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Detector response unfolding using artificial neural networks

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Abstract

We present new results on the identification and unfolding of neutron spectra from the pulse height distribution measured with liquid scintillators. The novelty of the method consists of the dual use of linear and nonlinear artificial neural networks (ANNs). The linear networks solve the superposition problem in the general unfolding problem, whereas the nonlinear networks provide greater accuracy in the neutron source identification problem. Two additional new aspects of the present approach are (i) the use of a very accurate Monte Carlo code for the simulations needed in the training phase of the ANNs and (ii) the ability of the network to respond to short-time and therefore very noisy experimental measurements. This approach ensures sufficient accuracy, timeliness, and robustness to make it a candidate of choice for the heretofore unaddressed nuclear nonproliferation and safeguards applications in which both identification and unfolding are needed.

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1. Introduction

Nuclear nonproliferation and nuclear safeguards applications require robust and efficient methods to identify and/or unfold the incident neutron energy spectrum from shielded or unshielded (mixtures of) fissile materials. Thus, it is of urgent interest to develop methods that allow fast and robust identification of neutron sources as well as unfolding of neutron spectra. In particular, for safeguards applications, it is important to identify specific neutron sources, such as ^{240}Pu, ^{252}Cf, or Am/Be neutron sources. In addition, the accurate unfolding of neutron spectra increases the sensitivity of assays performed on nuclear materials [1].

Liquid scintillators are widely used in nonproliferation applications because they have very good neutron/gamma pulse-shape discrimination properties. In general, unfolding with these types of detectors can be seen as a mapping from the *n*-dimensional space of the detector response to the *m*-dimensional space of the neutron energy flux [2]. To carry out the unfolding, several mathematical methods have been proposed, such as least-squares, iterative, and Monte Carlo methods. In addition to these traditional methods, previous works have shown that artificial neural networks (ANNs) are a promising tool in neutron spectrometry and neutron dosimetry. Recently, methods based on ANNs [3–6] have been used to unfold neutron spectra measured by Bonner spheres, and their application to neutron dosimetry has been analyzed. The application of a simple neural network without hidden layers for the unfolding in neutron spectrometry with a small NE-213 scintillation detector was performed by Koohi-Fayegh et al. [7].

The goal of this paper is to present a new method to unfold incident neutron spectra and to identify neutron sources on the basis of the pulse height distributions measured with liquid scintillators in a fast, accurate, and robust way. The method is based on the dual use of linear

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and nonlinear ANNs, whereby the linear networks solve the superposition problem occurring in general unfolding procedures and the nonlinear networks provide greater accuracy in the neutron source identification problem. The method is shown to be sufficiently fast, accurate, and robust for safeguards applications.

The paper is organized as follows. Section 2 describes the simulation and measurement of the detector response matrix, and Section 3 describes the use of a nonlinear ANN to perform identification of simulated and measured spectra from various neutron sources that are of interest in safeguards application. Section 4 describes the neural network approach based on the use of linear ANNs to unfold monoenergetic neutron spectra and simulated and measured spectra from a ^{252}Cf source. The final section summarizes our conclusions.

2. Detector response matrix

The detector response, the count rates, and the neutron spectrum are related through the Fredholm integral equation of the first kind:

$$N(L) = \int R(E_n, L)\,\Phi(E_n)\,\mathrm{d}E_n \tag{1}$$

where L is the measured light output (or pulse height), $N(L)$ the count rate density corresponding to L, and $R(E_n, L)$ the detector response matrix. Obtaining the energy distribution of the incident neutrons,$\Phi(E_n)$, from the measured detector pulse height distribution amounts to solving an ill-posed inverse problem, for which (i) the solution is not unique and (ii) the solution(s) do(es) not depend continuously on the data. The inverse problem (1) can be reduced to the discrete form of the continuous equation

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

where N_j is the binned count rate corresponding to a certain interval ΔL of the measured light output (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. In the response matrix, each row corresponds to a given neutron energy and each column corresponds to a given pulse height.

2.1. Monte Carlo simulations

Monte Carlo simulations were used to generate the response matrix R_{ij}. Previous works [8] have shown that the MCNP-PoliMi code [9] can be used to accurately calculate the detector response matrix. This method is faster and more practical than measuring directly the detector's response to neutrons at many different energies.

We used the MCNP-PoliMi code for detailed Monte Carlo simulations of neutron interactions occurring in the detector. We considered monoenergetic neutrons from a surface source emitting neutrons perpendicularly to one side of a cubic scintillator material. We used a post-processing Matlab code for the analysis of the interactions occurring in the scintillator material. This analysis takes into account neutron scattering on hydrogen, neutron scattering on carbon, and secondary photons that may be generated on carbon when the energy of the incident neutron is above 4.4 MeV. The light output from secondary charged particles produced by neutron reactions within the scintillator is computed using experimentally determined parameters that relate the energy deposited to the scintillator light output. The cumulative effect of multiple scatterings on light output is also taken into account. Further details on this simulation methodology can be found in Ref. [10].

The MCNP-PoliMi simulations were carried out for the detector exposed to direct, collimated, and monochromatic neutron beams. The final result of each simulation corresponds to the detector response function for a specific incident neutron energy.

We simulated two different response matrices with two energy binnings to investigate the accuracy of the evaluation of neutron energy spectra by neural networks having different energy resolutions. A few columns from the simulated response matrix R_{ij} with a fine regular structure of 0.1-MeV bin width in the energy interval between 0 and 15 MeV are shown in Fig. 1(a). A response matrix with the wider bins of 0.5 MeV in the same energy range has been separately generated, and columns of the response matrix are displayed in Fig. 1(b).

2.2. Comparison of the experimental and simulated response matrix

The measurement of the response matrix with the liquid scintillator was performed using a timed ^{252}Cf spontaneous fission source [11]. The time-of-flight method was used to discriminate neutrons from gamma rays. In the experiment, the ^{252}Cf source was placed a distance of 1 m from the liquid scintillator. Further details on the experimental setup can be found in Ref. [12].

A simulated response matrix having the same energy and pulse height bins as the experimental data was generated by the MCNP-PoliMi code. Fig. 2 provides a comparison of a few of the measured and simulated columns from the response matrix R_{ij}, with neutron energy bins of 0.1 MeV for a few pulse heights of 0.20, 0.25, and 0.35 MeVee (the MeVee is a unit used to measure pulse height in the detector; "ee" means electron equivalent). The columns represent the incident neutron spectrum that generates pulses of a given height in the detector. The agreement between the experimental and simulated response functions is very good for the pulse heights 0.20 and 0.25 MeVee. The response function for the pulse height 0.35 MeVee shows some discrepancy between the simulations and the measurements, especially at higher neutron energies. The error bars in the measured

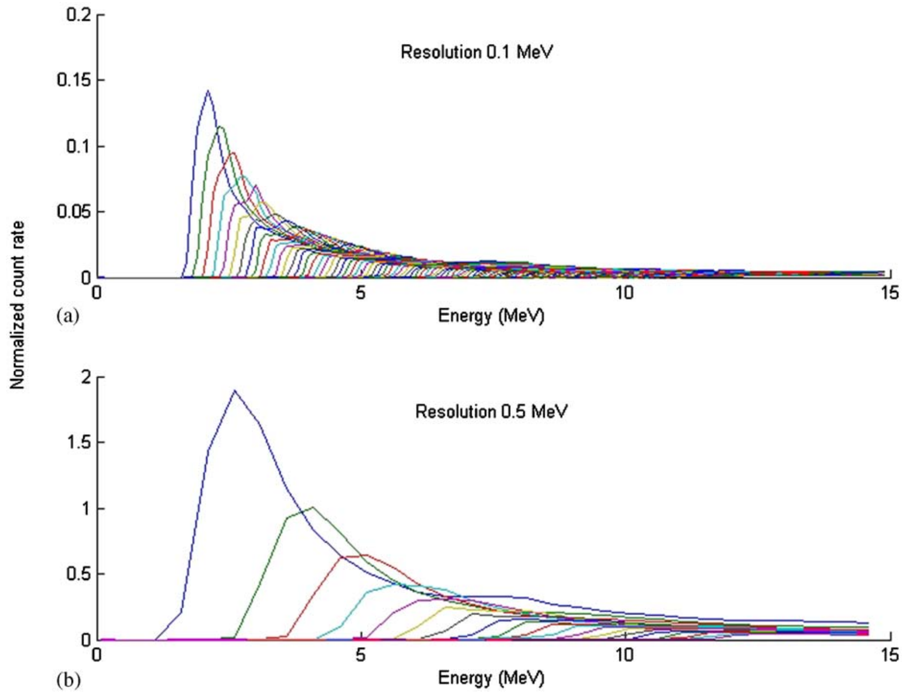

Fig. 1. Columns of the response matrix R_{ij} for energy resolutions of 0.1 MeV (a) and 0.5 MeV (b).

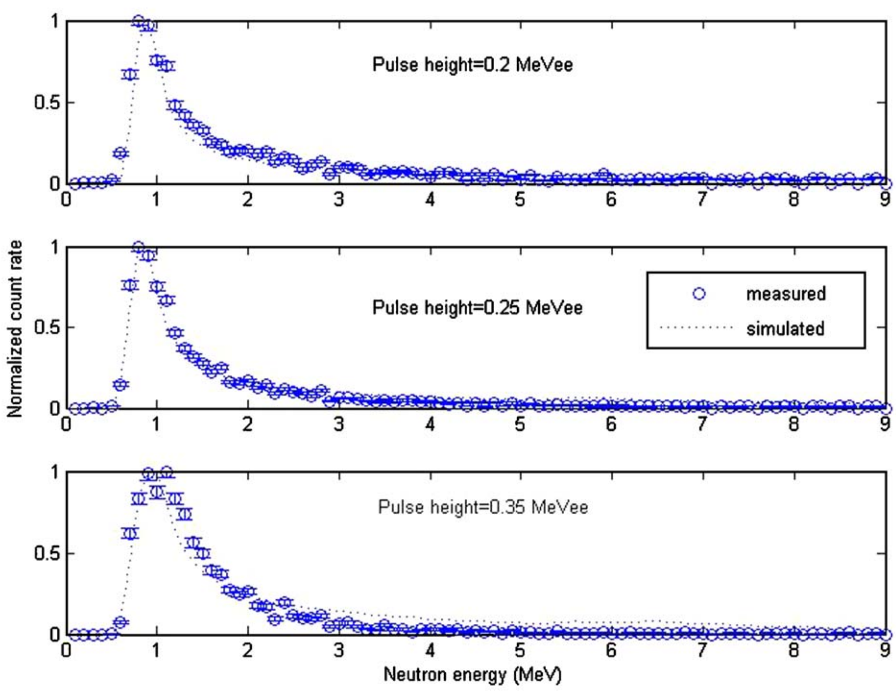

Fig. 2. Comparison of experimental and simulated columns of the response matrix R_{ij} corresponding to the pulse height of 0.20, 0.25, and 0.35 MeVee. Error bars show statistical error in experimental data.

data represent 1σ statistical uncertainty. However, the total measurement error in the response matrix includes systematic error in the experiment. This component of the total error will be investigated in a separate experiment, which will include measurements with a higher-energy monoenergetic neutron source. We do not anticipate major discrepancies to arise in these comparisons. In this paper, we used simulated data instead of experimental data for the generation of the response matrix used in training the ANNs.

3. Identification of neutron spectra with nonlinear ANNs

In this section, we describe the use of nonlinear ANNs [13] to identify monoenergetic and continuous neutron spectra.

3.1. Architecture of the nonlinear ANN

We applied a nonlinear ANN for the identification of monoenergetic neutron sources. The network performs a mapping of the measured detector data, N, to the neutron energy spectrum, Φ, i.e., $\Phi = f(N)$, where f is a nonlinear transfer function. We have constructed a nonlinear neural network with one hidden layer for the monoenergetic neutron source identification. The output of the network is given as

$$\Phi_i = b_i + a_i \cdot \sigma\left\{\sum_{j=1}^{q} \omega_{ij}\left[\sigma\left(\sum_{k=1}^{n} \Omega_{jk} \cdot N_k + B_j\right)\right] + \beta_i\right\} \tag{3}$$

where the matrix Ω_{jk} and the vector $\{B_j\}$ represents the weights and biases of the hidden layer with q nodes, respectively, ω_{ij} and β_i represent the weights and biases of the output layer, and a_i and b_i are scaling parameters. The index $i = 1, 2, \ldots, m$ is the number of neutron energy groups, and the index $k = 1, 2, \ldots, n$ is the number of pulse height distribution bins.

We found that taking the sigmoid function

$$\sigma(x) := \frac{1}{1 + \exp(-x)} \tag{4}$$

as the activation function works best in both layers of the network. This is the most common transfer function used in ANN structures [14] and is particularly suitable for neutron spectrometry because the output is always positive.

The training and test data for monoenergetic neutrons with energies up to 15 MeV with different energy steps were obtained by using the MCNP-PoliMi numerical code, as described in Section 2. The rows of the response matrix R_{ij} have been used as input data, whereas the energy spectra of the incident neutrons in discrete energy bins have been used as output data. All spectra have been normalized to one neutron. Separate nonlinear neural network were constructed and trained for the two energy binnings having 0.1- and 0.5-MeV steps, because any change in the energy resolution of the neutron spectra requires a change in the neural network architecture.

Unfortunately, there is no clear systematic theory to guide the choice of the number of nodes in each hidden layer or even the choice of the number of layers. The common practice is to infer these values using past experience and to do several trial-and-error runs on different architectures. Moreover, there is no unique training algorithm for the design of a neural network, either. Generally, networks are trained with different algorithms to speed up the most time-consuming part of the procedure. It has been found that the networks with resilient algorithm have the best performances. In this work, training and testing have been carried out using the Matlab Neural Network Toolbox [15].

We simulated two response matrices with 150 and 30 energy spectral groups and 140 and 20 pulse data groups. A multilayer feedforward network with backpropagation algorithm was used. The input layer consists of the corresponding number of nodes that simply accept the input pulse height distributions for two different energy resolutions. Successive layers of nodes include one hidden layer with 40 and 20 nodes and the output layer with 150 and 30 output nodes, representing the different number of neutron energy groups.

3.2. Identification of monoenergetic spectra with nonlinear ANNs

To use the ANN to identify monoenergetic spectra we proceeded as follows. To estimate the generalization error, all of the training data were split randomly into five mutually exclusive subsets of approximately equal size. The nonlinear ANN was trained using four of these subsets and then tested on the remaining (fifth) subset. This procedure was repeated five times, with the result that each subset was used once for testing. Very good results were obtained by averaging the test error over the five trials. The networks were able to identify all unknown spectra presented to them without errors. Excellent identification results were obtained for both energy resolutions. We concluded that the nonlinear network trained only by monoenergetic sources can be successfully used for identification of monoenergetic sources with different resolutions. The output of the trained neural networks to the unknown randomly presented monoenergetic spectra with energy resolution of 0.1 MeV is presented in Fig. 3.

Propagation of uncertainties in unfolding procedures is a subject that is under investigation. While some unfolding procedures can benefit from Bayesian methods to evaluate the uncertainties, there is no generally accepted theory on the propagation of uncertainty in ANN predictions [16]. In particular, it is unclear how to evaluate the uncertainty that derives from the non-uniqueness of the solution of this ill-posed problem. We therefore only include the predicted values in Fig. 3, without an estimate on the error of the prediction. The same is true for the ANN predictions discussed in the remainder of the paper.

We investigated the use of nonlinear ANNs trained with monoenergetic neutron spectra to the unfolding of discrete multienergetic and/or continuous neutron spectra. As we increased the number of energy peaks to 2, 3, and several (as required to model various continuous spectra) we noticed a progressive worsening of the unfolding results. This is to be expected because nonlinear ANN's lack the superposition property that only linear ANNs possess. On the other hand, the networks show high accuracy in

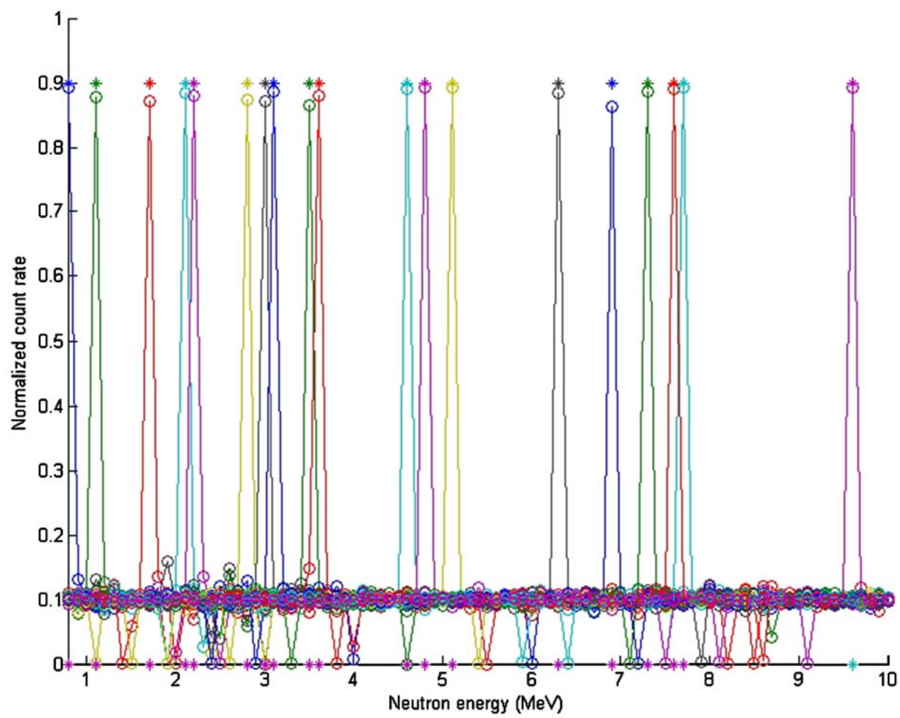

Fig. 3. Neural network output with an energy resolution of 0.1 MeV to randomly presented monoenergetic neutron sources. The stars show the target values and the circles show the ANN prediction.

determination of energy of randomly selected unknown monoenergetic neutron sources for different energy resolutions. It should be pointed out that the nonlinear neural network does not require any pre-processing of input data in contrast to the linear network, which is described in Section 4.

3.3. *Identification of continuous spectra with ANNs*

Fast identification of *unknown* neutron sources, without detailed information of the neutron energy spectrum, can be successfully performed by nonlinear ANNs. We investigated continuous neutron spectra by using a separate nonlinear ANN, trained on the *simulated* spectra with different levels of additive counting noise added. The added noise was Gaussian and equal to a few percent of each individual count rate value to simulate moderate uncertainties that can be expected in experimental conditions. For the preliminary investigations, we selected a few fast spectra such as Watt's fission spectra, ^{252}Cf, Am–Be and ^{238}U in the energy interval up to 10 MeV.

3.3.1. *Identification of simulated spectra using the network trained with data having simulated counting statistics noise added*

Since the nonlinear network trained only with monoenergetic neutron sources cannot be used for the identification of continuous neutron spectra, a new network has been constructed for classification of 40 continuous spectra such as Watt's fission spectra, ^{252}Cf, Am–Be, and ^{238}U. The simulated data were generated by the MCNP-PoliMi numerical code. The architecture of the network includes one input layer consisting of 10 nodes for the 10 selected input groups of pulse height data, one hidden layer with 40 nodes and an output layer with 40 nodes for each spectrum in a set of the training samples.

Table 1
Accuracy of the identification

Class	Identification by nonlinear ANN			
	^{252}Cf (%)	Watt (%)	Am–Be (%)	^{238}U (%)
^{252}Cf	100	0	0	0
Watt	0	100	0	0
Am–Be	0	0	100	0
^{238}U	20	0	0	80

The identification of continuous spectra has been made by applying a cut-off to the output value at the node. The network identifies ^{252}Cf, Watt's fission spectra, Am–Be, and ^{238}U with 100% accuracy for the training data. The network was able to identify 10 unknown spectra for each class of spectra randomly presented to the input without error for Watt's spectra, ^{252}Cf spectra, and Am–Be spectra. However, the network was able to predict the ^{238}U class of spectra in only 80% of the cases. In the remaining 20% of the cases, ^{238}U was identified as ^{252}Cf. The results of the spectra identification in the validation phase are given in Table 1.

3.3.2. Identification of experimental continuous spectra

We analyzed the measured pulse height data using the nonlinear ANN. The measured and simulated pulse height distributions from the ^{252}Cf neutron source are shown in Fig. 4. Both the simulated and measured data were normalized to the maximal values. Note the very good agreement between the simulated and measured pulse height distribution from the ^{252}Cf neutron source. Five experimental pulse height distributions from ^{252}Cf were obtained in different measurement times (given in Fig. 5), and thus with different levels of noise. These data were presented to the trained network, and four of five measured pulse distributions were correctly identified. Only the pulse height distribution with 1000 counts and with high statistical fluctuations could not be recognized correctly with the constructed network. It has been estimated that the ^{252}Cf (intensity 10^5 fission/s) placed at a distance of approximately 100 cm from a detector having dimensions $10\,\text{cm} \times 10\,\text{cm} \times 10\,\text{cm}$ can be quickly identified by the trained network with a measurement of pulse height distributions of approximately 1 s.

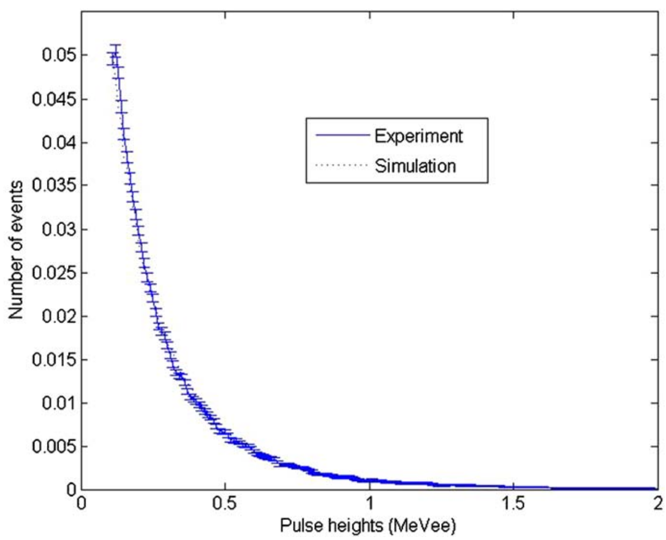

Fig. 4. Measured and simulated pulse height distributions from the ^{252}Cf neutron source. Error bars show statistical error.

4. Identification and unfolding of neutron spectra with linear ANNs

We have considered the application of linear ANNs in neutron spectrometry with the aim of optimizing a network that could be used for the identification of *both* mono-energetic and continuous energy spectra. The linear model is constructed with a linear transfer function, so that Eq. (3) is reduced to the following:

$$\Phi_i = \sum_j a_{ij} \cdot N_j. \tag{5}$$

In this case the principle of superposition is valid, and continuous spectra can be expressed as linear combinations of monoenergetic spectra. The linear transfer function f calculates the output for two independent inputs s_1 and s_2 as

$$f(as_1 + bs_2) = af(s_1) + bf(s_2). \tag{6}$$

This property of the linear neural network has been used for the unfolding of continuous spectra using a network that is trained only with monoenergetic spectra.

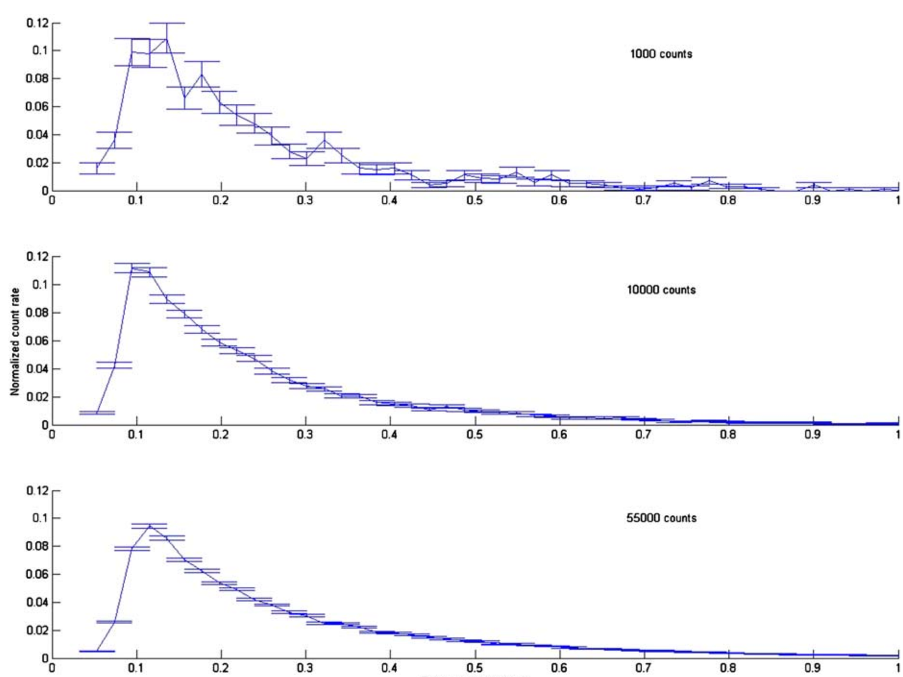

Fig. 5. Experimental pulse height distributions from ^{252}Cf obtained in different measurement times. Error bars show statistical error.

4.1. Identification of monoenergetic spectra

The response of the linear network with different energy resolutions of 0.1, 0.3, and 0.6 MeV to neutron monoenergetic sources is shown in Fig. 6.

We noticed that there are deviations between target and calculated values that can cause some uncertainties in the unfolded spectra. The discrepancy between the target and the predicted values is especially evident for an energy resolution of 0.1 MeV, particularly for monoenergetic sources of higher energy. This is clearly seen in Fig. 7, which presents the response of the linear network with an energy resolution of 0.1 MeV to a few randomly selected neutron monoenergetic sources.

The best results in the identification of unknown neutron energy peaks have been achieved with the linear network with an energy resolution of 0.6 MeV, which represents a trade-off between energy resolution and accuracy of the unfolding procedure. In the case of the identification of monoenergetic neutron sources, the nonlinear network shows better performances, including higher reliability, than the linear one, since the nonlinear network shows very small deviation from the target values and thus can cause smaller uncertainties in the unfolding results. Using a more involved method of processing input data could improve the performance of the linear network.

4.2. Unfolding of continuous spectra

The linear network trained only with monoenergetic neutrons was used to analyze a very simple spectrum consisting of two neutron beams of energies 2 and 5 MeV, with equal probability. The results of the identification of the neutron energies, including the smoothing procedure, are presented in Fig. 8(a). The energy of the neutron peaks has been correctly identified; however, their intensities deviate somewhat from the target values. A similar behavior of the linear network response can be observed in the case of neutron beams with three different energies, shown in Fig. 8(b), as well as in the case of a spectrum with four different neutron energy peaks, shown in Fig. 8(c). This deviation in the peak intensities is mostly due to the smoothing procedure applied to the detected peaks; in fact, some spurious peaks can be eliminated and/or attenuated by the smoothing procedure. Fig. 9 shows the unfolding of two neutron peaks at the energies 4 and 6 MeV before and after the smoothing procedure.

We also found that the smallest energy difference between neutron peaks that can be resolved by this network is 1.5 MeV.

The linear neural network trained by monoenergetic sources was used for the unfolding of continuous spectra such as Watt's fission spectrum and the neutron spectrum of ^{252}Cf. The input pulse height distributions were

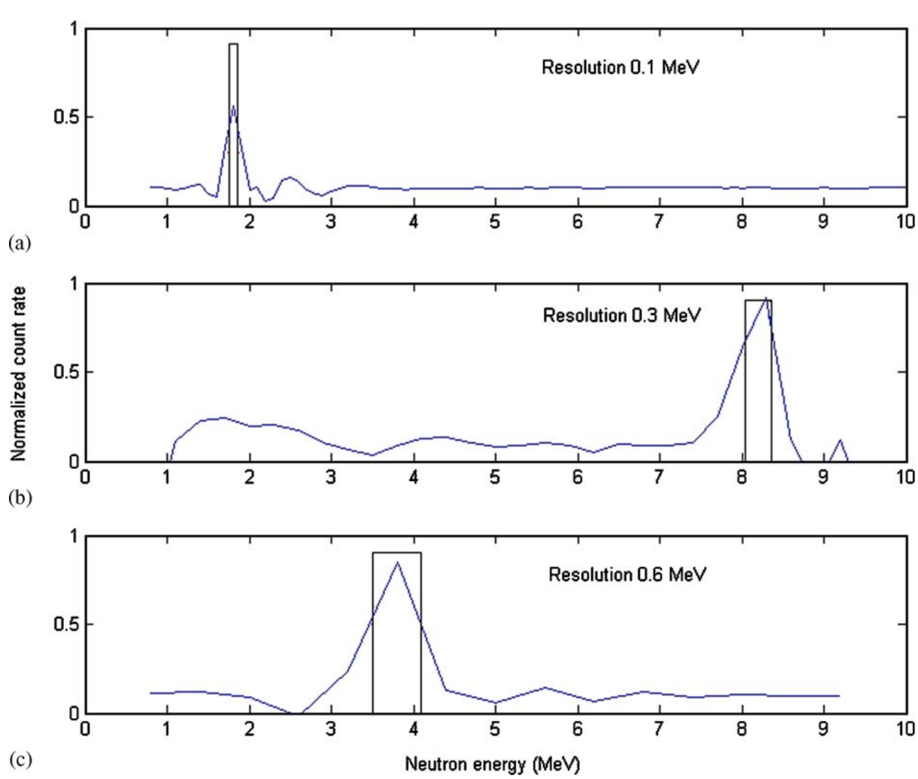

Fig. 6. Response of the linear network to monoenergetic sources for various energy resolutions. The rectangles show the target values, and the continuous lines show the ANN prediction.

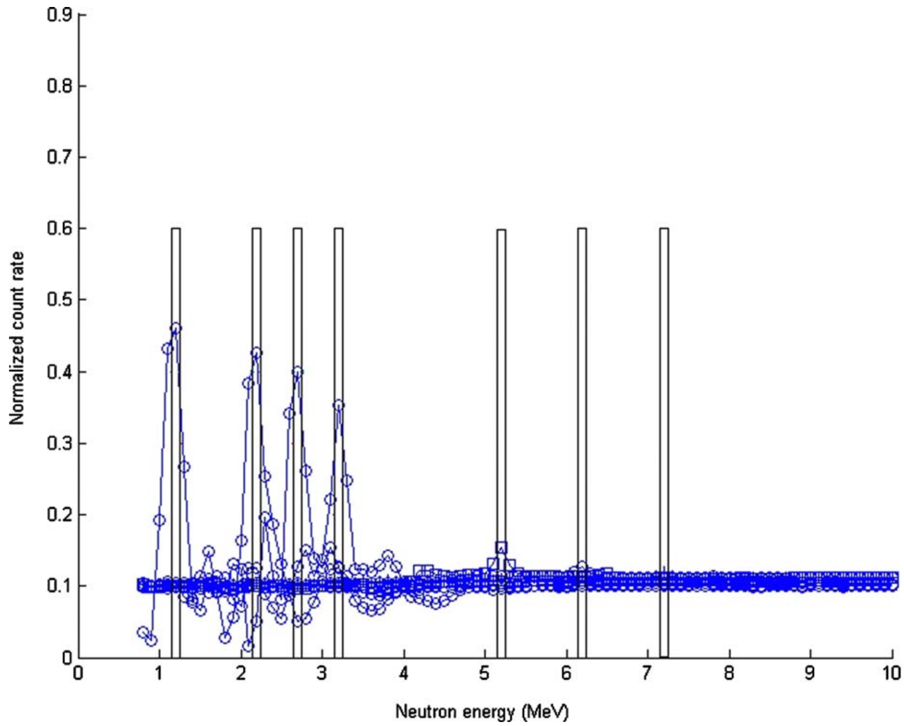

Fig. 7. Output of the linear neural network with an energy resolution of 0.1 MeV to randomly selected monoenergetic neutron sources. The rectangles show the target values, and the circles show the ANN prediction.

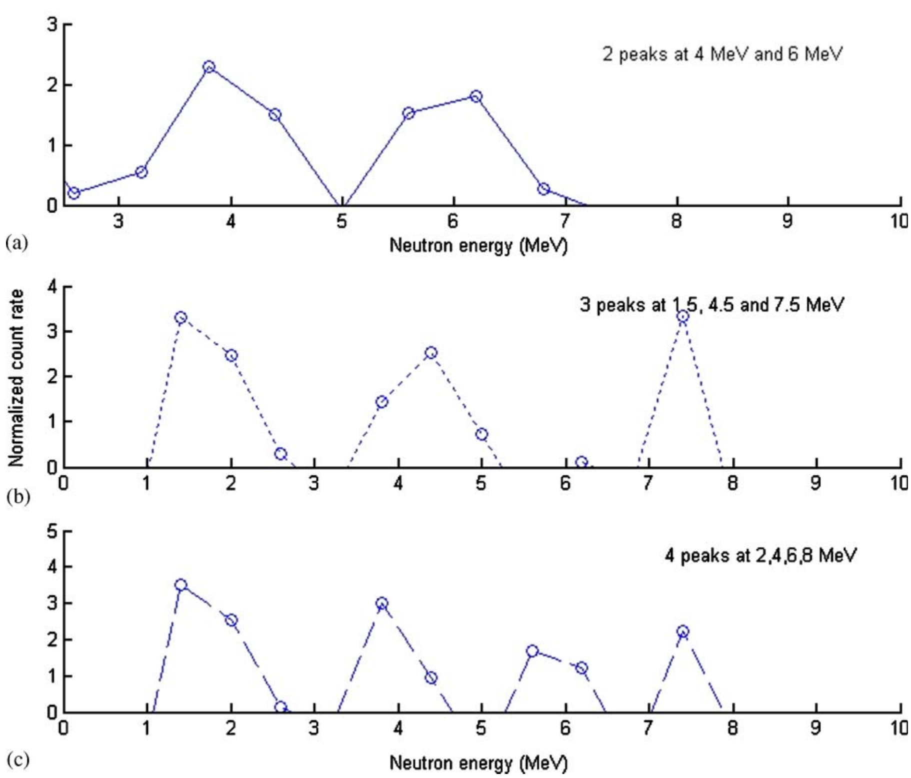

Fig. 8. Response of the linear network to incident spectra with 2, 3, and 4 energy peaks.

simulated with the MCNP-PoliMi code. Comparison between the ^{252}Cf neutron source spectrum unfolded by the linear neural network from the simulated data and the reference one is given in Fig. 10. Both spectra were normalized so that they have the same area between 0.8 and 8 MeV.

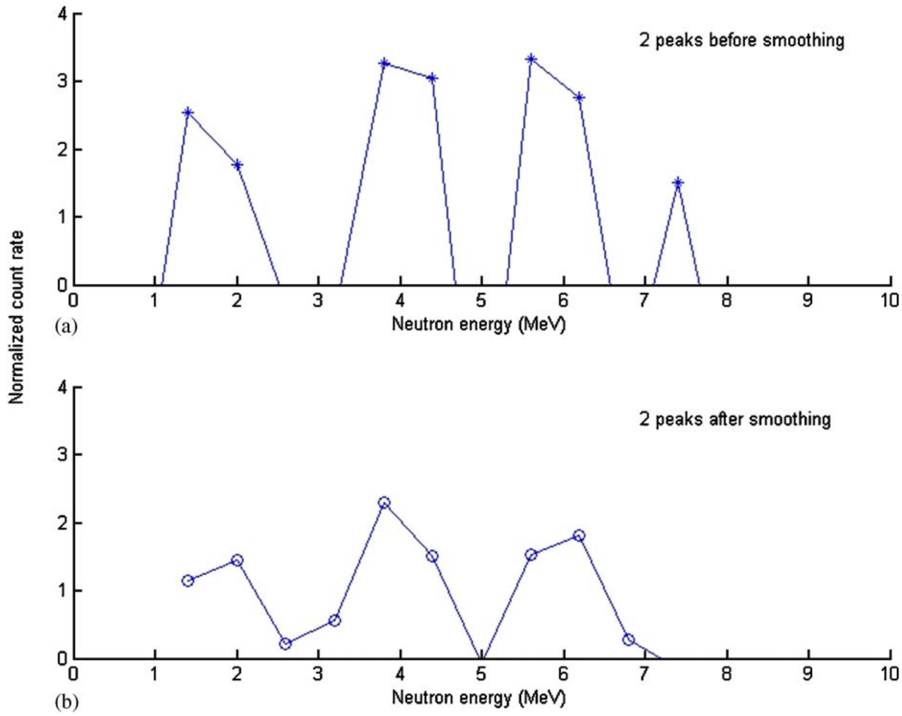

Fig. 9. Output of the linear network before and after smoothing.

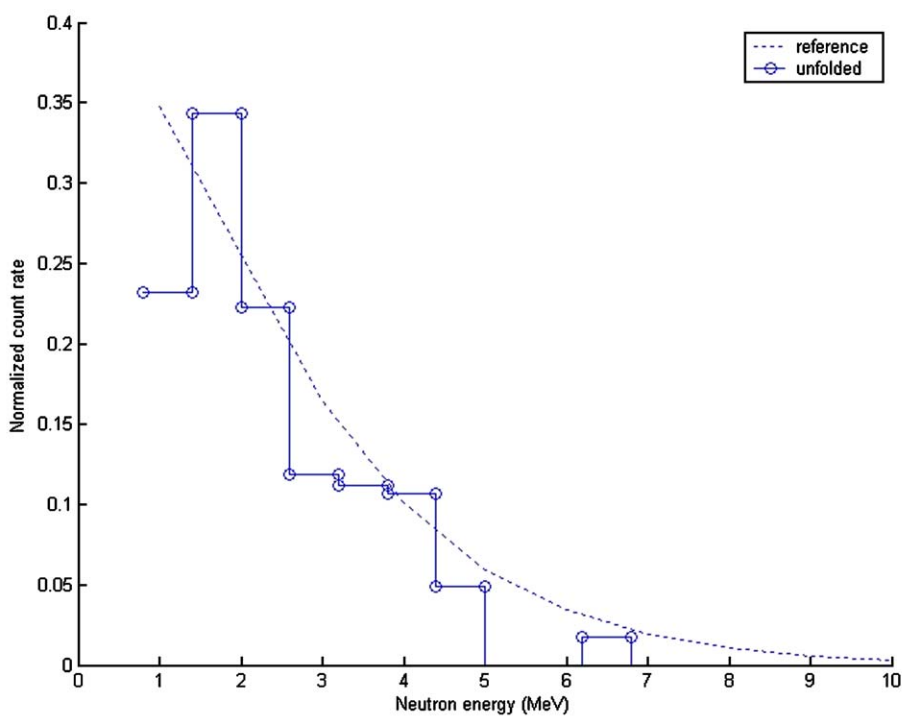

Fig. 10. Comparison of the ^{252}Cf spectrum unfolded from the simulated data and the reference one.

The pulse height distribution from the ^{252}Cf neutron source was measured using the liquid scintillator and a timed ^{252}Cf [8]. Discrimination of neutron and gamma pulses was performed by the time-of-flight method in order to determine the neutron energy spectrum. In the experiment, the ^{252}Cf source was placed at a 1-m distance from

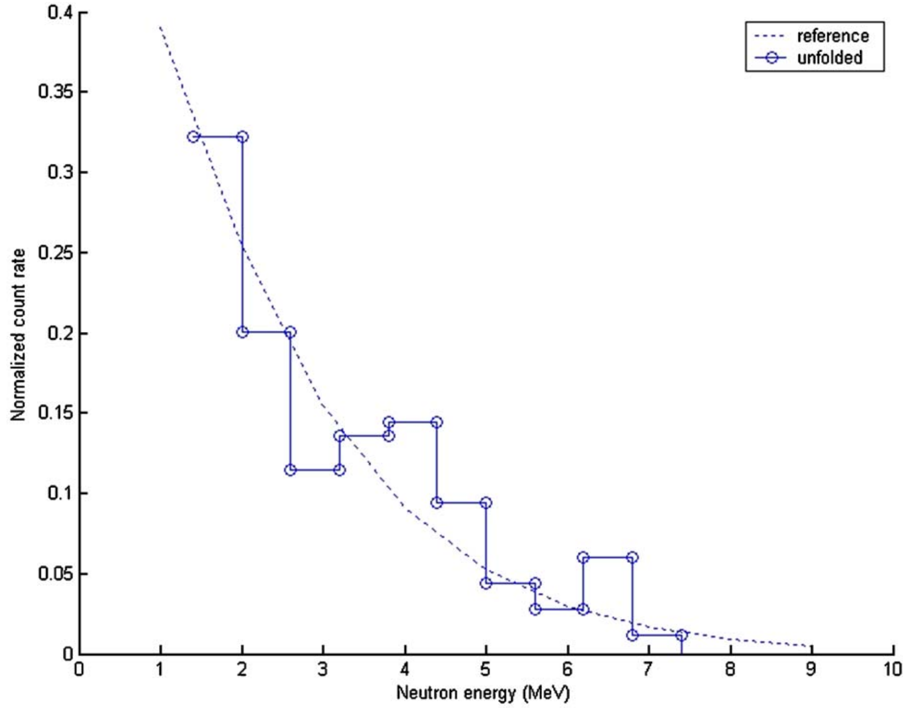

Fig. 11. Comparison of the ^{252}Cf spectrum unfolded from the measured data and the reference one.

the liquid scintillator. The data acquisition was performed using a custom-built Matlab program running on a Tektronix TDS-5104 digital oscilloscope [17]. The use of the Matlab Instrument Control Toolbox allowed a totally automated data collection process. Fig. 11 shows the ^{252}Cf reference spectrum and the spectrum unfolded by the linear neural network from the measured pulse height distribution from the ^{252}Cf neutron source. Both spectra were normalized to the same area between 1.4 and 8 MeV. The unfolded spectrum is in reasonable agreement with the reference spectrum.

5. Conclusions

The results presented in this paper clearly show the existing capabilities and future potential offered by the combined use of *linear and nonlinear* ANN techniques for the identification and unfolding of pulse height distributions measured by liquid scintillation detectors.

We showed that the use of a linear neural network trained only with simulated monoenergetic neutron response functions can be used to unfold *unknown* spectra from monoenergetic or continuous, simulated or measured neutron sources. We also showed that nonlinear ANNs can be efficiently used to perform neutron source identification. This capability was demonstrated successfully on both simulated and experimental data obtained using a ^{252}Cf neutron source. In particular, we showed that the Cf source can be identified in a manner of seconds, a capability that is highly desirable in nonproliferation applications.

Future work includes investigations of the neural network response to experimental data obtained from various neutron sources and comparison of the neural network unfolding technique with conventional unfolding methods, as well as examination of the influence of statistical fluctuations, measurement time, measurement error on the evaluated spectra data, and the effect of shielding.

Acknowledgments

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