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Determination of Fluence-to-Dose Conversion Coefficients by Means of Artificial Neural Networks

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Abstract: In this paper is presented an Artificial Neural Network (ANN) that has been designed, trained and validated to determinate the effective dose e, ambient dose equivalent h*(10) and personal dose equivalent hp(10,θ) fluence-to-dose conversion coefficients at different positions, having as only input data 7 count rates obtained with a Bonner Sphere Spectrometer (BSS) system. A set of 211 neutron spectra and the fluence-to-dose conversion coefficients published by the International Atomic Energy Agency (IAEA) were used to train and validate the ANN. This set was divided into 2 subsets, one of 181 elements to train the ANN and the remaining 30 to validate it. The ANN was trained using the BSS count rates as input data and the fluence-to-dose conversion coefficients as output data. The network was validated and tested with the set of 30 elements that weren't used during the training process. Good results were obtained proving that ANNs are a good choice for calculating the fluence-to-dose conversion coefficients having as only data the count rates obtained with a BSS.

Keywords: Fluence-to-dose; conversion coefficients; artificial neural networks; neutrons.

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1. Introduction

There are a significant number of neutrons generating facilities and industrial applications of radiation that have the potential for delivering occupational neutron exposures. Workers that are exposed to these radiations have to be well monitored and protected according to relevant national regulations [1-4].

The dosimetry of neutron radiation is one of the most complicated tasks in radiation protection [2,3,5], mainly because of several factors, related to either the definition of the operational quantities, or the practical problems in the instrument design and calibration [5].

The multisphere or Bonner sphere spectrometer (BSS) system is the multi-element system most used for radiation protection purposes, due to advantageous characteristics such as isotropic response, wide energy range (from thermal to GeV neutrons), large variety of active or passive thermal sensors allowing adapting the sensitivity to the specific workplace, good photon discrimination simple electronic circuits and simple signal management [3,5,6-13].

The BSS consists of a thermal detector such as ^{6}LiI(Eu), that is placed at the center of various high-density polyethylene spheres with different diameters functioning as moderating spheres [3,7-9,11,12,14-19].

Like many other neutron spectrometers, BSS do not provide a direct measurement of the neutron energy spectrum [19], it provide us count rates C. When an specific dosimetric quantity such as H*(10) needs to be determined, we just need to consider that is obtained simply with the product of the measurement of total neutron fluence ϕ and the fluence-to-dose conversion coefficient h*(10) as stated in the equation [1,20]:

$$H^*(10) = \phi \cdot h^*(10) \qquad (1)$$

The same formula can be applied to the specific doses of interest like the personal Hp and effective E with their respective fluence-to-dose conversion coefficients h_p and e [1]. To obtain these fluence-to-dose conversion coefficients the technology of Artificial Neural Networks (ANN) is proposed.

Essentially, an ANN consists of a "n" number of networks nodes connected by links, and the specific pattern of these connections defines the network´s topology [2]. ANNs has minimum 3 layers of neurons: input, hidden and output; these are connected by synaptic weights where the

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knowledge is stored. In the training process the ANN learns by updating the synaptic weights in such a manner that the error between the outputs of the networks and the actual response being model is minimized [3,6,9,14-16,21].

In general, the development of a good ANN model depends of the data being used, the network architecture, and the model size and complexity [21]. However there are no rules for choosing these parameters and often they are selected by the trial and error technique [4,21].

In this work is presented an ANN capable of determine the effective dose **e**, ambient dose equivalent **h*(10)** and personal dose equivalent $\mathbf{h_p(10,\theta)}$ fluence-to-dose conversion coefficients at 10 different positions using the 7 count rates obtained with a BSS system with 0.4 Ø $\times$ 0.4 cm^2 ^{6}LiI(Eu) scintillator and 0, 2, 3, 5, 8, 10 and 12 inches-diameter spheres.

2. Materials and Methods

A set of 211 neutron spectra published by the IAEA [1] were used to train and validate the ANN. This data is given per unit lethargy in 60 energy groups ranging from 1 MeV to 398 MeV.

For the input layer the BSS count rates were used, and these were calculated by multiplying each neutron spectrum of the IAEA by the response matrix of the UTA4. The calculations were made for a set of 7 Bonner spheres of diameters 0” (bare), 2”, 3”, 5”, 8”, 10” and 12”.

For the output layer of the ANN the fluence-to-dose conversion coefficients had to be calculated with the data given by the IAEA and the neutron spectra. They had to be multiplied and then summed.

The fluence-to-dose conversion coefficients published by the IAEA that we used are 10 in total, e_{AP}, e_{PA}, e_{RLAT}, e_{ROT}, e_{ISO}, for the effective dose; h*(10) for the ambient dose equivalent; and $h_p(10, \theta)$ for the personal dose equivalent, were θ=0°, 45°, 60°, 75°. Having this information calculated, the set was divided into 181 neutron spectrums (approximately 85%) for the training of the network and the remaining 30 neutron spectrums (approximately 15%) for the validation. The data selected for the validation of the net was taken randomly.

The ANN was trained and validated using the MATLAB® neural network toolbox and the **trainscg** algorithm. For the designing of the ANN, the method of “trial and error” was used because there is no rule that can tell us exactly how to determine the network architecture. The only information that we knew about the design of network is that there would be 7 input neurons and 10 output neurons.

The amount of hidden layers and the number of neurons in each hidden layer were modified in each trial. The modifications of these parameters were made until an appropriate architecture was found for our particular problem.

3. Results

After several trials, the ANN with the best results has feedforward architecture of 7:8:9:10. This indicates that the net has 2 hidden layers of 8 and 9 neurons each, an input layer of 7 neurons (corresponding to the BSS counts) and an output layer of 10 neurons (corresponding to the fluence-to-dose conversion coefficients).

To end the network training 1E(5) epochs were used. It was trained in a time of 0:37:29. With this amount of time and epochs the network reached a mean square error (mse) of 1.86E(-8), this mse indicates us the performance of the net.

The ANN was validated with 30 different sets of data that weren’t used during the training phase; here are shown the best and worst cases. The quality of the results was defined by comparing the ANN calculated fluence-to-dose conversion coefficients with the actual fluence-to-dose conversion coefficients published by the IAEA compendium; this comparison was carried out firstly through the mse and secondly through the correlation values.

For the best case the data have a correlation coefficient R^2=0.99982 and a mse=3.69E(-5). The regression for this case is shown in figure 1 and in figure 2 is shown the comparison between the fluence-to-dose conversion coefficients obtained by the ANN (ANN) and the actual fluence-to-dose conversion coefficients published by the IAEA compendium (IAEA).

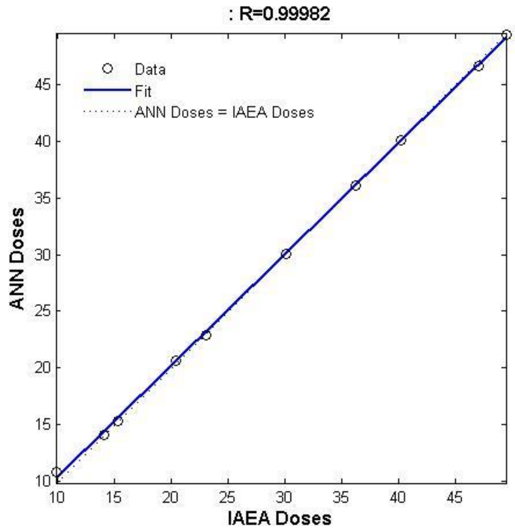

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Figure 1. Best case regression

In figure 2 the fluence-to-dose conversion coefficients are: 1=e_{AP}, 2=e_{PA}, 3=e_{RLAT}, 4=e_{ROT}, 5=e_{ISO}, 6=h*(10), 7=$h_p(10,0°)$, 8=$h_p(10,45°)$, 9=$h_p(10,60°)$, 10=$h_p(10,75°)$.

In figure 2 can be noticed that there is almost a perfect match between the fluence-to-dose conversion coefficients. For the worst case the data have a correlation coefficient R^2=0.99871 and a mse=1.40E(-3).

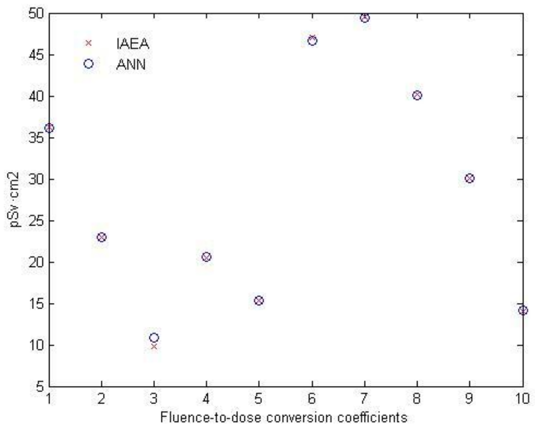

Figure 2. Actual and ANN fluence-to-dose conversion coefficients comparison

For this case the correlation between the ANN-calculated doses and the IAEA doses are shown in figures 3 and 4.

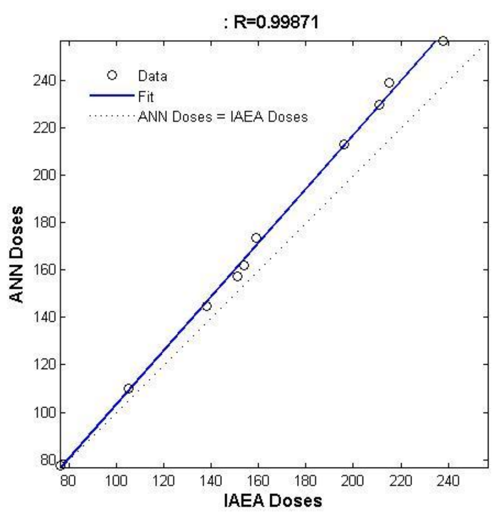

Figure 3. Worst case regression

Here can be noticed that the comparison between the fluence-to-dose conversion coefficients obtained by the ANN (ANN) and the actual fluence-to-dose conversion coefficients published by the IAEA compendium (IAEA) has a good agreement.

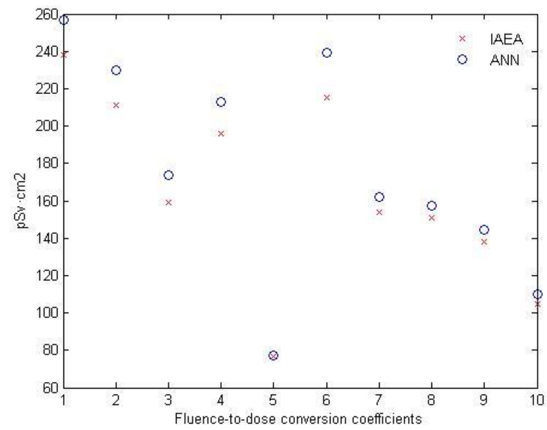

Figure 4. Actual and ANN fluence-to-dose conversion coefficients comparison

In this figure we can notice that the fluence-to-dose conversion coefficients now have a noticeable difference, however it is important to calculate the actual to the ANN-calculated fluence-to-dose conversion coefficients ratios to give a valid interpretation of the results.

The actual to the ANN-calculated fluence-to-dose conversion coefficients ratios for the best and worst cases are shown in Table 1.

Table 1. Actual to ANN-calculated fluence-to-dose conversion coefficients ratios

Fluence-to-dose coversion coefficients	Best case	Worst case
e_{AP}	0.99797805	1.07831272
e_{PA}	0.99772671	1.08911179
e_{RLAT}	1.10592281	1.09247322
e_{ROT}	1.00993354	1.08578467
e_{ISO}	1.00450167	1.01096544
h*(10)	0.99039862	1.11165399
$h_p(10,0°)$	0.99871867	1.05046403
$h_p(10,45°)$	0.99783834	1.04191991
$h_p(10,60°)$	0.99940061	1.04804573
$h_p(10,75°)$	1.00898078	1.04912844

4. Conclusions

The ANN design has a very good performance calculating the fluence-to-dose conversion coefficients desired, proving that ANNs and the **trainscg** algorithm are a good choice for solving this kind of problem.

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One important advantage of this method is that the ANN is trained only one time, and after that is ready to calculate the fluence-to-dose conversion coefficients.

This ANN is capable of calculate 10 fluence-to-dose conversion coefficients using the count rates measured with a BSS. To evaluate the ANN performance two criteria were used, one was the correlation between the fluence-to-dose conversion coefficients and the actual fluence-to-dose conversion coefficients; the second was the mean square error.

To test the ANN 30 sets of data were used, the best performance has a correlation coefficient of 0.99982, while the worst has a correlation coefficient of 0.99871.

We have to keep in mind that when we are designing an ANN we will always have to face the problem that there are no rules for choosing the architecture of the net and this will cause us to spent much time selecting the right net. This problem will persist until a method for choosing the architecture is founded.

In the best case the actual and the ANN-calculated fluence-to-dose conversion coefficients were practically the same, but in the worst case noticeable differences between the actual and the ANN-calculated fluence-to-dose conversion coefficients were appreciated being the largest of only 11%.

Acknowledgements

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