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Application of artificial neural networks for unfolding neutron spectra by using a scintillation detector

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The unfolding of neutron spectra from the pulse height distribution measured by a BC501A scintillation detector is accomplished by the application of artificial neural networks (ANN). A simple linear neural network without biases and hidden layers is adopted. A set of monoenergetic detector response functions in the energy range from 0.25 MeV to 16 MeV with an energy interval of 0.25 MeV are generated by the Monte Carlo code O5S in the training phase of the unfolding process. The capability of ANN was demonstrated successfully using the Monte Carlo data itself and experimental data obtained from the Am-Be neutron source and D-T neutron source.

artificial neural network, unfolding neutron spectra, scintillation detectors, O5S

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1 Introduction

In fast neutron spectroscopy, organic liquid scintillation detectors are widely used, for the liquid scintillators can be shaped into the desired size for a specific application and due to their high detection efficiencies and excellent n-γ pulse shape discrimination (PSD) properties. In the neutron energy spectra measurements with proton-recoil method, the pulse height distribution measured by the scintillation detector directly is needed to be converted into the neutron energy spectrum, which can be seen as a mapping from the measured n-dimensional space of detector response to the m-dimensional space of neutron energy flux. In order to carry out this process, several mathematical methods and computing algorithms, such as the least-squares [1], iterative [2], Monte Carlo methods [3], and genetic algorithm [4] have been proposed. In addition to these traditional methods, the artificial neural networks (ANN) [5–7] are now being used in a wide variety of data processing applications. The ANN technique is suitable for unfolding the neutron spectra and has such advantages as saving time and requiring few samples.

In this paper, a simple linear ANN architecture without biases and hidden layers has been developed and trained for unfolding neutron spectra measured by a Φ2″×2″ BC501A scintillation detector. The training data are a set of response functions of monoenergetic neutrons generated by the Monte Carlo code O5S [8] according to the actual BC501A scintillation detector with the same size, and the training method is the resilient backpropagation algorithm recommended by Senada [6]. An energy spectra measurement system was also set up for the validation of the unfolding capability by using Am-Be neutron source and D-T neutron source. The resultant unfolded Am-Be source spectrum is in agreement with the results provided in the literature for neutron spectroscopy.

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2 Spectrum unfolding

2.1 The principle of spectrum unfolding

The response $N(E')$ of an organic scintillation detector, such as BC501A, to a neutron spectrum $\Phi(E)$ can be expressed through the Fredholm integral equation of the first kind as below:

$$N(E') = \int_{E\min}^{E\max} R(E,E')\Phi(E)\mathrm{d}E, \tag{1}$$

where $R(E,E')$, the detector response matrix, is the probability per unit energy that a neutron of energy E deposits an energy between E' and $(E+\mathrm{d}E')$ in the detector. If we break E and E' into discrete intervals, we can write (1) in matrix notation as

$$N_j = \sum_i R_{ij}\Phi_i, \tag{2}$$

where N_j is the binned count rate corresponding to a certain interval ΔE of the measured pulse height in the jth channel, Φ_i is the incident neutron fluence in the ith energy group, and R_{ij} is the corresponding element of the response matrix where each row corresponds to a given neutron energy and each column corresponds to a given pulse height. So

$$\Phi_i = \sum_j R_{ji}^{-1} N_j. \tag{3}$$

Because the uncertainties in R for the matrix is usually not square, and moreover the inversion of R is ill-conditioned, the statistical uncertainties (either systematic or random) on R or N will affect the determination of Φ, so that small changes in either R or N would give rise to large variations in Φ. In a word, the unfolding problem is to determine Φ_i from the measured detector response N_j.

2.2 Artificial neural network (ANN) unfolding

The simple linear ANN architecture used in our study is shown in Figure 1. It is implemented by using the Matlab Neural Network Toolbox [9]. The detector response functions of monoenergetic neutrons with a certain interval are used as the input data p_i, whereas the energy spectra of the incident neutrons in discrete energy bins are used as the output data a_i in the ANN training phase.

For there is no clear systematic theory to guide the choice of the number of neurons in each layer, the most common practice is to infer these values using past experience and to do several trial-and-error runs on different architectures. In our case, the numbers of input neurons and output neurons depend on the choice of the energy interval. Considering the energy resolution of the BC501A scintillation detector is about 15% to 5% in the energy range from several keV to 16 MeV, an equal energy interval of 0.25 MeV is feasible in the neutron energy range from 0.25 MeV to 16 MeV. Therefore, our simple linear ANN has 64 neurons in the input layer and output layers, respectively. Another special feature of this simple ANN is that there is no hidden layer between the input and output units. The expected output data are calculated by the linear transfer function as below:

$$a_i = \sum_j w_{ij} p_i + b_i, \tag{4}$$

where w_{ij} and b_i represents the weights and biases of each neuron of the input layer, respectively. It is obvious that if the biases b_i is omitted or equal to zero, with the comparison of eqs. (3) and (4), the weights w_{ij} is identical to the inverse response matrix R_{ji}^{-1}. Hence, the net training process is similar to the solving of the inverse response matrix with the minimum errors.

2.3 Response function generation

The training data, i.e., the response functions of the Φ2″×2″ BC501A scintillation detector induced by monoenergetic neutrons was generated by O5S. The O5S is a Monte Carlo code which directly simulates the experimental techniques used to obtain the pulse height distribution for a parallel beam of monoenergetic neutrons incident on organic scintillator systems. The response functions, in the energy range from 1 MeV to 16 MeV with an energy interval of 1 MeV are shown in Figure 2.

Since the ^{1}H(n,n)^{1}H reaction, whose cross-section data is well known, is the predominant reaction at energies below about 10 MeV, while the non-elastic carbon reactions ^{12}C(n,α)^{9}Be and ^{12}C(n,3α) at higher energies above 10 MeV, become significant to the response function, the cross-sections data and angular distributions of ^{12}C(n,α)^{9}Be and ^{12}C(n,3α) reactions were taken from the ENDF/B4 and

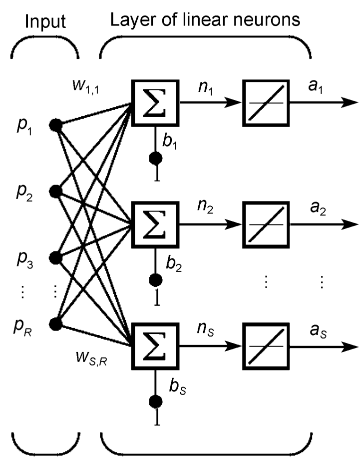

Figure 1 Schematic diagram of the neural network architecture.

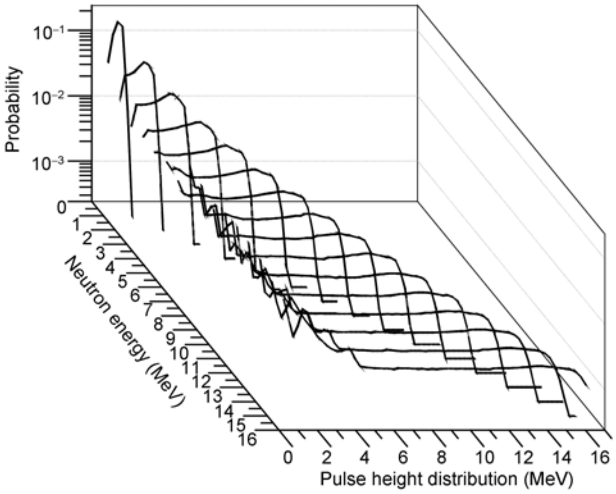

Figure 2 Response functions for the Φ2″×2″ BC501A scintillation detector in energy range of 0.25–16 MeV, generated by O5S.

ENDF/B5. In order to verify the reliability of the calculated response functions by O5S, the D-T neutron with energy of about 15 MeV generated by a Cockcroft-Walton accelerator neutron generator, was used to carry out the comparison of the detector responses between the calculated and measured results as shown in Figure 3. It is shown that the experimental result agrees with the calculation result on the whole. For there was no background measurement induced by the wall-scattering of the experiment hall in the low energy range, the experimental result below 6 MeV is slightly higher than the calculation result.

3 Unfolding capability test

3.1 Monte Carlo data test

The simple linear ANN trained only with the Monte Carlo data of the response functions of monoenergetic neutron should be verified self-consistency. Therefore, we used single and superposition of several Monte Carlo response functions of monoenergetic neutrons as the input data and the corresponding single-peak and multi-peak spectra as the output data to test the unfolding capability. The proportions of the response functions superposed on each other are divided into two categories. One is with the same proportions equal to 1, so that the unfolded spectra peaks should have the same amplitude. Figure 4 shows the results of the unfolded

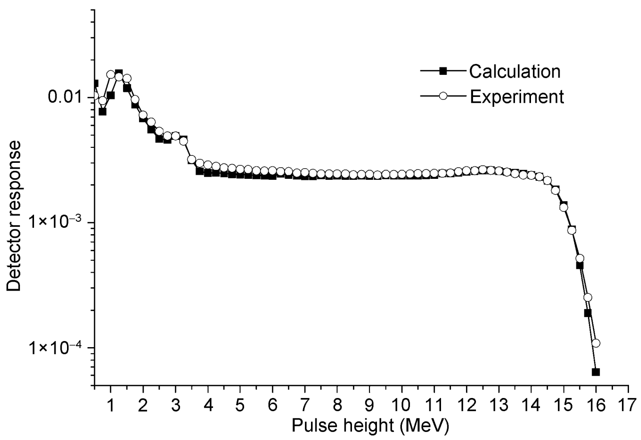

Figure 3 Comparison of measured and calculated detector response function to the D-T neutron source.

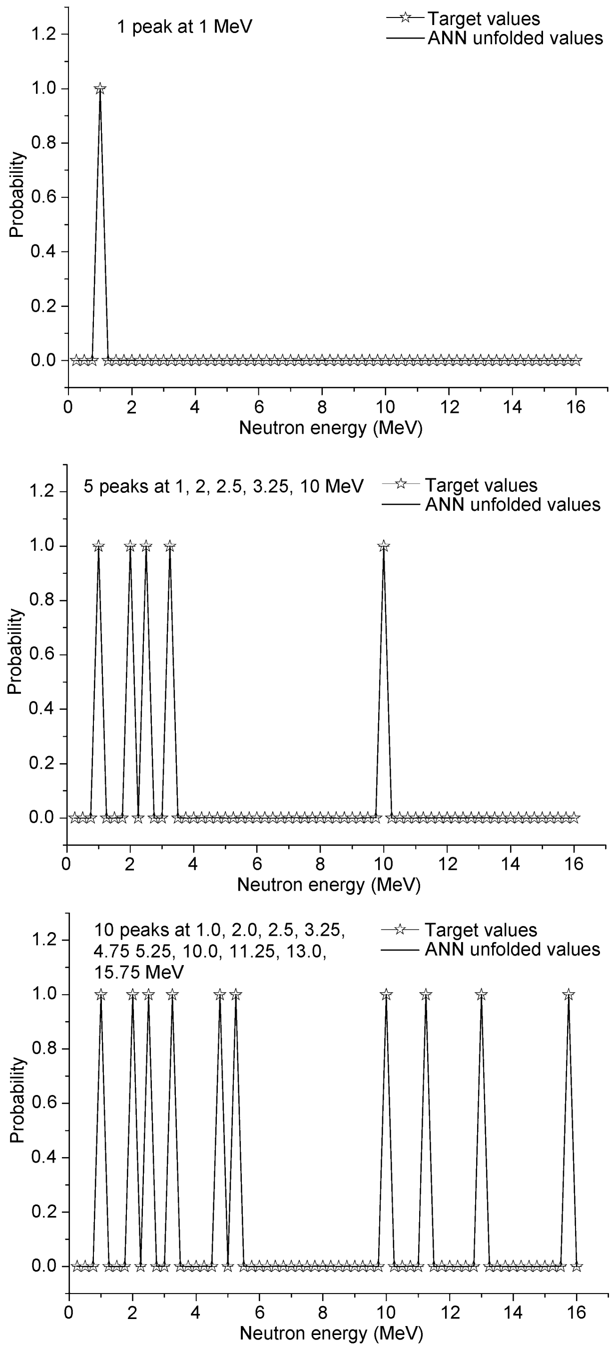

Figure 4 Unfolded spectra of simple linear ANN to incident spectra superposed with the same proportion for 1, 5 and 10 monoenergetic neutrons.

spectra for 1, 5 and 10 peaks. Another is inversely proportional to the neutron energy $1/E$, which causes the degressive amplitude of the unfolded multi-peak. The results of the unfolded spectra for 5 and 10 peaks are shown in Figure 5. It is obvious that the ANN prediction values agree with the target values accurately.

3.2 Experimental data test

A BC501A scintillation detector, consisted of a commercial Φ2″×2″ BC501A liquid scintillator cell, and coupled to a 9807B photomultiplier tube with silicone oil, was used to measure the pulse height distribution induced by the Am-Be neutron source. The n-γ discrimination was carried out by conventional zero-crossing method, and two-dimensional information of n-γ discrimination and pulse height distribution were acquired by a multi-parameter data acquisition system.

The Am-Be neutron source was positioned at a distance of about 90 cm from the center of the detector on its central axis, and it is placed in a commodious experiment hall and about 1.5 m high above the ground in order to decrease the effect of the backscattering neutrons. A 5.08 cm in diameter and 80 cm in length iron bar was placed between the Am-Be neutron source and the BC501A scintillation detector to measure the background. The unfolded Am-Be neutron energy spectrum in our experiment was compared with the reference spectrum provided by ISO for Am-Be neutron source [10] and the experimental result measured by Kluge and Weise [11] as shown in Figure 6. The two experimental results are normalized to the ISO reference spectrum. The error bars of the ANN unfolded result and Kluge and Weise's result only include the statistic errors. It is clear that the positions of energy peaks of our experiment are in agreement with the ISO reference neutron spectrum and Kluge and Weise's result, and the deviation of the neutron flux is due to the different fabrication procedure and use the history of the difference Am-Be neutron sources.

For the neutron energy of Am-Be neutron source is predominantly smaller than 10 MeV, the D-T neutron source was used to test the unfolding capability of the trained ANN at higher energy above 10 MeV, as shown in Figure 7.

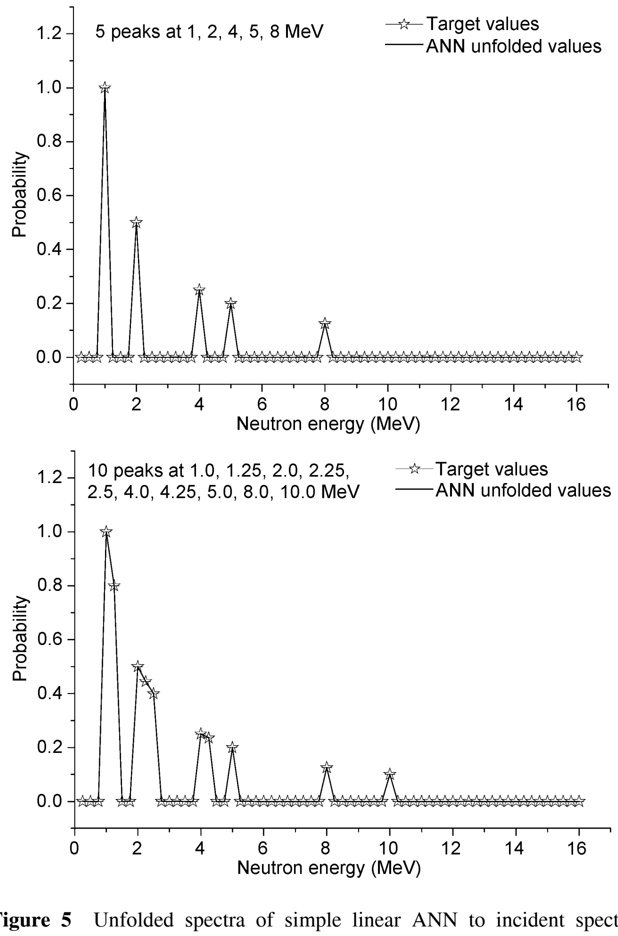

Figure 5 Unfolded spectra of simple linear ANN to incident spectra superposed with the degressive proportion for 5 and 10 monoenergetic neutrons.

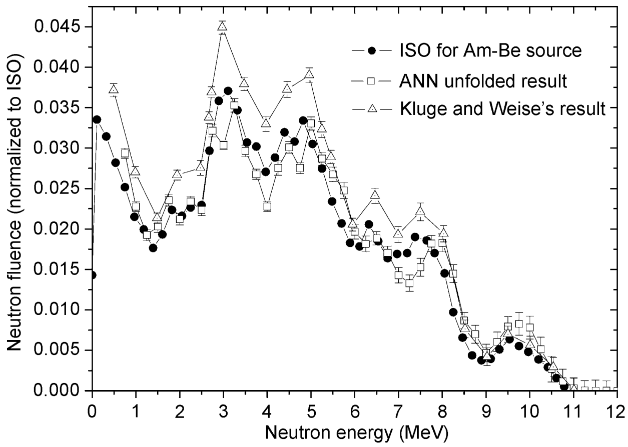

Figure 6 Comparison of the Am-Be neutron source energy spectra unfolded by ANN (open square) with the ISO reference neutron spectrum of Am-Be source (solid circle) and the experimental result of Kluge and Weise (open triangle).

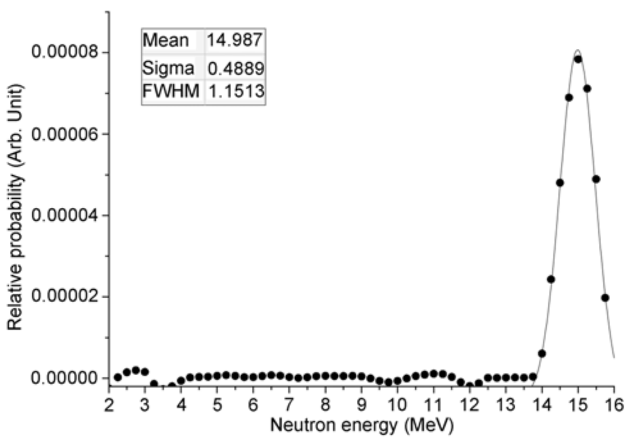

Figure 7 Unfolded result to the D-T neutron source.

Although the D-T neutron is a monoenergetic neutron with energy of about 15 MeV, the measured energy distribution is slight broadened. The solid line is a Gaussian fit for the peak distribution with the fitting parameters labeled on. The peak value is about 14.99 MeV which is consistent with the predicted D-T neutron energy of 15 MeV. The FWHM is about 1.15, that means the energy resolution of the detector is about 7.6 %. Taking into account the electronics noise of the detection system, it agrees with the energy calibration result of the BC501A scintillation detector in Reference [12]. The fluctuation in the lower energy region is due to the background and wall-scattering neutrons.

4 Conclusions and discussion

In this paper, a simple linear ANN has been developed and applied to the neutron spectra unfolding. The calculated detector response functions generated by the Monte Carlo code O5S provide sufficient sample data to train this ANN. The trained ANN has an excellent performance on unfolding the pulse height distribution of the discrete energy neutron generated by the Monte Carlo code and the continuous energy neutron measured from the Am-Be neutron source and D-T neutron source. Those results clearly show that our simple linear ANN trained only with monoenergetic neutron spectra response functions calculated by Monte Carlo code can be used to accomplish the unfolding of unknown spectra from monoenergetic or continuous, simulated or measured neutron source efficiently.

The time consuming of the unfolded process of the trained ANN is less than 0.1 s in our case of using Compaq dc7800 computer with two 2.66 GHz CPU and 2 GB memory. It is exceedingly susceptible for the on-line neutron spectrum unfolded. This approach ensures sufficient accuracy, timeliness, portability and robustness to make the proposed ANN to be programmed in a programmable chip such as FPGA. It is a candidate of choice for the on-line spectrum unfolding application of the digital neutron spectrum measurement system.

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