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Application of Neural Networks for unfolding neutron spectra measured by means of Bonner Spheres

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Abstract

A Neural Network structure has been used for unfolding neutron spectra measured by means of a Bonner Sphere Spectrometer set. The present work used the "Stuttgart Neural Network Simulator" as the interface for designing, training and validation of a MultiLayer Perceptron network. The back-propagation algorithm was applied. The Bonner Sphere set chosen has been calibrated at the National Physical Laboratory, United Kingdom, and uses gold activation foils as thermal neutron detectors. The neutron energy covered by the response functions goes from 0.0001 eV to 10 MeV. Two types of neutron spectra were numerically investigated: monoenergetic and continuous. Good results were obtained, indicating that the Neural Network can be considered an interesting alternative among the neutron spectrum unfolding methodologies.

Keywords: Neural Network; Neutron; Spectrum unfolding; Bonner Spheres

1. Introduction

A system commonly used for neutron field dosimetry is the Bonner Sphere Spectrometer (BSS) set. This type of spectrometer has the advantages of isotropic response and the ability to measure the neutron spectrum from thermal energies to tens of MeV. The response of each detector of an array may be written as a homogeneous set of Fredholm equations. When the detector responses are known for discrete energy groups, this set of equations may be rewritten as a sum of products between the neutron fluence rate, the detector response and the energy width of the group.

$$C_i = \sum_{j=1}^{n} \phi_j \Delta E_j R_{ij}$$

where C_i is the reaction rate from the ith Bonner Sphere; ϕ_j is the fluence rate of neutrons in the jth energy interval; ΔE_j is the jth energy interval; R_{ij} is the Bonner Sphere response function corresponding to the jth energy interval.

For the case of BSS spectrometers, the deconvolution methods applicable for solving this set of equations are usually grouped into three categories: parametric, quadrature and Monte Carlo. The present work adopts an approach to the problem using a Neural Network structure [1–4].

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2. Neural Network architecture

Neural Network models are algorithms for cognitive tasks, such as learning and optimization, which are in a loose sense based on concepts derived from research into the nature of the brain. It simulates a highly interconnected, parallel computational structure with many individual processing elements, or neurons. In mathematical terms a Neural Network model has the following properties:

(a) a state variable v_k is associated with each node k;
(b) a real-valued weight w_{kj} is associated with each link (kj) between two nodes k and j;
(c) a real-valued bias θ_k is associated with each node k;
(d) a transfer function $f_k[v_k, w_{kj}, \theta_k, (k \neq j)]$ is defined, for each node k, which determines the state of the node as a function of its bias, of the weights of its incoming links, and of the states of the nodes connected to it by these links.

In standard terminology, the nodes are called neurons, the links are called synapses, and the bias is known as the activation threshold. The transfer function is either a discontinuous step function or its smoothly increasing generalization known as a sigmoidal function [5–7]. This standard network structure with several layers is called MultiLayer Perceptron (MLP).

Among the many interesting properties of a Neural Network, the property that is of primary significance is the ability of the network to learn from its environment, and to improve its performance through learning; the improvement in performance takes place over time in accordance with some prescribed measure. A Neural Network learns through an iterative process of adjustments applied to its synaptic weights and thresholds.

A prescribed set of well-defined rules for the solution of a learning problem is called a learning algorithm. There is no unique learning algorithm for the design of Neural Networks. Basically, learning algorithms differ from each other in the way in which the adjustment to the synaptic weight is formulated.

The present work used the "Stuttgart Neural Network Simulator" (SNNS) as the interface for designing, training and validation of the network. The back-propagation algorithm was applied.

The Bonner Sphere set chosen is the one calibrated at the National Physical Laboratory, United Kingdom, which uses gold activation foils as thermal neutron detectors [8]. The neutron energy covered by the response functions goes from 0.0001 eV to 10 MeV. Two types of neutron spectra were investigated: monoenergetic and continuous.

2.1. Training and test files

The network consisted of three neuron arrays: the input, hidden and output arrays (see Fig. 1). The input array was built of 10 neurons and corresponds to each reaction rate of the Bonner Sphere. The output array consisted of 52 neurons and corresponds to each energy bin chosen for the neutron spectrum. A sigmoid activation function was used normalized in the interval from −2 to 2. Several neutron spectra were chosen for training: monoenergetic, Maxwellian, Watt, $1/E$ and a

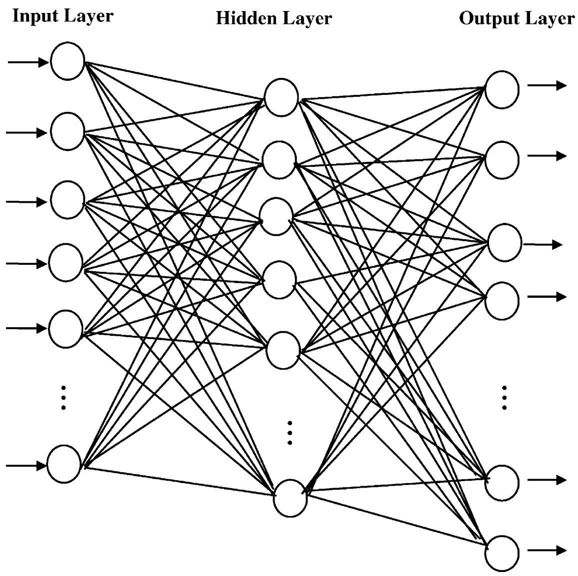

Fig. 1. Multilayer Perceptron 10-50-52 used for unfolding neutron spectra.

combination of these. All spectra were normalized to unity neutron fluence.

The first simulation considered only monoenergetic neutrons. Fifty-two spectra were chosen, corresponding to each of the energy bins available from the Bonner Sphere response function table. The training has been performed with 44 monoenergetic spectra randomly selected from the group of 52. The remaining eight spectra were used for testing. The training was repeated until the Standard Error was 0.0019 which was achieved after 3×10^5 iterations. The training rate was 0.2 and the momentum constant parameter was 0.06. The final network consisted of $10:50:52$ neurons in the input, hidden and output layers, respectively.

The second simulation considered a new network trained for continuous neutron spectra. Twenty-one spectra were chosen: Watt, Maxwell, $1/E$ and combinations of these with different cut-off energies. The training was repeated until the Standard Error was 0.0016 which was achieved after 3×10^5 iterations. The training rate was 0.4 and the momentum constant parameter was 0.1. The final network had the same structure as before: $10:50:52$ neurons in the input, hidden and output layers, respectively. A typical training spectrum is shown in Fig. 2.

3. Results and discussion

The present work investigated numerically some Bonner Sphere problems occurring in practice. Excellent results were obtained with monoenergetic neutrons. The network was able to predict precisely the results for all the eight unknown spectra presented to the network. Since the input data for the network comes from counting rates, they are subjected to statistical fluctuations. For this reason, an additional test has been performed simulating a Normal distribution of counting rates around the expected mean. The relative standard deviation has been varied from 5% to 10%. The output spectrum distribution showed a spread around the true energy value, as shown in Fig. 3, indicating that statistical changes in the counting rates result in a moderate loss of energy resolution. However, the output mean value matched the expected neutron energy.

For continuous spectra, despite the small number of training cases, the network was able to predict with good accuracy the unknown neutron spectrum presented to the network, as shown in Fig. 4. The network output integral fluence rate was 1.0026 which is in good agreement with the unity value from the normalized integral fluence rate of the test case.

In both simulations, the network predicted precisely the energy bin and the neutron fluence. It was observed that as the Standard Error became smaller, the network was able to predict the results

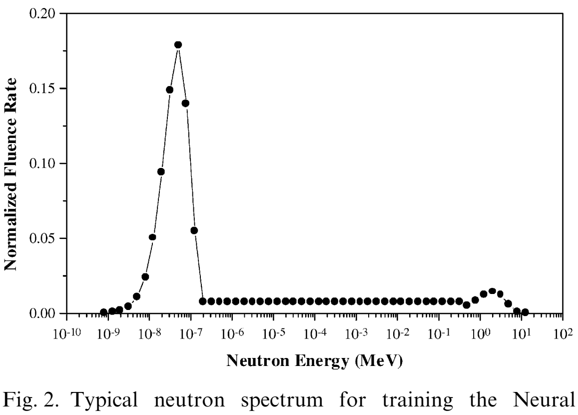

Fig. 2. Typical neutron spectrum for training the Neural Network (Maxwell, $1/E$ and Watt).

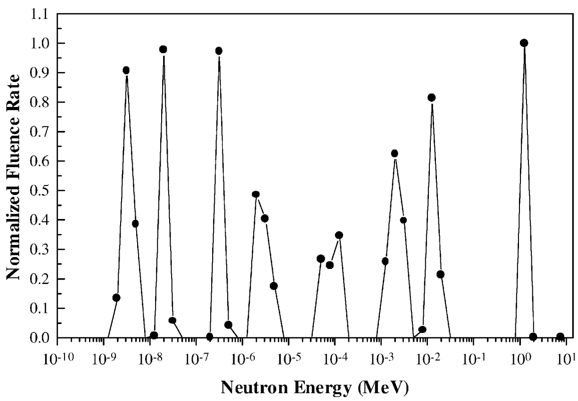

Fig. 3. Neural Network output spectrum for eight different monoenergetic neutron beams. The input data corresponding to the Bonner Sphere counting rates were allowed to spread, in order to simulate a Normal distribution with 5% relative standard deviation.

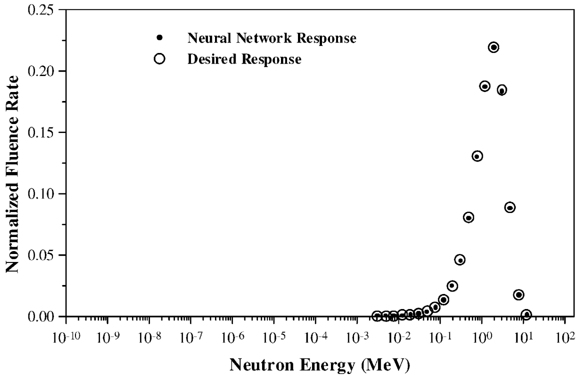

Fig. 4. Comparison between Neural Network output and the expected neutron spectrum.

with better accuracy. Therefore, the accuracy is a function of the number of iterations, momentum constant parameter and learning rate parameter. These results indicate that the Neural Network can be considered an interesting alternative for neutron spectrum unfolding using a BSS. Further studies must be performed in order to obtain the spectrum shape as a function of the neutron lethargy and to compare the Neural Network with other unfolding methodologies.

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