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ARTIFICIAL NEURAL NETWORKS IN NEUTRON DOSIMETRY

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Abstract

An artificial neural network has been designed to obtain the neutron doses using only the Bonner spheres spectrometer's count rates. Ambient, personal and effective neutron doses were included. 187 neutron spectra were utilized to calculate the Bonner count rates and the neutron doses. 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, UTA4 response matrix and fluence-to-dose coefficients were used to calculate the count rates in Bonner spheres spectrometer and the doses. Count rates were used as input and the respective doses were used as output during neural network training. Training and testing was carried out in MATLAB® environment. The artificial neural network performance was evaluated using the χ^2-test, where the original and calculated doses were compared. The use of Artificial Neural Networks in neutron dosimetry is an alternative procedure that overcomes the drawbacks associated in this ill-conditioned problem.

Keywords: Artificial Neural Networks, Neutron Dosimetry, Monte Carlo

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INTRODUCTION

There is a tendency to substitute the film or TLD badge by electronic dosimeters[1] however, passive detection systems, like track detectors, albedo or film dosimeters with foil-filters, are heavily utilized to monitoring the occupational radiation exposure in neutron fields[2, 3]. Their response is energy-dependent, for low energy and thermal neutrons albedo dosimeters have a good response[4] while track detectors have good efficiency to fast neutrons[5].

Neutron dose-equivalent meters are survey instruments used to estimate the ambient dose equivalent; these, have an active neutron detector located inside a polyethylene moderator. Geometry and moderator dimensions are set to look for wide and energy-independent responses. Through electronics the detector count rate is converted to dose that is displayed as a single number.

Neutron dosimetry is also realized through neutron spectrometry where a multi-element system is utilized. Each element has a response that depends from the neutron energy. These have better detection efficiency in a wider energy range allowing a better dose assessment [3,6]. 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. With the neutron fluence-to-dose conversion coefficients and the neutron spectrum the dose is calculated. The main advantage of having the neutron spectrum information is that different dose quantities can be estimated [8].

During calibration the performance of all those devices is reviewed, this is realized with calibrated or standard neutron fields that, normally, are different from the actual neutron field where the instruments are utilized, resulting in a wrong dose assessment[9]. With the Bonner spheres spectrometer (BSS), also known as multi-spheres spectrometer, neutron spectrum from thermal up to several MeV can be obtained[10,11], BSS combines a thermal neutron detector, passive or active, that is located at the center of a high-density polyethylene sphere with different diameters; each sphere-detector combination has a particular response; the whole set of responses defines the matrix response[12,13]. Different modifications to moderating spheres have been realized to improve the efficiency to high-energy neutrons[14,15,16].

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 first kind Fredholm´s integro-diferential equation, whose discrete version is[17].

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

where C_j is the j^{th} detector's count rate; $R_{i,j}$ is the j^{th} detector's response to neutrons at the i^{th} energy interval; Φ_i is the neutron fluence within the i^{th} energy interval; and m is the number of spheres utilized.

Once the neutron spectrum, $\Phi_E(E)$, has been obtained the dose, Δ, can be calculated using the fluence-to-dose conversion coefficients, $\delta_\Phi(E)$, as shown in equation 2.

$$\Delta = \int_{E\,min}^{E\,max} \delta_\Phi (E)\, \Phi_E (E)\, dE \tag{2}$$

Dose calculation is not a trivial task because equation 1 is an ill-conditioned equations system with an infinite number of solutions. To unfold the neutron spectrum, $\Phi_E(E)$, several methods are used, Monte Carlo[18], regularization[19], parameterization and iterative procedures[20]. All of them has difficulties that motivate the development of complementary procedures[21, 22]. Recently, methods based upon maximum entropy[23], genetic algorithms[24, 25] and artificial neural networks[2, 3, 9, 26, 27] have been utilized.

The application of artificial neural networks (ANN) to unfold actual neutron spectra still have some problems, the need of more investigation has been suggested[26].

ANN are nonlinear black-box model structures that can be used with conventional parameter estimation methods[2]. ANN technology is widely recognized as powerful modeling tool[28]. An artificial 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[29].

An artificial neural network simulates a highly interconnected, parallel computational structure with many individual processing elements, or neurons. It learns through an iterative process of adjustments to its synaptic weights and thresholds. A defined set of rules for the solution of a learning problem is the learning algorithm[3, 26].

In general, an ANN is a set of input nodes that link directly to a series of output nodes or indirectly through one or more hidden layers[2]. The use of ANN requires the training of the network and the test of the trained network. During training a set of synaptic weights are obtained.

For first time the ANN technology has been applied to determine different neutron doses without the neutron spectrum information. Doses are directly obtained from the count rates of a BSS without the neutron spectrum unfolding.

MATERIALS AND METHODS

With Monte Carlo code MCNP 4C[30] a point-like neutron source in an empty space was modeled, 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 185 spectra obtained from literature[31]. There, the spectra are defined per unit lethargy in 60 energy groups ranging from thermal to 631 MeV. Neutron spectra were converted from lethargy to energy, then with the MCNP code the spectra were re-binned to 31 energy-groups, ranging from thermal to 400 MeV, defined in the BUNKIUT unfolding code[32], used to unfold the neutron spectra from the Bonner spheres' count rates.

Re-binned spectra were normalized to 1 cm^{-2} and the expected count rates in a BSS 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 detector[12, 21]. Calculations were performed for 7 spheres (0, 2, 3, 5, 8, 10 and 12 inches-diameter). With the use of fluence-to-dose conversion coefficients[33], the spectra were also utilized to calculate the Effective doses: E_{AP}, E_{PA}, E_{LAT}, E_{LLAT}, E_{ROT}, E_{ISO}; Ambient dose equivalent H*(10), and personal dose equivalent: $H_{p,slab}(10, 0^o)$, $H_{p,slab}(10, 15^o)$, $H_{p,slab}(10, 30^o)$, $H_{p,slab}(10, 45^o)$, $H_{p,slab}(10, 60^o)$ and $H_{p,slab}(10,75^o)$[34].

From the 185 data sets, a subset of 154 was selected to the ANN training: 154 BBS´ count rates sets were utilized as inputs and 154 sets of 13 respective doses were used as outputs. A subset of 31 BSS´ count rates was reserved to test the ANN performance. Testing data were randomly selected from the 185 sets.

The artificial neural network (ANN) was designed with 9 layers, the first one (input layer) has 7 neurons, corresponding to count rates of 7 polyethylene spheres, from second to eighth layer (hidden layers) have 9, 11, 30, 70, 100, 60 and 40 neurons respectively, and the ninth layer has 13 neurons, one for each dose. The ANN is shown in figure 1, here the neurons are linked through the synaptic weights.

The nine-layer feed-forward neural network, 7:9:11:30:70:100:60:40:13, was trained with a back propagation algorithm with variable learning rate used as the learning function. In the application of this algorithm there are two well defined computational stages: the forward pass and the backward pass. In the forward pass the synaptic weights remain unaltered throughout the network, and the function signals of the network are computed on a neuron-by-neuron basis[29].

During feed-forward the input layer neurons pass the input values on to the hidden layer. Each of the hidden layer neurons computes the weighted sum of its inputs. After computation of the weighted sum of each neuron in the output layer, the sum is passed through its activation function, resulting in one output value for the network. The logistic function log-sigmoid was used as activation function in this application. This is shown in equation 2; it is a s-shaped squashing function that maps the input to the interval (0, 1).

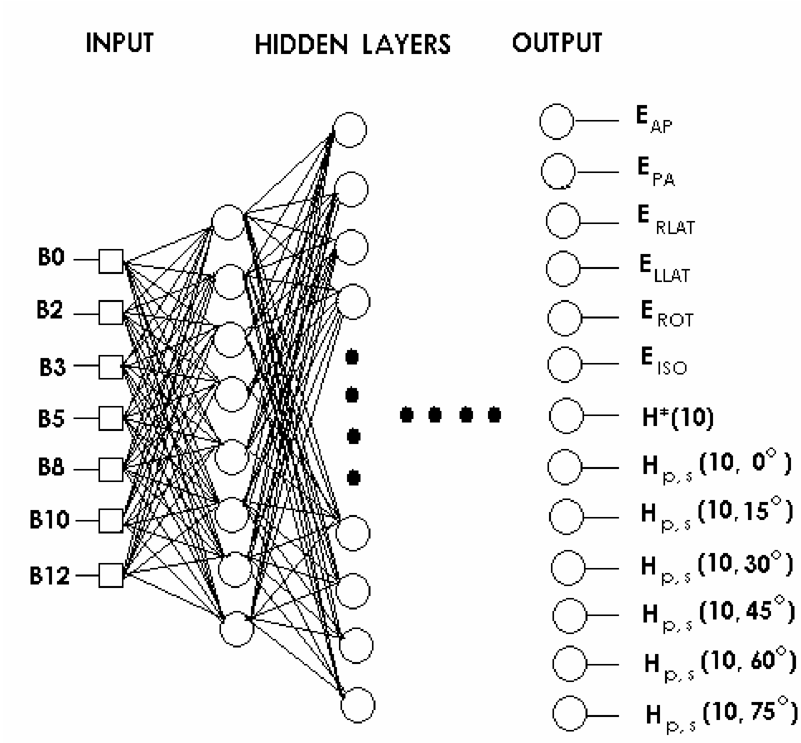

Figure 2.- Artificial Neural Network.

$$f_j = \frac{1}{1 + \mathrm{Exp}\left(- \sum \omega_{ji}\, o_i \quad + \quad b\right)} \tag{2}$$

Here, b is the bias, is used to calculate the net input of a neuron from all neurons connected to it. The bias is a neuron activation threshold.

In the back-propagation pass, the error between the network outputs and the desired output values is calculated with the generalized delta rule(29) and weights between neurons are updated from the output layer to the input layer as follows:

$$\omega_{ji}^{n+1} = \omega_{ji}^{n} \left(1 + \lambda\, \delta_j\, o_j + \mu\right), \tag{3}$$

where ω_{ji} is the linking weight from neuron i, in the lower layer, to neuron j, in the upper layer, o_j is the output of neuron i; initially, this is a small pseudo-random number, n is the iteration number, δ_j is the error signal at neuron j while δ and μ are the learning rate and momentum respectively. The learning rate controls the rate at which the network learns while the momentum constant controls the changes in the weights. The training process is successfully completed when the iterative process has converged(35).

The ANN was trained and tested using MATLAB® software(36). From the training a set of synaptic weights were obtained, these and the ANN topology is ready to calculate 13 neutron doses by feeding the ANN with 7 count rates obtained with the 0, 2, 3, 5, 8, 10 and 12 inches-diameter Bonner spheres. The ANN training was ended when an error of 5.3 x 10^{-7} was reached, this situation occurs after 142551 epochs.

The network was tested using 31 sets of Bonner spheres count rates that were not used during the ANN training. The χ^2-test (α = 95%, ν = 12 degrees of freedom) was applied to compare the original doses with those obtained with the ANN.

RESULTS AND DISCUSSION

The subset of neutron spectra used to test the ANN is shown in figure 2. In this set there is a wide selection of spectra, ranging from soft to hard. The count rates that these spectra produce when they are measured with a BSS, as well the 13 types of doses were calculated. The BSS count rates were used as input in the trained ANN, this gives out 13 values that correspond to the neutron doses.

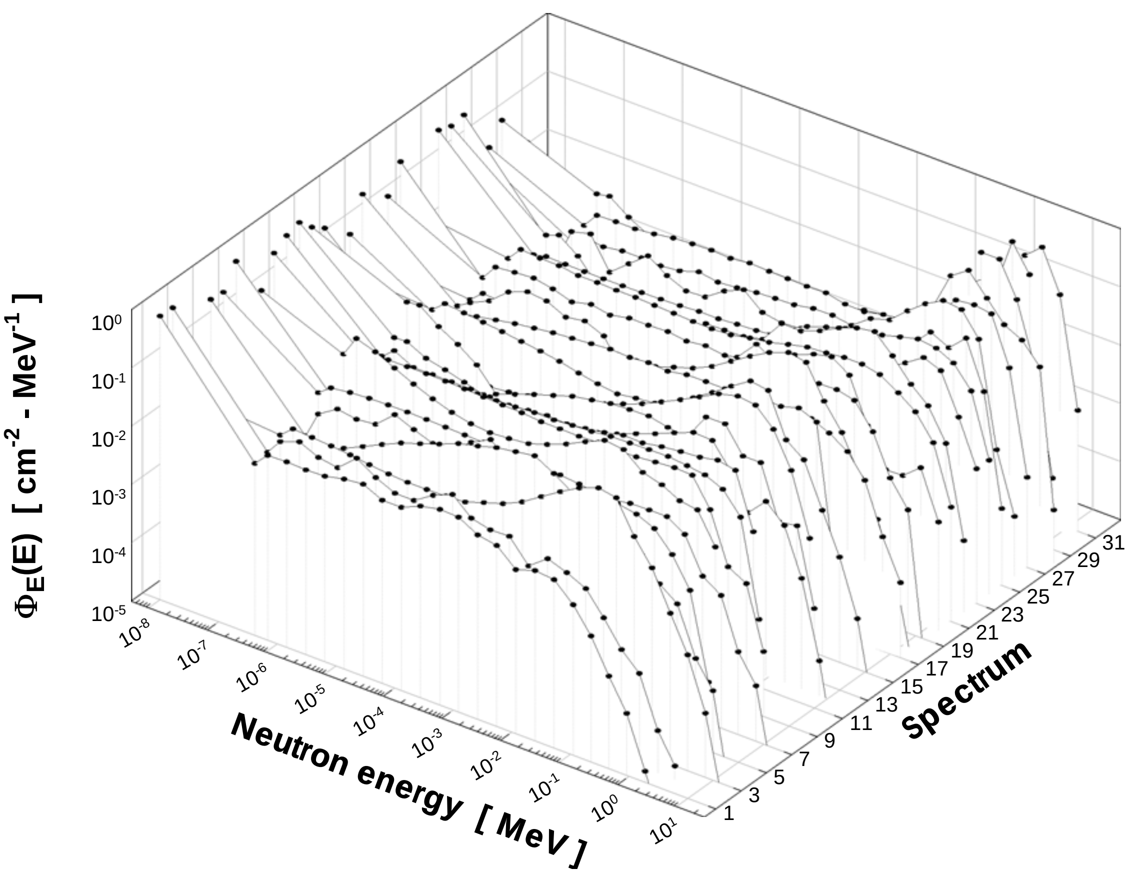

Figure 2.- Neutron spectra used to test the ANN.

The ANN performance was carried out using the χ^2-test, where the actual doses were compared with those obtained with the trained ANN. The set of χ^2-calculated values is shown in figure 3, where the maximum χ^2-value represents the critical.

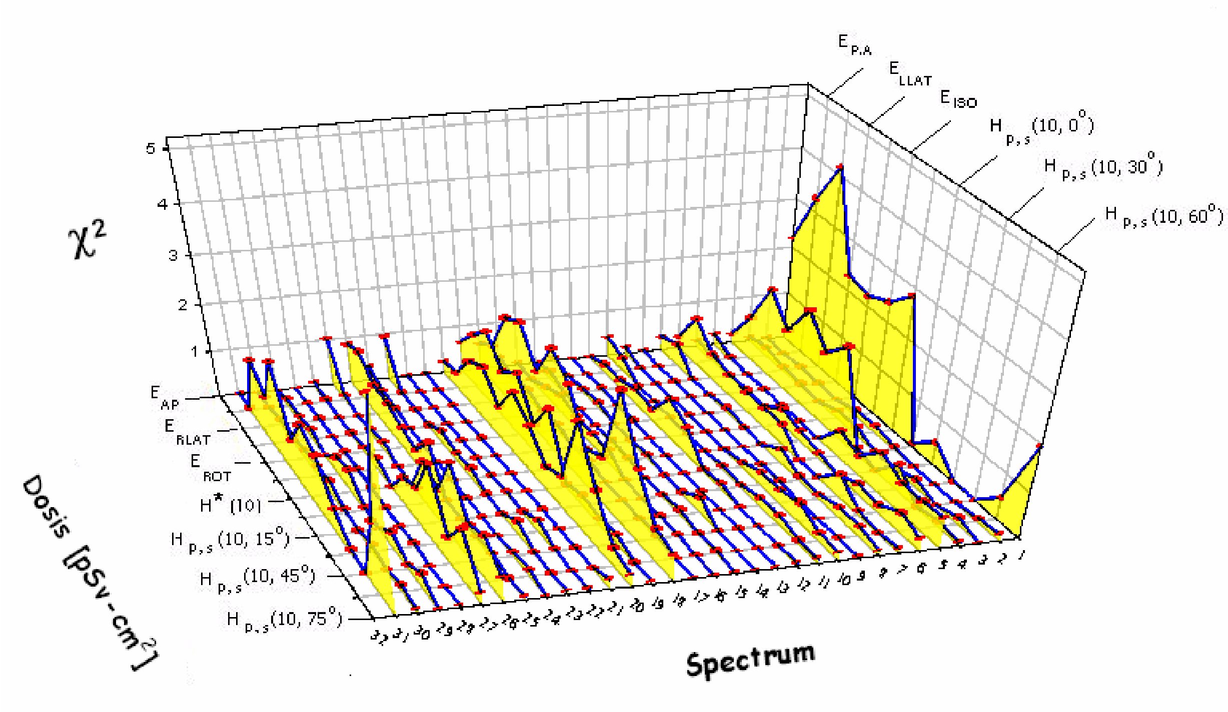

Figure 3.- χ^2-values for each spectrum

None of the χ^2 calculated values are close to the critical value, 5.226, therefore there is not significant difference between the calculated doses obtained with the ANN and the actual ones.

The ANN performance is similar to those reported by Braga and Dias[26] and Kardan *et al*.[2, 27]. They, used the ANN technology to unfold the neutron spectra, using as input the BSS count rates, with the spectra the dose was calculated. Here, the doses are directly obtained without the need of neutron spectrum information. In published results[2, 26, 27] ANN were applied to unfold few channels spectra, in this investigation few output data, 13 types of doses, are given away by the ANN. In both situations the BSS count rates are used as input in the ANN.

Nevertheless the ANN input information is the same and the output is different, the ANN technology has been utilized to overcome the same ill-conditioned problem.

CONCLUSIONS

Artificial neural networks technology has been successfully utilized to calculated 13 types of neutron doses directly from Bonner spheres spectrometer count rates.

A total of 187 neutron spectra were utilized, 17% were randomly selected to test the ANN and 83% of the spectra were used to train an ANN. The spectra were processed to obtain the BSS count rates and the doses, this information was respectively used as input and output during the training.

An 9-layer feed-forward ANN, 7:9:11:30:70:100:60:40:13, with back propagation and variable learning rate was trained and tested using MATLAB®.

The trained ANN was tested with 31 sets of BSS count rates. The performance was done by comparing the actual doses with those obtained with the ANN. With this comparison no significant differences were observed.

The use of ANN technology, using only the count rates measured with the Bonner sphere spectrometer, is an alternative procedure in neutron spectrometry. Once the network has been trained neutron doses are obtained without the need of neutron unfolding, overcoming the difficulties associated with the solution of such ill-conditioned problem.

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