Neutron spectrometry and dosimetry by means of bonner spheres system and artificial neural networks applying robust design of artificial neural networks

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Abstract

An Artificial Neural Network has been designed, trained and tested to unfold neutron spectra and simultaneously to calculate equivalent doses. A set of 187 neutron spectra compiled by the International Atomic Energy Agency and 13 equivalent doses were used in the artificial neural network designed, trained and tested. In order to design the neural network was used the robust design of artificial neural networks methodology, which assures that the quality of the neural networks takes into account from the design stage. Unless previous works, here, for first time a group of neural networks were designed and trained to unfold 187 neutron spectra and at the same time to calculate 13 equivalent doses, starting from the count rates coming from the Bonner spheres system by using a systematic and experimental strategy.

Keywords: Neutron spectrometry, ANN, RDANN, Taguchi method, Optimization techniques.

1. Introduction

The term radiation spectrometry can be used to describe measurement of the intensity of a radiation field with respect to energy, frequency or momentum. The distribution of the intensity with one of these parameters is commonly referred to as the "spectrum". A second quantity is the variation of the intensity of these radiations as a function of angle of incidence on a body situated in the radiation field referred as "dose". The neutron spectra and the dose are of great importance in radiation protection physics. This work is concerned primarily with measurements of the neutron spectrum with the Bonner sphere spectrometer (BSS) system and the simultaneous dose calculus for radiation protection porpoises. [1]-[8]

Determination of neutron dose received by those exposed to workplaces or accidents in nuclear facilities, generally requires knowledge of the neutron energy spectrum incident on the body. Spectral information must generally be obtained from passive detectors which respond to different ranges of neutron energies such as the multispheres Bonner system. BSS system has been used to unfold the neutron spectra chiefly because it has an almost isotropic response, can cover the energy range from thermal to GeV neutrons, and is easy to operate. The BSS consists of

a thermal neutron sensor such as LiI(Eu), which is placed at the centre of a number of moderating spheres made of polyethylene of different diameter. The combination of a thermal neutron detector plus moderating sphere has sensitivity to neutrons over a broad energy range. However, the sensitivity of each sphere peaks at a particular neutron energy depending of the sphere diameter. From the measured readings of a set of spheres, information can be derived about the spectrum of the neutron field in which measurements were made. The derivation of the spectral information is not simple; the unknown neutron spectrum is not given directly as a result of the measurements. If a sphere d has a response function $R_d(E)$, and is exposed in a neutron field with spectral fluence $\Phi_E(E)$, the sphere reading M_d is obtained by folding $R_d(E)$ with $\Phi_E(E)$, i.e.

$$M_d = \int R_d(E)\Phi_E(E)dE \tag{1}$$

This folding process takes place in the sphere itself during the measurement. Although the real $\Phi E(E)$ and $R_d(E)$ are continuous functions of neutron energy, they cannot be described by analytical functions, and, as a consequence, a discretised numerical form is used, showed in equation 2. Where C_j is the jth detector's count rate, $R_{i,j}$ is the jth detector response to neutrons at the ith energy interval and N is the the number of spheres used.

$$C_j = \sum_{i=1}^{N} R_{i,j}\Phi_j \tag{2}$$

Once the neutron spectrum ($\Phi(E)$) has been obtained, the dose Δ can be calculated using the fluence-to-dose conversion coefficients ($\delta\Phi(E)$) as shown in equation 3.

$$\Delta = \int_{E_{\min}}^{E_{\max}} \delta_{\Phi}(E)\Phi_E(E)dE \tag{3}$$

Neutron spectrometry and dosimetry are not trivial problems; both are ill-conditioned systems with an infinite number of solutions and have difficulties that have motivated researches to propose new and complementary approaches. Artificial Neural networks (ANNs) is the most popular approach among nuclear spectrometry and dosimetry researchers. [9]-[12] Some of them have proposed the use of ANNs to unfold the neutron spectra from BSS [13]-[17]; and just one author has proposed the use of ANN to calculate equivalent doses [18] considering each problem separately; however, they do not use a systematical methodology to design the neural network.

The trial-and-error technique is the usual way to get a better combination of network architecture and parameters. This method cannot identify interactions between the parameters and do not use systematic methodologies for the identification of the "best" values, consuming much time and does not systematically target a near optimal solution, which may lead to a poor overall neural network design. An easier and more efficient way to overcome this disadvantage is the Robust Design of Artificial Neural Networks (RDANN) methodology which has become in a new approach used for solving the optimization problems in neutron spectrometry and dosimetry fields. In this study, for first time, a systematic, methodological and experimental approach known as RDANN is used to obtain the optimum design of an ANN to solve the unfolding neutron spectra problem and simultaneously to calculate 13 different equivalent doses for each neutron spectra [19]-[23].

2. Materials and methods

RDANN methodology is used to unfold neutron spectra and simultaneously to calculate 13 equivalent doses. The steps followed to obtain the optimum design of the ANN in consideration can be summarized in four main stages: Planning, Experimentation, Analysis and confirmation. [23]-[28] At planning stage were established the objective function and the design and noise variables. At Experimentation stage was selected an appropriate crossed OA with the configuration $L_9(3^4)$, $L_4(3^2)$. At analysis stage was used the JMP statistical software to calculate the optimum ANN parameters and finally at confirmation stage was determined the optimum ANN topology and carried out chi square and correlation statistical tests to validate the calculated data.

3. Results

In the design process of the ANN a 187 neutron spectra data set compiled by IAEA [43] and 13 different equivalent doses per spectra were used. RDANN methodology was utilized to design the ANN.

3.1. Planning Stage

After select the objective function the design variables were established each at three levels as follows: A = 13, 26, 39; B = 0, 26, 39; C = 0.1, 0.3, 0.5; and D = 0.001, 0.1, 0.3, where A is the number of neurons in the first hidden layer, B is the number of neurons in the second hidden layer, C is the momentum, D is the learning rate. Similarly the noise variables were selected each at two levels as follows: V = 60% / 40%, 80% / 20%; and W = Training1/Test1, Training2/Test2, V is the size of training set versus size of testing set, W is the selection of training and testing sets. Since in this problem the objective function is the performance or mse output of the ANN trained by means of backpropagation learning algorithm, the mse was established in a value equal to 1e-4 and the network was trained with the trainscg training algorithm.

3.2. Experimentation Stage

The trials performed in the experimentation stage are shown in table 1.

Table 1. ANN measured responses with a crossed OA with L_9, L_4 configuration

Exp No.	Response 1	Response 2	Response 3	Response 4	Average	Signal-Noise R
1	2.1E-04	2.2E-04	2.3E-04	1.7E-04	2.1E-04	-1.8E+01
2	1.8E-04	3.7E-04	2.7E-04	1.9E-04	2.5E-04	-9.5E+00
3	1.6E-04	3.1E-04	2.5E-04	2.2E-04	2.4E-04	-1.1E+01
4	2.3E-04	2.5E-04	2.4E-04	2.4E-04	2.4E-04	-3.0E+01
5	2.4E-04	3.2E-04	4.1E-04	2.6E-04	3.1E-04	-1.3E+01
6	4.7E-04	6.5E-04	2.4E-04	2.1E-04	3.9E-04	-6.3E+00
7	1.6E-04	4.0E-04	2.2E-04	2.0E-04	2.5E-04	-7.7E+00
8	2.0E-04	1.9E-04	3.4E-04	1.9E-04	2.3E-04	-1.1E+01
9	3.6E-04	2.7E-04	2.7E-04	2.8E-04	3.0E-04	-1.6E+01

3.3. Analysis and conirmation stage

With the Signal-to-Noise relation calculated at experimental stage, and using the JMP® statistical software, the parameters selected with the best levels are as follows: selection one: A = 13, B = 0, C = 0.1, D = 0.001; selection two: A = 26, B = 39, C =0.1, D = 0.1. Then, confirmation experiments were carried out in order to select the parameters with the optimal levels, being selection two the best choice. Once the best ANN topology was determined with the following architectural and learning parameters: 7:26:39:44 whit a momentum = 0.1 and a learning rate = 0.1, mse = 1e-4 and a trainscg learning function, a final training and testing was carried out in order to solve the neutron spectra and equivalent dose calculus. 80% of the whole data set was used to train the ANN and the rest for the testing stage. In the final ANN validation was performed the correlation and Chi square statistical tests to the spectra used in the testing stage (37 from 187) to evaluate and validate the data obtained.

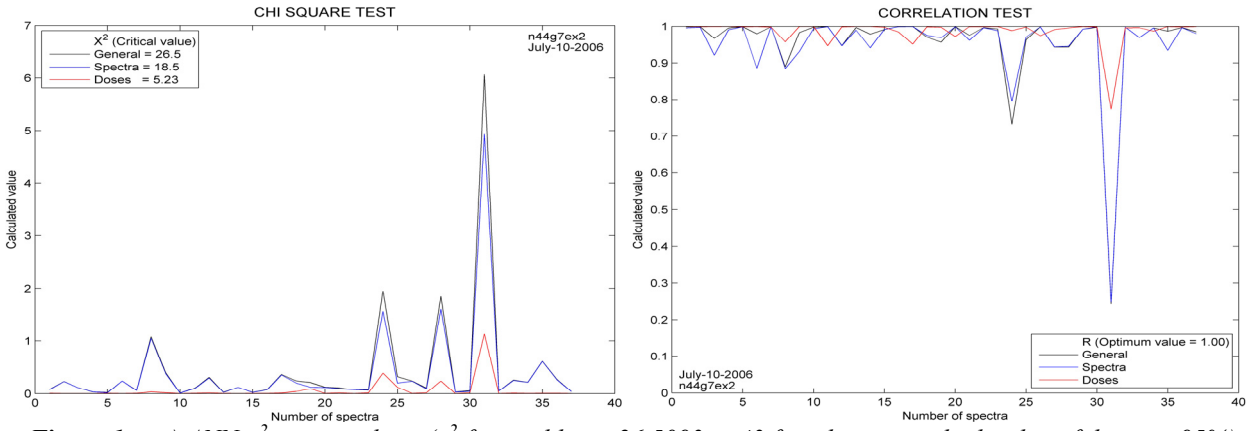

Figure 1. ***a)*** *ANN χ^2 statistical test (χ^2 from tables = 26.5093 to 43 free degrees and a level confidence = 95%)*
b) *ANN Correlation statistical test (Optimum value = 1.00)*

From figure 1 a), can be seen that all neutron spectra pass the Chi square test, which demonstrates that statistically there is not difference among the neutron spectra reconstructed by the designed ANN and the target neutron spectra. Similarly in figure 1 b) from the correlation test applied to 37 neutron spectra, can be seen that the whole data set is near of the optimum value equal to one, which demonstrate that the values of the mse ANN output obtained in the OA are of high quality.

Figures 2 and 4 shown the best and worst neutron spectra unfolded at final testing stage of the designed ANN. Whereas figures 3 and 5 shoun the best and worst doses calculated. The corresponding images include information such as: the statistical tests and statistical margin to each spectrum, the ANN's performance, the training time, the date when the ANN was trained and tested and the final ANN architecture.

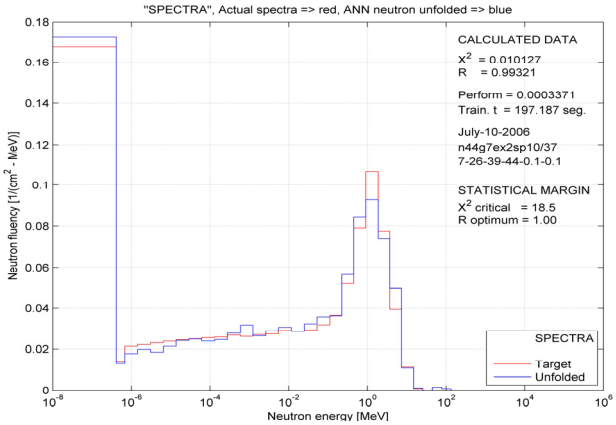

Figure 2. *Spectrum 10/37 (187 spectra and 13 equivalent doses). The best case*

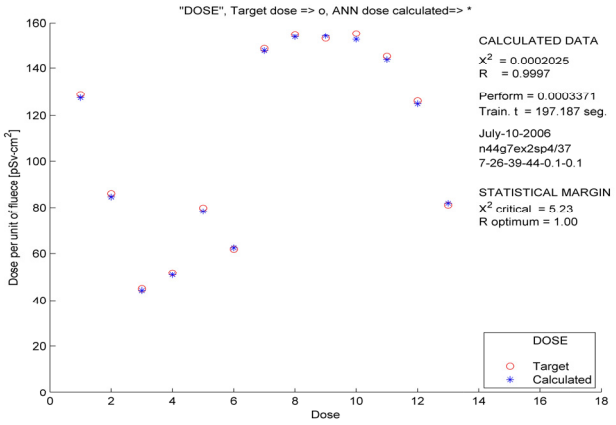

Figure 3. *Dose 4/37 (187 spectra and 13 equivalent doses). The best case*

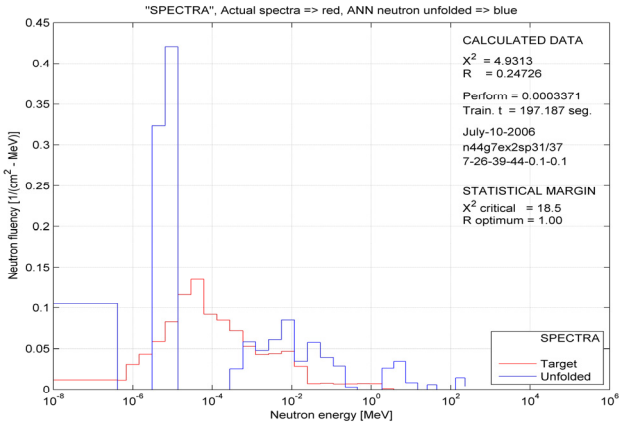

Figure 4. *Spectrum 31/37 (187 spectra and 13 equivalent doses). The worst case*

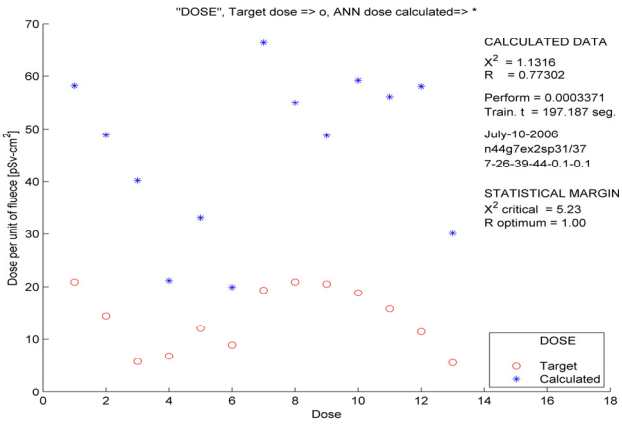

Figure 5. *Dose 31/37 (187 spectra and 13 equivalent doses). The worst case*

4. Conclusions

In this paper, a systematic and experimental strategy named RDANN has been used for first time in neutron spectrometry and dosimetry, to find the "best" ANN design parameters. The ANN topology obtained with the RDANN is as follows: 7:26:39:44 whit a momentum = 0.1 and a learning rate = 0.1, mse = 1e-4 and a trainscg learning function.

Unlike other works, with the use of RDANN methodology the time spent in determine the optimum ANN architecture, is reduced significantly when it's compared with the trial-and-error approach, which take from several days to several months to prove different ANN architectures and parameters which may lead to a poor overall ANN design. With RDANN it takes from minutes to a couple of hours to determine the best and robust ANN architectural and learning parameters allowing to researches more time to solve the problem in question.

The proposed experimental approach is a useful alternative for the robust design of ANN. It offers a convenient way of simultaneously considering design noise variables, and incorporating the concept of robustness in the ANNs design process.

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