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Neutron Spectrometry with Artificial Neural Networks

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Resumen

An artificial neural network has been designed to obtain the neutron spectra from the Bonner spheres spectrometer's count rates. The neural network was trained using 129 neutron spectra. These include isotopic neutron sources; reference and operational spectra from accelerators and nuclear reactors, spectra from mathematical functions as well as few energy groups and monoenergetic spectra. The spectra were transformed from lethargy to energy distribution and were re-binned to 31 energy groups using the MCNP 4C code. Re-binned spectra and UTA4 response matrix were used to calculate the expected count rates in Bonner spheres spectrometer. These count rates were used as input and the respective spectrum was used as output during neural network training. After training the network was tested with the Bonner spheres count rates produced by a set of neutron spectra. This set contains data used during network training as well as data not used. Training and testing was carried out in the Matlab® program. To verify the network unfolding performance the original and unfolded spectra were compared using the χ^2-test and the total fluence ratios. The use of Artificial Neural Networks to unfold neutron spectra in neutron spectrometry is an alternative procedure that overcomes the drawbacks associated in this ill-conditioned problem.

1. INTRODUCTION

The monitoring of occupational radiation exposure in neutron fields is mainly done with passive detection systems like track detectors, albedo dosimeters or film dosimeters with foil-filters. [1, 2] These dosimetric systems have a response that strongly depends upon neutron energy. Thus, for low energy and thermal neutrons albedo dosimeters have a good response [3] while track detectors have good efficiency to fast neutrons [4].

At regular basis dosimeters are calibrated with a neutron field whose energy distribution is different to that where dosimeters are utilized resulting in wrong dose assessment [5]. Dose quantities like personal dose equivalent Hp(10), recommended by ICRP, requires of personal dosimeters with larger neutron detection efficiency [6].

Neutron dosimeters are also utilized as multi-element systems where each element has a particular response to neutrons. Usually these dosimeters have better detection efficiency in a wider energy range allowing a better dose assessment. [2] This is achieved using the integral counts, obtained by the active detector, that are weighted by factors that belong to each element [7] or using the integral counts to unfold the neutron spectrum that is multiplied by neutron fluence-to-dose conversion coefficients. With the neutron spectrum information different dose quantities, like Hp(10), H*(10), can be estimated [8].

With the Bonner spheres spectrometer (BSS), also known as multi-spheres spectrometer, neutron spectrum from thermal up to several MeV can be obtained, [9] this is a thermal neutron detector that is located at the center of a high-density polyethylene sphere whose diameters are 2, 3, 5, 8, 10, 12, 16 and 18 inches [10]. Modifications in moderating spheres have been realized to increase the BSS's response to neutrons with higher energies [11-13].

The weight, time consuming procedure, the need to use an unfolding procedure and the low resolution spectrum are the BSS drawbacks. The BSS response matrix, the count rates and the neutron spectrum are related through the Fredholm integro-diferential equation, whose discrete version is. [14]

$$C_j = \sum_{i=1}^{N} R_{i,j} \; \Phi_i \qquad j = 1, 2, ..., m, \tag{1}$$

where Cj is the jth detector's count rate; Ri, j is the jth detector's response to neutrons at the ith energy interval; Φi is the neutron fluence within the ith energy interval; and m is the number of spheres utilized.

Equation (1) is an ill-conditioned equations system with an infinite number of solutions. To unfold the neutron spectrum, Φ(E), several methods are used, Monte Carlo [15], regularization [16], parameterization and iterative procedures [17]. Each of them has difficulties that motivate the development of complementary procedures [14, 18, 19]. Recently methods based upon maximum entropy [20], genetic algorithms [21, 22] and artificial neural nets [2, 5, 23, 24] have been utilized. Artificial neural networks (ANN) require the use of detectors whose response functions are independent. The application of neural networks to unfold actual neutron spectra still has some problems and the need of more investigation has been suggested [23].

Neural networks are nonlinear black-box model structures that can be used with conventional parameter estimation methods. [1] Neural network techniques are widely recognized as powerful modeling tools [25]. A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge, previously acquired through a learning process, making it available for use [26].

A neural network simulates a highly interconnected, parallel computational structure with many individual processing elements, or neurons. It learns through an iterative process of adjustments applied to its synaptic weights and thresholds. A defined set of rules for the solution of a learning problem is the learning algorithm [2, 24].

In general a neural network consists of a set of input nodes that link directly to a series of output nodes or indirectly through one or more hidden layers [26]. The use of an artificial neural network requires the training of the network and the test of the trained network. During training a set of synaptic weights are obtained.

In aim of this study was to use artificial neural networks to unfold neutron spectra from the count rates obtained from a Bonner spheres spectrometer.

2. MATERIALS AND METHODS

With Monte Carlo code MCNP 4C [27] a point-like neutron source in an empty space was modeled and the neutrons were transported from the source to a detector located at 10 cm to modify its energy structure distribution. This procedure was carried out for one hundred and twenty nine spectra, 105 spectra were obtained from literature [28, 29] and 24 were built as monoenergetic and few energy groups spectra: 13 spectra has a single peak, 3 has two peaks, 2 has three peaks, 3 has four peaks, 2 have five peaks and one spectrum has six peaks.

From 105 spectra obtained from IAEA, a set is originally defined from thermal to 435 MeV in 55 energy groups [28] while, other set is defined from thermal to 630 MeV in 60 energy groups [29]. Using MCNP 4C code those spectra were converted from thermal to 400 MeV in thirty-one energy groups defined in the BUNKIUT unfolding code [30].

Re-binned spectra were normalized to 1 cm^{-2} and the expected count rates in a Bonner sphere spectrometer were calculated using the UTA4 response matrix. This, is for a BSS with a 0.4 Ø x 0.4 cm^{-2} ^{6}LiI(Eu) scintillator as thermal neutron [10, 18]. The count rates were utilized as inputs in a neural network while the respective neutron spectra were utilized as the network output during the neural network training.

After several trials, where the amount of hidden layers and neurons in those layers, the artificial neural network that gave acceptable results was 7:21:42:140:200:400:31. Feed forward back propagation algorithm with variable learning rate was used as the learning function. The logistic function (logsig) was used as transfer function that is the most common function used in ANN

[25]. The ANN was trained and tested using Matlab® code [31]. From the training process a set of synaptic weights are obtained, these and the ANN topology is used to calculate the neutron spectra by feeding the ANN with just the 7 count rates obtained with the 0, 2, 3, 5, 8, 10 and 12 inches-diameter Bonner spheres.

The network was tested using nine spectra, four are form the set utilized during training and five were not used along the ANN training. From this last group two belong to actual cases and three were obtained from mathematical functions: the Watt's fission, Evaporation and Fusion spectra. This set was considered appropriate to test the ANN performance because has a variety of spectra. The χ^2-test was applied to compare the original spectra with those unfolded with the ANN. Other way to compare the original and ANN unfolded spectra was through the unfolded-to-original total fluence ratio.

3. MATERIALS AND METHODS

In figures 1 to 4 are shown the results obtained with the set of neutron spectra used along the ANN training, while in figures 5 to 9 are shown those obtained with neutron spectra that were not used along the ANN training.

In figures 1 and 2, the original and the unfolded neutron spectra, of ^{241}AmF and ^{252}Cf/D_2O neutron sources are shown. The total fluence ratios are 1.0145 and 1.0227 respectively. In figures 3 and 4, the actual and unfolded spectra of neutrons produced during solar flare and the ideal spectrum with three peaks respectively. Here, the total fluence ratios are 0.9995 and 1.0202 respectively.

Caorso nuclear reactor and Microtron, original and ANN unfolded, neutron spectra are shown in figures 5 and 6, their respective total fluence ratios are 1.1505 and 0.9719. In figures 7, 8 and 9 are the expected and the ANN unfolded spectra of Evaporation, Fusion and Watt´s fission neutron spectra whose total fluence ratios are 0.9913, 1.0101 and 0.9962 respectively.

In the case of monoenergetic spectra this ANN gives good results that are better to those reported by Cordes et al., [5]. They, and Fehrenbacher et al., [2] used similar training algorithm but a simplest network, 6:16:10:6. Although 273 spectra were used during training they reported large deviations in some spectra that were poorly represented in the training set.

For 30 degrees of freedom and α = 0.05 the critical χ^2-value is 18.4927. The χ^2-calculated value for each spectrum is shown in table I.

Table I.- Calculated χ^2 -values

Spectrum	χ^2	Spectrum	χ^2	Spectrum	χ^2
^{241}AmF	4.4132E(-4)	Three peaks	0.0293	Evaporation	0.3247
^{252}Cf/D_2O	1.1614E(-3)	Caorso	0.1354	Fusion	3.1692(-3)
Solar flare	2.9367E(-3)	Microtron	0.0912	Watt´s fission	1.249

All values are less than χ^2 critical-value; therefore there is a not a significant difference between the expected neutron spectra and those unfolded by ANN.

So far neutron spectra unfolded with Artificial Neural Networks are better compared with those unfolded using Genetic algorithms. [21, 22].

4. CONCLUSIONS

Artificial neural networks technology has been utilized to unfold the neutron spectra from Bonner spheres spectrometer count rates. One hundred twenty nine neutron spectra and their count rates were used during the ANN training. The trained network was tested with 9 neutron spectra; during testing network performance was compared with the few results reported in literature where different networks are used.

The use of ANN to unfold neutron spectra from the count rates measured with the Bonner sphere spectrometer is an alternative procedure in neutron spectrometry. Once the network has been trained the neutron spectrum is obtained without the need of a matrix response and an initial guess spectrum, overcoming the problems associated with such ill-conditioned problem.

Comparing the results reported in literature, where neutron spectrometry was performed by different measuring methods and using ANN, the set of neutron spectra used during training have strong influence in the unfolded spectra's quality, as a secondary factor the network architecture was found, however more extensive studies should be realized in order to obtain an optimal ANN topology.

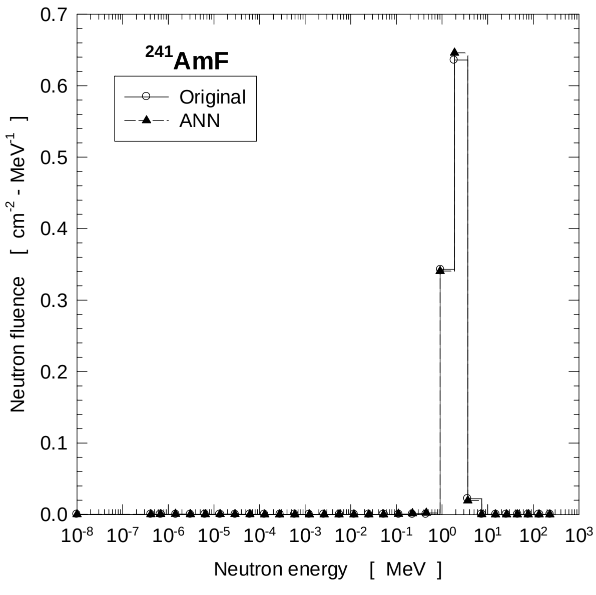

Figure 1. Comparison between ANN output and the original neutron spectrum of ^{241}AmF.

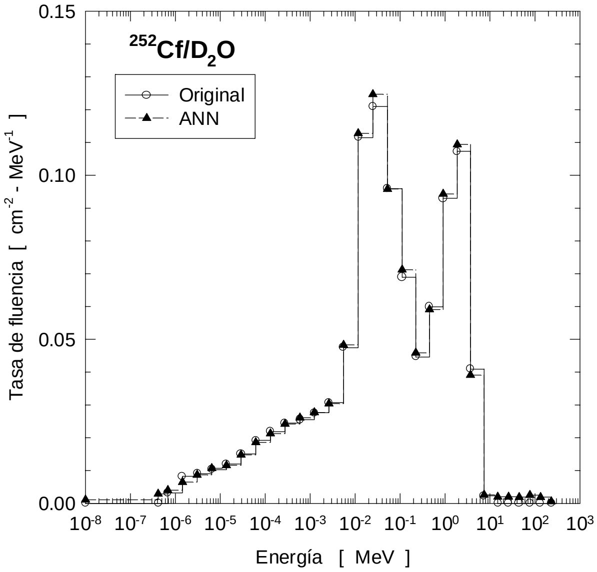

Figure 2. Comparison between ANN output and the original neutron spectrum of ^{252}Cf/D$_2$O.

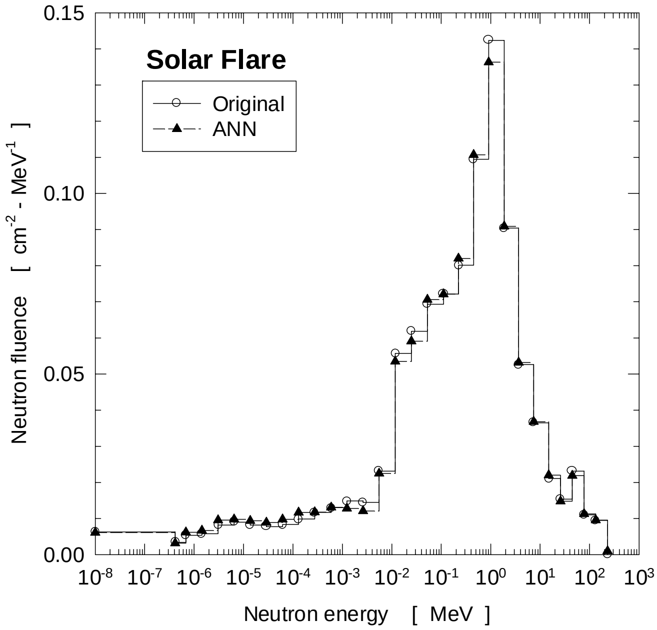

Figure 3. Comparison between ANN output and the original neutron spectrum of Solar flare.

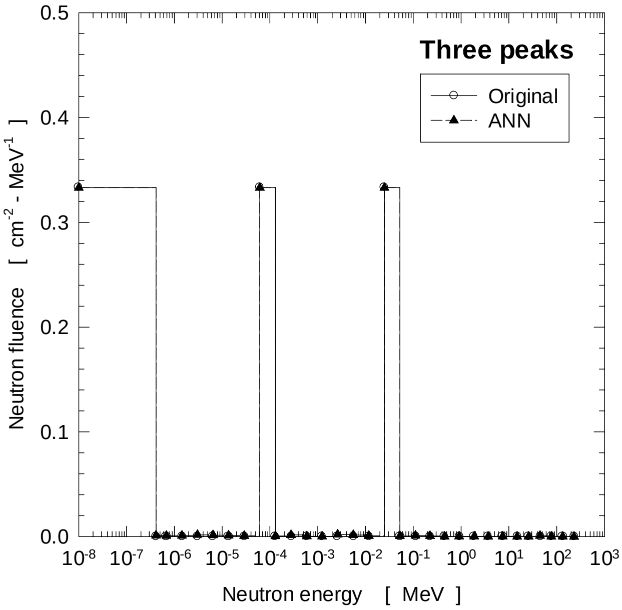

Figure 4. Comparison between ANN output and the original spectrum.

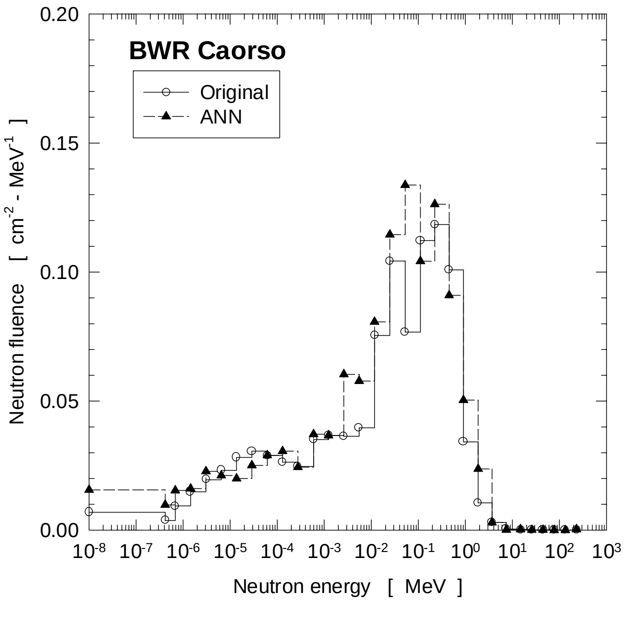

Figure 5. Comparison between ANN output and the original neutron spectrum of Caorso nuclear reactor.

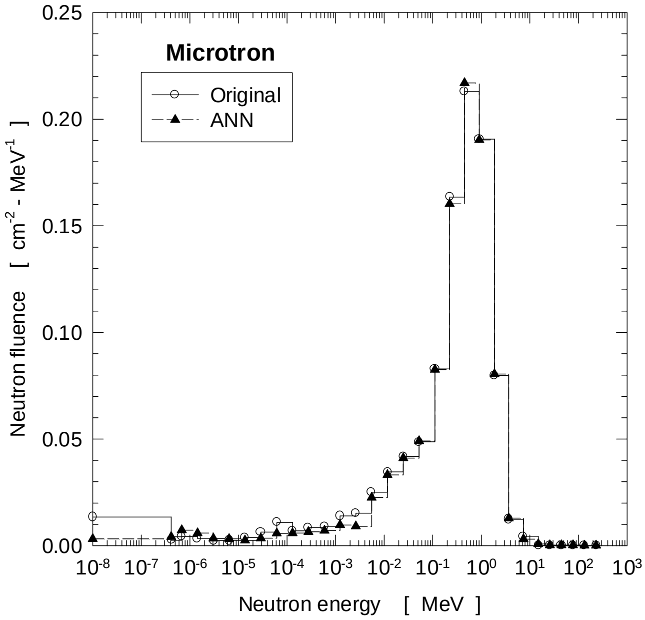

Figure 6. Comparison between ANN output and the original neutron spectrum of a Microtron.

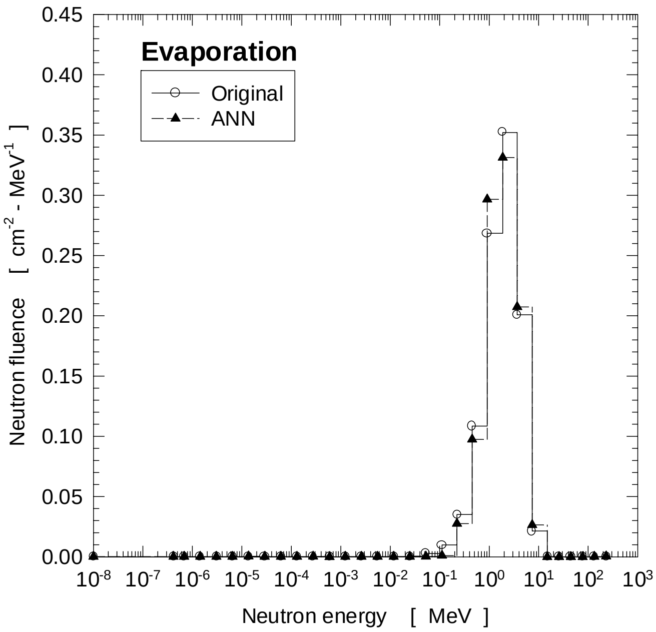

Figure 7. Comparison between ANN output and the original Evaporation neutron spectrum.

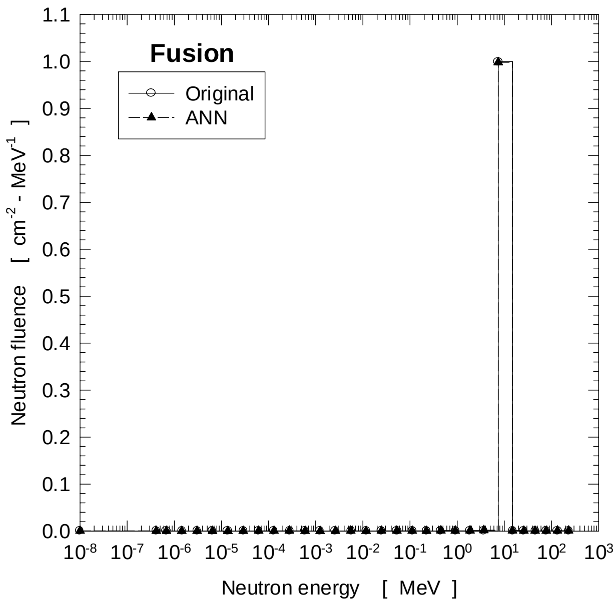

Figure 8. Comparison between ANN output and the original Fusion neutron spectrum.

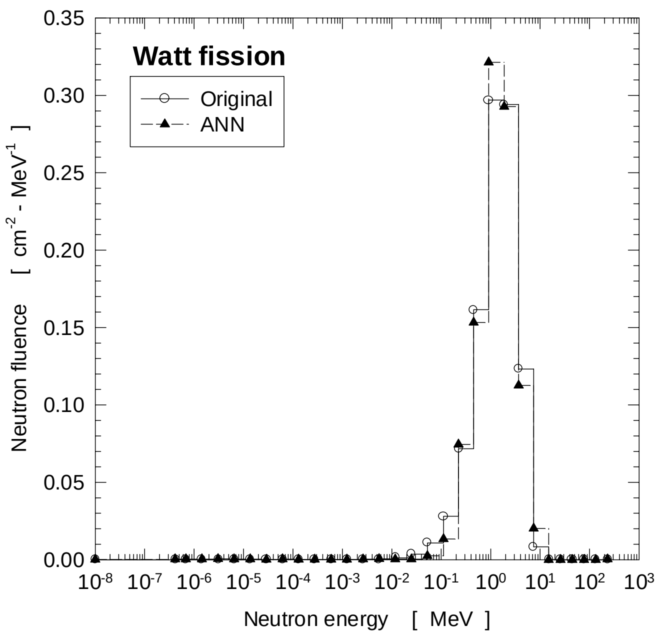

Figure 9. Comparison between ANN output and the original Fission neutron spectrum.

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