1, n_l - 2, \ldots, 2$, calculate the corresponding residual:

$$\delta(l) = \left(\left(W(l)\right)^T * \delta(l+1)\right) * f'\left(z\left(l\right)\right) \tag{2}$$

4. Calculate the partial derivative value corresponding to each neuron:

$$\nabla_{W(l)} J(W, b; x, y) = \delta(l+1) * \left(a(l)\right)^T \tag{3}$$

$$\nabla_{b(l)} J(W, b; x, y) = \delta(l+1) \tag{4}$$

5. Bring the calculated partial derivative value into the update formula corresponding to the weight W and the bias b:

$$W_{ij}(l) = W_{ij}(l) - \alpha\left[\frac{1}{K}\sum_{k=1}^{K}\delta_i(l+1) * a_j(l) + \lambda W_{ij}(l)\right] \tag{5}$$

$$b_i(l) = b_i(l) - \frac{\alpha * 1}{K}\sum_{k=1}^{K}\delta_i(l+1) \tag{6}$$

In above formula, n_l represents the number of layers ($l = 1,2, \ldots, n_l$), y is the expected neutron flux, $J(W, b; x, y)$ is the cost function, α is the learning rate, $z(l)$ is the output value of the neuron of lth layer (calculated neutron flux), $\delta(l)$ is the residual of lth layer, K is the number of samples, W and b are weights and bias. In this research, $n_l = 3$, $\alpha = 0.001$, $J(W, b; x, y) = \frac{1}{N}\sum_{i=1}^{N}(z(n_l) - y)^2$, $K = 3398$.

Because of its characteristics, the artificial neural network model may fall into the situation of overfitting when its structure is too complicated, which leads to a decrease in its predictive ability. Given this feature, this work used the neutron flux of each energy segment of the neutron spectrum as the output value of the ANN model, and established multiple ANN models to predict the entire neutron spectrum, thus, effectively improved the training efficiency and accuracy of the ANN model [26].

In the training set, the data of the neutron spectrum in the database and the response function of detectors calculated by the Monte Carlo program SuperMC were used to obtain the corresponding recorded values of the neutron spectrum in the database and the recorded values were used as the input data for the ANN model. The neutron flux of each energy segment of the neutron spectrum corresponding to the recorded values was taken as the output data of the ANN model. After cross-validation, a three-layer structure was constructed with input layer, output layer and one hidden layer consisting of 25 neuron nodes. At the same time, the ReLu function was selected as the activation function.

After validation, the unfolded spectrum with ANN mentioned above still had room for improvement for some energy segment positions. For example, the neutron flux near the resonance region had a large bounce, and the neutron flux of the region with high probability of noise data was difficult to be accurately predicted by the ANN model, resulting in a decrease in the accuracy of the entire unfolded spectrum.

In order to further improve the accuracy of the unfolded spectrum, this work optimized the neutron flux with large spectral fluctuations by using the idea of adaptive deviation-resistant based on transfer learning. The reason for using transfer learning is that the neutron spectrum database is not sufficient enough and the spectrum of reactor core is different at different positions. Because of this, it is unlikely to predict an accurate neutron spectrum through ANN at one time. Transfer learning could take into account

the differences in neutron spectrum at different positions and it could obtain a more accurate neutron spectrum data by adding new input features.

Most current work on transfer learning focuses on "What to transfer" and "How to transfer". In this paper, we transfer the ability to predict the neutron spectrum based on the detector values by retaining the previously trained ANN structure. Transfer learning algorithms can be divided into instance-based transfer learning, feature-based transfer learning, model-based transfer learning and relationship-based transfer learning. Brief description of different approaches to transfer learning is shown in Table 1 [20]. Previously, we have used ANN to unfold the neutron spectrum, and considering the similarity between models, in this study, the model-based transfer learning algorithm was used to further optimize the unfolded spectrum of the previous ANN.

Most model-based transfer learning approaches assume that individual models for related tasks should share some parameters or prior distributions of hyperparameters. It aims at boosting the performance of the target domain by utilizing the source domain data. Thus, in transfer learning, weights in the loss functions for different domains can be different. To make sure that it could achieve better performance in the target domain, it often assigns a larger weight to the loss function of the target domain [20]. The process of the adaptive deviation-resistant neutron spectrum unfolding method based on model-based transfer learning is shown in Fig. 4.

As shown in Fig. 4, the model-based transfer learning algorithm maintained the model structure of the previous ANN and brought its output as a new input to the subsequent ANN training. At the same time, new specific eigenvalues such as material information were added to the new input data. Just like Fig. 4, the model-based transfer learning algorithm contained two layers of ANN, the first layer is a feedforward neural network, and the second layer is an adaptive deviation-resistant ANN. The so-called "adaptive deviation-resistant" refers to the process of using the transfer learning algorithm to predict the neutron flux fluctuation values of each energy segment of the unfolded spectrum and achieve adaptive reverse correction. In other words, it means that the unfolded spectrum could be automatically and adaptively optimized itself according to different conditions to realize the effect of reducing the deviation of the unfolded spectrum.

The model based on transfer learning could greatly improve the computational efficiency of the ANN, effectively avoided unnecessary replicated counting, and made full use of the previously learned knowledge to deal with the new problem of predicting the fluctuation values of the neutron flux in different energy segments. After obtaining the neutron flux fluctuation values of each energy segment, the reverse correction was used for the fast region and resonance region with large fluctuation, which well improved the accuracy of the results.

2.3. Evaluation criteria

For the sake of inspecting the effect of spectrum unfolding with ANN, this study selected three commonly used evaluation values as the validation criteria, which were the mean square error (MSE),

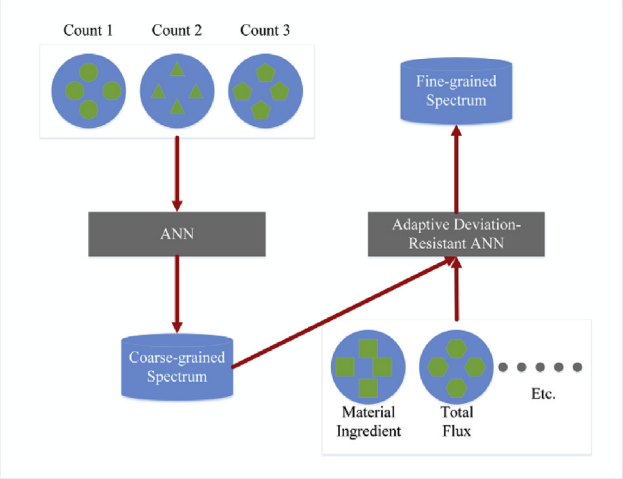

Fig. 4. Process of the model-based transfer learning.

average relative deviation (ARD) and neutron spectrum quality (Qs) between the unfolded spectrum and the true spectrum. The MSE characterizes the degree of difference between the predicted neutron spectrum and the true neutron spectrum. In an ideal case, MSE is close to 0. The ARD characterizes the degree of deviation between the predicted neutron spectrum and the true neutron spectrum; Qs value represents the closeness of the predicted neutron spectrum to the true neutron spectrum. The definition of the three evaluation values are as shown in equations (7)–(9) [9,24,27].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\phi(E_i)_{output} - \phi(E_i)_{actual}\right)^2 \tag{7}$$

$$ARD = \left(\sum_{i=1}^{N}\frac{|\phi(E_i)_{output} - \phi(E_i)_{actual}|}{\phi(E_i)_{actual}}\right) \Big/ N \tag{8}$$

$$Q_S = \left[\frac{\sum_{i=1}^{N}\left(\phi(E_i)_{output} - \phi(E_i)_{actual}\right)^2}{\sum_{i=1}^{N}(\phi(E_i)_{actual})^2}\right]^{\frac{1}{2}} \tag{9}$$

In Equation (7) (8) and (9), $\phi(E_i)_{output}$ represents the neutron flux of the reconstructed spectrum when the energy is E_i and $\phi(E_i)_{actual}$ represents the neutron flux of the true spectrum when the energy is E_i, and N is the number of energy bin groups.

3. Verification on BN-600 reactor

This research verified the superiority of the developed method by comparing the spectrum unfolding results among the ANN method with adaptive deviation-resistant, the ANN method

Table 1
Brief description of different approaches to transfer learning.

Transfer Learning Approaches	Brief Description
Instance-based	To re-weight some labeled data in the source domain for target domain
Feature-based	Find a well feature representation that reduces difference between the source and the target domains and the error of models
Model-based	Discover shared parameters or priors between the source domain and target domain models
Relationship-based	Build mapping of relational knowledge between the source relational domain and the target relational domains.

without adaptive deviation-resistant and the traditional iteration method on a benchmark.

The BN-600 is a commercial fast reactor with thermal power of 1470 MW (electric power of 600 MW) in Russia. Containing 306 assemblies, in which different enrichment fuels are arranged in different areas of the core, there are 19 compensation rods inserted into the middle part of the core, 6 safety rods are raised to the core plane 5.5 cm. Also included on the outside of the core are 300 stainless steel reflector assemblies and 102 boron carbide shield assemblies. The three-dimensional model structure of the BN-600 core is shown in Fig. 5 [28].

The recorded values of the neutron spectrum were obtained by the calculation of the neutron spectrum in the database and the response function of detectors calculated by the Monte Carlo program SuperMC. The detector response function was obtained as shown in equation (10) [29].

$$R(E_n) = \frac{C}{\Phi(E_n)} = \frac{W*N*n*\sigma*Tl}{N\ /\ as} = T*\sigma*as*n*V \tag{10}$$

where T (cm^{-2}) is the neutron fluence calculated by SuperMC. N is the total number of neutrons, W is the weight of the particles, Tl is the sum of the average free path of particles, as is the neutron source area (cm^2), n is atomic density ($10^{24}cm^{-3}$) of the sensitive material, V is sensitive volume (cm^3) of the probe, and σ (barn) is the micro reaction cross section of the sensitive material at the corresponding energy.

The response function results of the three detectors are shown in Fig. 6. It can be seen from the figure that these three detectors have different high response thresholds.

After all the data that needs to be obtained in advance had been collected, the research conducted the verification of spectrum unfolding. This work randomly selected the neutron spectra of four locations in the BN-600 reactor for validation and used three different methods to unfold the spectrum. The positions are shown in Fig. 5 and the normalized results are shown in Fig. 7.

It is worth mentioning that the work of this paper regarded the neutron flux in the thermal region as one energy group, represented by $3*10^{-9}$ MeV. Besides, the predicted fluctuation of resonance region was not accurate because the neutron flux of the region had a large bounce, the work chose to optimize the neutron

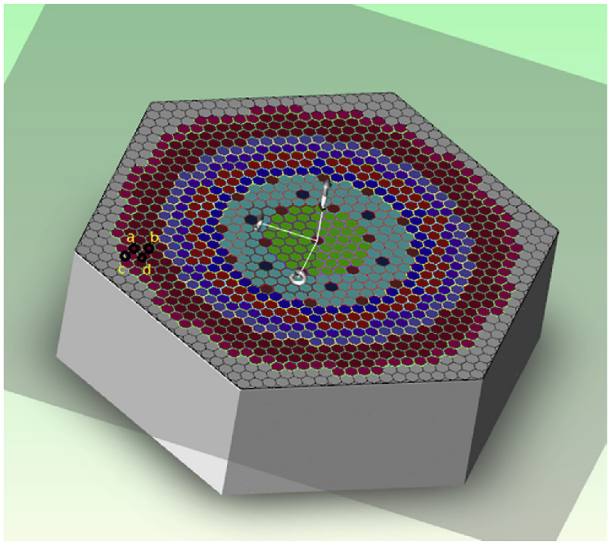

Fig. 5. Position a, b and c are in the same plane as the center position, and d is above that plane.

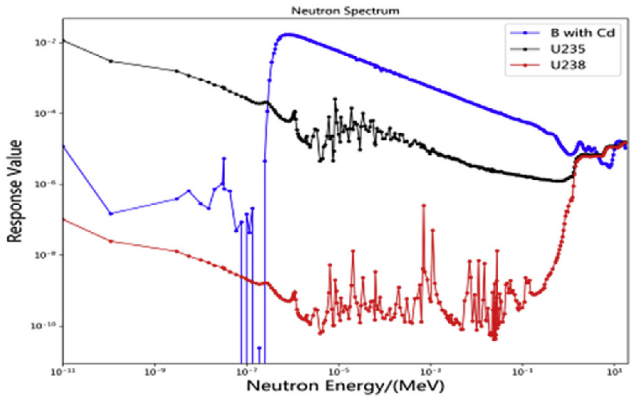

Fig. 6. Results of response function.

flux of fast region (neutron energy above 0.1 MeV) and resonance region with large fluctuation. After normalizing the results of the three methods, the work of this paper compared the closeness of the unfolded spectrum of the three methods and the true spectrum. The results of the spectral evaluation values of the four locations are shown in Tables 2–5.

It could be seen from the four tables above that the spectrum unfolding effect of the ANN algorithm is better than that of the traditional iterative method. Comparing the results of the two methods (2nd and 3rd rows of four tables), the ANN algorithm reduced MSE by 46.07%, ARD by 47.00%, and Qs by 26.53% respectively in the worst case (position *c*), confirming the potential of ANN algorithm in the field of spectrum unfolding. Generally, (a-d) are the positions of the fuel region, but their distance from the center is not the same. After analysis, *c* is the position farthest from the fuel center and it is at the edge of the material junction. This shows that the neutron spectrum farther from the fuel center is more difficult to predict and correct. And the neutron spectrum at the junction of materials is more difficult to predict. It is speculated that this may be because the neutron spectrum law becomes less obvious as it moves farther away from the core, especially when it is at the junction of materials, which increases the difficulty of ANN prediction.

In addition, as could be seen from Fig. 7, the adaptive deviation-resistant algorithm of this study could make the result more accurate. Taking figure (c) as an example, we could find that the blue line is more consistent with the red line than the other two lines. Just like Fig. 8, especially in the circled position as shown below, the blue line is significantly better than the other lines.

According to the results of the four Tables (1–4), ANN with adaptive deviation-resistant is better than the one without adaptive deviation-resistant; ANN with adaptive deviation-resistant reduced 21.11% on MSE, 23.53% on ARD, and 11.08% on Qs compared to those without adaptive deviation-resistant in the worst of conditions (position *c*), which demonstrates the reliability of the adaptive deviation-resistant algorithm of this study.

Further, we took into account the uncertainty of the true spectrum calculated by SuperMC. The standard deviation and confidence intervals of several energy bin groups of position ãd are shown in Table 6.

Generally, SuperMC regards that the calculation result with a standard deviation less than 0.005 has a high degree of credibility. From the calculation results of SuperMC, it could be seen that when the neutron energy is low, the standard deviation is small enough. And the standard deviation increase significantly when the neutron energy exceeds 10 MeV. This situation is understandable because the share of high-energy neutrons is relatively small and the

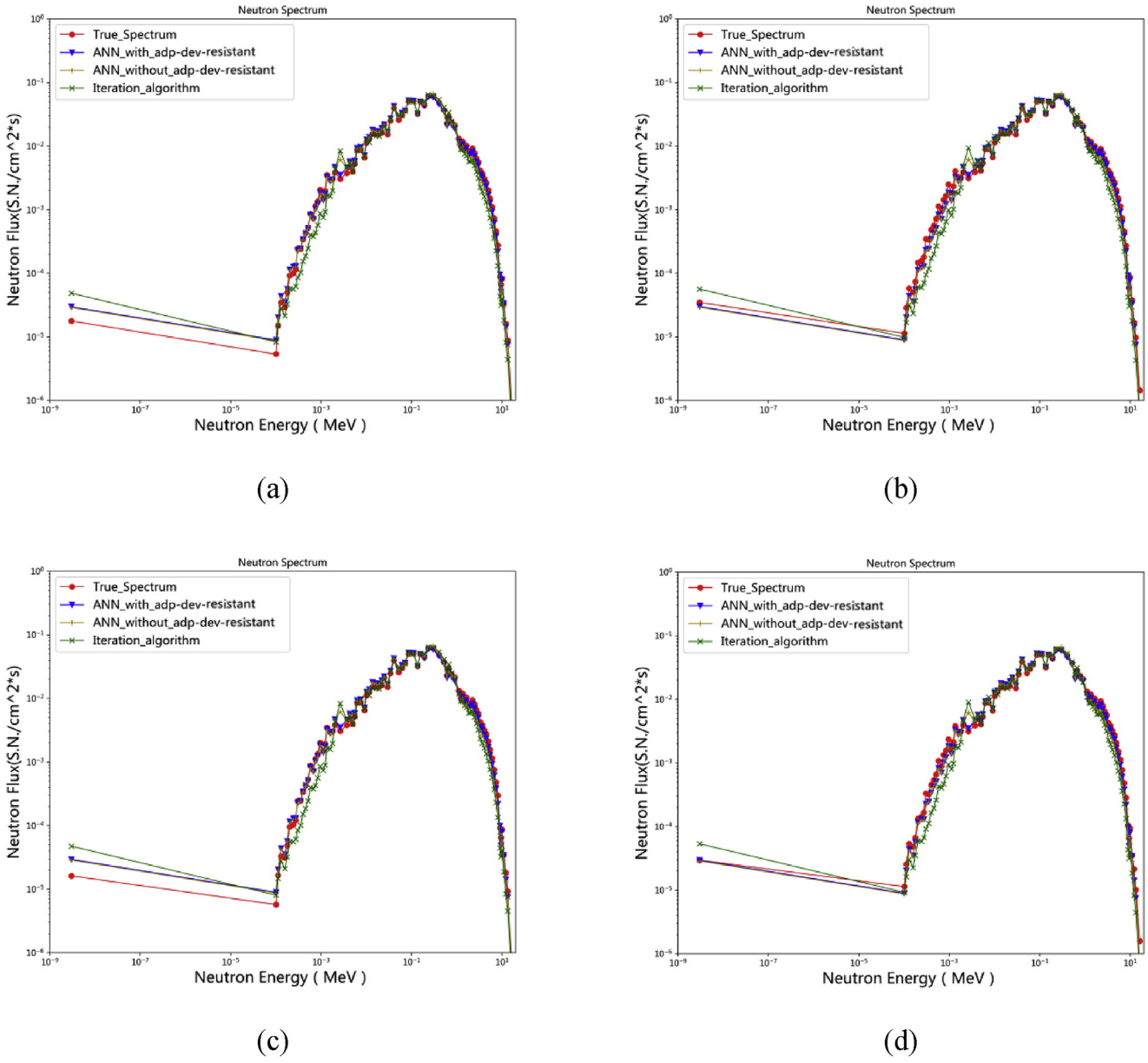

Fig. 7. Performances of spectrum unfolding on BN-600 in position a,b,c,d.

Table 2
Results of spectrum unfolding in position a.

Method	MSE	ARD	Qs
ANN with adaptive deviation-resistant	1.16E-06	11.70%	0.0559
ANN without adaptive deviation-resistant	1.71E-06	15.99%	0.0677
Iteration algorithm	3.77E-06	32.84%	0.1006

Table 3
Results of spectrum unfolding in position b.

Method	MSE	ARD	Qs
ANN with adaptive deviation-resistant	9.65E-07	13.85%	0.0512
ANN without adaptive deviation-resistant	1.72E-06	18.87%	0.0684
Iteration algorithm	3.89E-06	35.58%	0.1029

Table 4
Results of spectrum unfolding in position c.

Method	MSE	ARD	Qs
ANN with adaptive deviation-resistant	1.57E-06	13.23%	0.0650
ANN without adaptive deviation-resistant	1.99E-06	17.30%	0.0731
Iteration algorithm	3.69E-06	32.64%	0.0995

Table 5
Results of spectrum unfolding in position d.

Method	MSE	ARD	Qs
ANN with adaptive deviation-resistant	1.31E-06	13.87%	0.0596
ANN without adaptive deviation-resistant	1.91E-06	18.75%	0.0720
Iteration algorithm	3.67E-06	35.09%	0.0998

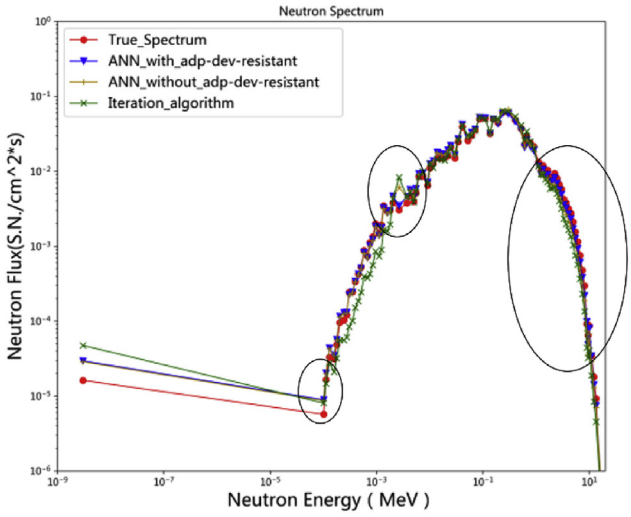

Fig. 8. Results analysis of position c.

number of high-energy neutrons is limited, leading to large deviations in the simulation.

The research showed the qualitative comparison of the unfolding results in the form of error bars. The work used the neutron spectrum at position *c* as an example, as shown in Fig. 9.

The black vertical line indicated the confidence interval of the neutron flux deviation in each energy bin group. As can be seen from the figure, the uncertainty of most energy bin groups is very low. After calculation and analysis, the flux of each energy bin group of the iterative method is basically not in the error bar. The flux values of the 11th and 86th bins of ANN without adaptive deviation-resistant are within the error bar, while the fluxes of the 10th, 11th, 12th, 83rd, and 86th bins of ANN with adaptive deviation-resistant are within the error bar, just like in Fig. 9. In addition to these energy bins, for the proposed method, the neutron fluxes in other bins are closer to the true value calculated by SuperMC, compared with other two methods. Combining the data in Tables 2–5, it could be regarded that ANN with adaptive deviation-resistant once again improves the accuracy of the unfolded spectrum based on ANN without adaptive deviation-resistant.

Table 6
Analysis of the calculation results of SuperMC.

Position	Energy bin groups	Standard deviation	Confidence interval
A	11th: (3.981E-04, 4.540E-04)	0.01588	(3.35E-04, 3.46E-04)
	83rd: (1.105E+01, 1.221E+01)	0.07692	(3.05E-05, 3.55E-05)
	86th: (1.649E+01, 1.964E+01)	0.47929	(4.63E-07, 1.32E-06)
B	11th: (3.981E-04, 4.540E-04)	0.01395	(4.75E-04, 4.89E-04)
	83rd: (1.105E+01, 1.221E+01)	0.07254	(3.50E-05, 4.04E-05)
	86th: (1.649E+01, 1.964E+01)	0.42641	(8.20E-07, 2.04E-06)
C	11th: (3.981E-04, 4.540E-04)	0.01591	(3.31E-04, 3.42E-04)
	83rd: (1.105E+01, 1.221E+01)	0.07180	(3.20E-05, 3.69E-05)
	86th: (1.649E+01, 1.964E+01)	0.73058	(1.32E-07, 8.49E-07)
D	11th: (3.981E-04, 4.540E-04)	0.01463	(4.41E-04, 4.54E-04)
	83rd: (1.105E+01, 1.221E+01)	0.07253	(3.25E-05, 3.75E-05)
	86th: (1.649E+01, 1.964E+01)	0.35737	(1.02E-06, 2.14E-06)

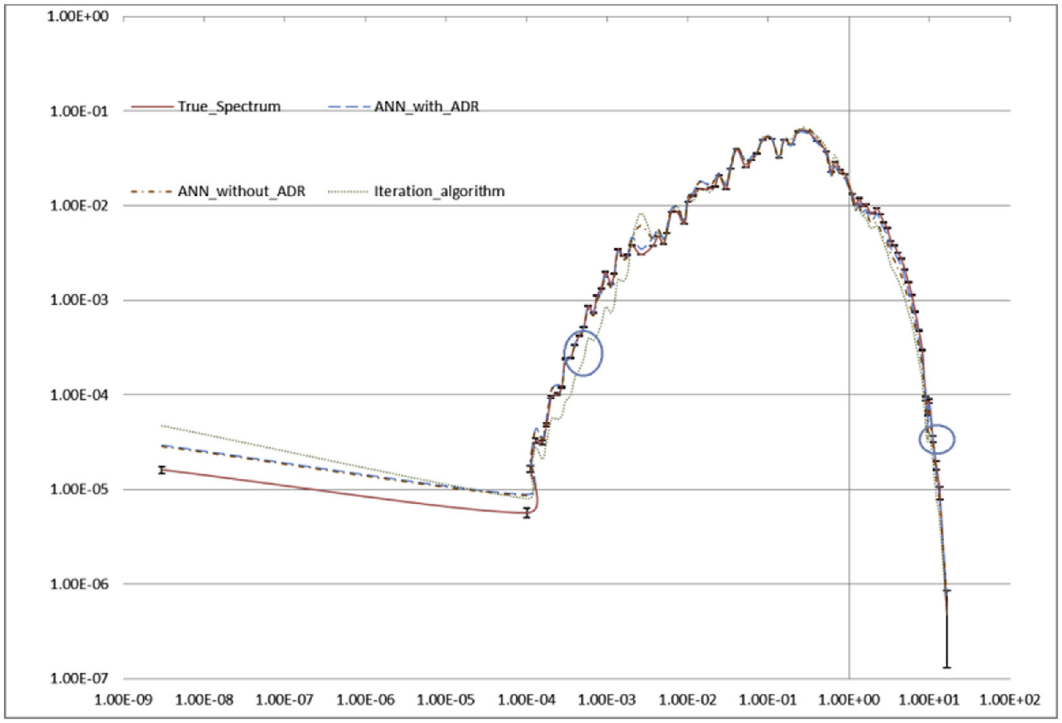

Fig. 9. Comparison of unfolding results with error bars.

The accuracy of the traditional iterative method depends on the number of detectors and the performance of the default spectrum, while the accuracy of ANN mainly depends on the quantity and quality of the training set data. ANN does not require an initial default spectrum and does not directly depend on the number of detectors. Therefore, on the "few-channel spectrum unfolding" problem with only three detectors, if the training set data is sufficient and effective, the advantage of ANN is higher than the iterative method. On the basis of general ANN, ANN with adaptive deviation-resistant has realized the adaptive optimization of the unfolded spectrum of ANN, it could correct the neutron flux value with a large fluctuation in the general ANN unfolded spectrum. Therefore, the deviation of the entire unfolded spectrum is reduced. The proposed method is an optimization of the general ANN, and it is better than the general ANN algorithm in terms of the accuracy of the unfolded spectrum.

4. Conclusion

A neutron spectrum unfolding method using ANN with adaptive deviation-resistant based on transfer learning was proposed in this paper. Firstly, the method trained ANN model by massive neutron spectra which could predict the neutron spectrum according to their recorded values from detectors. Secondly, based on the idea of transfer learning algorithm, the ANN structure of the previous step was maintained, and information such as materials was added to train a deeper ANN model.

The numerical validation for a lead-based fast reactor BN-600 was carried out. The results showed that the spectrum unfolding algorithm using ANN with adaptive deviation-resistant was reduced 21.11% on MSE, 23.53% on ARD and 11.08% on Qs, as compared to the ANN algorithm without adaptive deviation-resistant. 46.07%, 47.00%, and 26.53% were reduced on MSE, ARD and Qs compared to the traditional iterative spectrum unfolding method. The results demonstrated the reliability of the developed method, such as the advantages of high accuracy, high efficiency in the field of spectrum unfolding with wide coverage of energy domain. Also, it is suitable for neutron spectrum measurement for different radiation fields.

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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