Neural Networks for Predicting Neutron Ambient Dose Equivalent Measured by Means of Bonner Spheres

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Abstract-- **A Neural Network structure has been applied for predicting neutron Ambient Dose Equivalent measured by means of a Bonner Sphere Spectrometer (BSS) set. The present work used the SNNS ("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. A set of 27 continuous neutron spectra was used for training and validating the neural network. Excellent results were obtained, indicating that the Neural Network can be considered an interesting alternative for estimating neutron Ambient Dose Equivalent measured by means of Bonner Spheres.**

I. 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. The present work adopts an approach to solve these equations by applying a Neural Network structure. The SNNS ("Stuttgart Neural Network Simulator") was used as interface for designing, training and validation of a MultiLayer Perceptron network. 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.

A previous paper describes the use of this technique for unfolding neutron spectra measured by means of Bonner Spheres [5]. The present work is focused in determining the Ambient Neutron Dose Equivalent.

II. Methodology

A. *Deconvolution Method*

When the detector responses are known for discrete energy groups the set of Fredholm equations may be rewritten as a sum of products between the neutron fluence rate , the detector response and the energy width of the group.

$$\boldsymbol{C_i = \sum_{j=1}^{n} \phi(E_j) \Delta E_j \, R_{ij}} \tag{1}$$

where:
C_i is the reaction rate from the *i-th* Bonner sphere;
ϕ_j is the fluence rate of neutrons in the *j-th* energy interval;
ΔE_j is the *j-th* energy interval;
R_{ij} is the Bonner Sphere response function corresponding to the *j-th* 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]. The Network output corresponds to the Ambient Neutron Dose Equivalent.

B. *Ambient Neutron Dose Equivalent: H*(10)*

The Bonner Sphere Spectrometer can be used for estimating neutron dose. For this purpose, conversion factors are necessary because there is no fundamental relationship between neutron detection probability at the center of the sphere and the neutron dose in the biological tissue. The present work applies the Ambient Neutron Dose Equivalent concept, which is part of the operational unit system introduced by the ICRU for radiation monitoring [10]. In this system the Ambient Dose Equivalent is suitable for using with strongly penetrating radiations such as neutrons.

This quantity is given by:

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$$H^*(10) = \sum_{i=1}^{n} \phi(E_i)\, h(E_i)\, \Delta E_i \qquad (2)$$

where:

$\phi(E)$ = neutron fluence as a function of energy;

$h(E)$ = neutron fluence to dose conversion factor as a function of energy;

ΔE = energy interval.

The behavior of the Ambient Equivalent Dose conversion factor h(E) with neutron energy is shown in figure 1. Some numerical values are given in table 1 for monoenergetic neutrons incident on the ICRU sphere [10].

Table 1 Ambient Equivalent Dose conversion factor h(E) with neutron energy.

Energy (MeV)	h(E) (10^{-12} Sv.cm^{-2})	Energy (MeV)	h(E) (10^{-12} Sv.cm^{-2})
1.00E-09	6.6	3.00E-01	233
1.00E-08	9.0	5.00E-01	322
2.53E-08	10.6	7.00E-01	375
1.00E-07	12.9	9.00E-01	400
2.00E-07	13.5	1.00E+00	416
5.00E-07	13.6	1.20E+00	425
1.00E-06	13.3	2.00E+00	420
2.00E-06	12.9	3.00E+00	412
5.00E-06	12.0	4.00E+00	408
1.00E-05	11.3	5.00E+00	405
2.00E-05	10.6	6.00E+00	400
5.00E-05	9.9	7.00E+00	405
1.00E-04	9.4	8.00E+00	409
2.00E-04	8.9	9.00E+00	420
5.00E-04	8.3	1.00E+01	440
1.00E-03	7.9	1.20E+01	480
2.00E-03	7.7	1.40E+01	520
5.00E-03	8.0	1.50E+01	540
1.00E-02	10.5	1.60E+01	555
2.00E-02	16.6	1.80E+01	570
3.00E-02	23.7	2.00E+01	600
5.00E-02	41.1	3.00E+01	515
7.00E-02	60	5.00E+01	400
1.00E-01	88	7.50E+01	330
1.50E-01	132	1.00E+02	285
2.00E-01	170	1.25E+02	260

This factor remains between 6.6 and 13.6 pSv.cm^2 in the 10^{-9} to 10^{-3} MeV range. Above this energy the value of h(E) raises monotonically reaching a maximum of 600 pSv.cm^2 at 20 MeV and drops at higher energies.

The purpose of the present work was to develop a neural network which yields the neutron Ambient Equivalent Dose from the Bonner Sphere set responses without knowledge of the neutron energy spectrum.

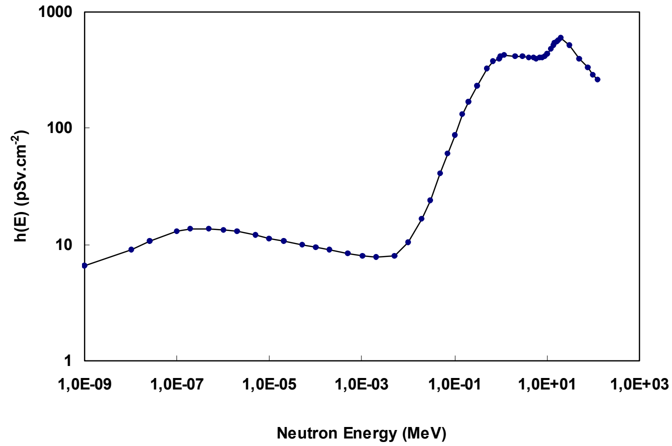

Fig. 1 Behavior of the Ambient Equivalent Dose conversion factor h(E) with neutron energy.

C. 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 ν_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 [ν_k, w_{kj}, θ_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 the 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 [6-8]. This standard network structure with several layers is called MultiLayer Perceptron (MLP) (figure 2).

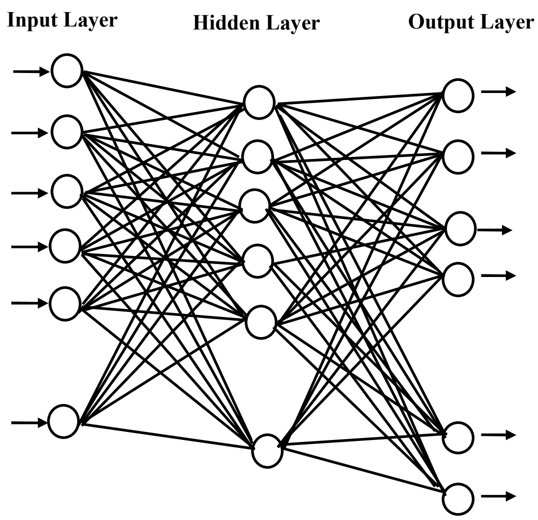

Fig. 2 Multilayer Perceptron network architecture.

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

The Bonner Sphere set chosen is one Calibrated at the National Physical Laboratory, United Kingdom, which uses gold activation foils as thermal neutron detectors [9]. The neutron energy covered by the response functions goes from 0.0001 eV to 10 MeV. A set of continuous neutron spectra was investigated.

D. Training and test files

The network consisted of three neuron arrays: input, hidden and the output array (see figure 2). The input array was built of 10 neurons and corresponds to each reaction rate of the Bonner Sphere. The output array consisted of a single neuron and corresponds to the calculated Neutron Ambient Dose Equivalent. A sigmoid activation function was used normalised in the interval from –2 to 2. Several neutron spectra were chosen for training: Maxwellian, Watt, 1/E and combination of these. All spectra were normalized to unity neutron fluence.

Interpolations were performed in order to obtain the conversion factors for the neutron energies corresponding to the Bonner Sphere response table. The reaction rates corresponding to each of the 27 selected neutron spectra were determined numerically. From this data a neural network was built having input given by reaction rates from the Bonner Spheres and a single output corresponding to the Neutron Ambient Equivalent Dose. The training was performed with 21 neutron spectrum sets and testing was performed with the remaining 6 sets.

The training was repeated until the Standard Error was 0.0005 which was achieved after 10^5 iterations. The training rate was 0.1 and the momentum constant parameter was 0.08. The final network consisted of 10:2:1 neurons in the input, hidden and output layers respectively.

II. Results and Discussion

Table 2 shows the results obtained with the six SANDLIB testing neutron spectra. The network was able to predict the results for all the 6 unknown neutron Ambient Equivalent Dose with an accuracy between 1 to 6 %. Spectra numbered 25, 30 and 42 correspond to fast neutrons and spectra 3, 34 and 59 have a higher component of thermal neutrons. This behavior explains the higher values of neutron Ambient Equivalent Dose in the former spectra as compared to the latter cases.

Table 2 Comparison between Ambient Equivalent Dose values expected for six testing neutron spectra from SANDLIB with those obtained by Neural Network.

SANDLIB Neutron Spectrum Number	Expected Ambient Dose Equivalent H*(10) (10^{-12} Sv)	Obtained Ambient Dose Equivalent H*(10) (10^{-12} Sv)
6	78.0	78.7
25	220.6	215.4
30	329.7	336.4
34	147.0	142.9
42	385.4	401.9
59	167.8	158.9

These results indicate that, once trained, the neuron network can supply a quick result for the Neutron Ambient Equivalent Dose with good accuracy, based on Bonner Sphere measurements.

III. Acknowledgements

The authors are grateful to Dr. David J. Thomas from NPL (UK) for supplying the NPL Bonner Sphere response functions for gold foils and to Dr. Homero E. B. Perez from IPEN for the valuable discussions.

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