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TECHNICAL REPORT

Unfolding neutron spectra from simulated response of thermoluminescence dosimeters inside a polyethylene sphere using GRNN neural network

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Abstract: Neutron spectrometry using a single-sphere containing dosimeters has been developed recently, as an effective replacement for Bonner sphere spectrometry. The aim of this study is unfolding the neutron energy spectra using GRNN artificial neural network, from the response of thermoluminescence dosimeters, TLDs, located inside a polyethylene sphere. The spectrometer was simulated using MCNP5. TLD-600 and TLD-700 dosimeters were simulated at different positions in all directions. Then the GRNN was used for neutron spectra prediction, using the TLDs' readings. Comparison of spectra predicted by the network with the real spectra, show that the single-sphere dosimeter is an effective instrument in unfolding neutron spectra.

Keywords: Spectrometers, Neutron detectors (cold, thermal, fast neutrons), Detector modelling and simulations I (interaction of radiation with matter, interaction of photons with matter, interaction of hadrons with matter, etc)

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2017 JINST 12 T07007

Contents

1 Introduction

Multi-sphere systems or Bonner sphere spectrometers, which have been widely used in neutron spectrometry, were introduced by Bramblett and Bonner in 1960 [1]. This spectrometer consists of moderating polyethylene spheres with different dimensions. The readings of thermal neutron detector located at the center of spheres are used for unfolding the neutron energy spectra up to 20 Mev. Adding high atomic number caps like lead the upper limit of energy detection can be increased to about several Gev [2].

Spectrometry using Bonner spheres is very complicated, it needs a long time period, and the spheres are heavy [3, 4]. To solve these problems, Lis et al. designed a single sphere spectrometer containing several TLDs (TLD-600) at X, Y, and Z directions [5].

They investigated the applicability of this device in unfolding neutron spectra using the MAXED, GRAVEL and FRUIT unfolding codes. FRUIT [3], models the neutron spectrum as the superposition of elementary spectra described by a set of physical parameters; GRAVEL [6, 7], is based on a non-linear least squares method; and MAXED [8], uses the principle of maximum entropy.

Different methods such as Monte Carlo [9], regularization [10], parameterization, iterative [11], artificial neural networks (ANN) [12–14], and maximum entropy [15], have been used so far for unfolding neutron spectra.

Qing-Jun et al., showed that the results of unfolding neutron spectra using ANN, are comparable with those obtained by the Maximum entropy method,[1] which has a clear mathematical and physical

[1]MEM.

meaning. They showed that the ANN has several advantages over the MEM, such as better stability and accuracy, no need to iteration process, and higher speed [16].

There are two very different of types of neural networks: Back Propagation (BPNN) [17, 18] and Probabilistic (PNN) neural networks [19–21] & [22]. BPNN has been shown effective in unfolding neutron spectra [12, 13, 23–25] & [26]. However, proper determination of the network architecture is difficult. More over enough neutron spectra as the data to train the networks which is not always available for BPNN [27].

Generalized Regression Neural Network (GRNN), which falls into the category of PNN [19, 21], is much faster to train Comparing to BPNN [21, 22, 28, 29] & [30].

Bahadorzadeh et al. investigated the application of this single sphere light weight spectrometer in unfolding neutron energy distribution using feedforward artificial neural networks [31].

The purpose of this study is to investigate the ability Generalized Regression Neural Network[2] GRNN artificial neural network in unfolding the neutron spectra using from the response matrix and reading of TLDs inside the single-sphere spectrometer.

2 Materials and method

2.1 Calculation of the response matrix for each TLD

A polyethylene sphere with 6 inch radius, and density of 0.95 g/cm^3 including TLD-600, and TLD-700 pairs in radial distances of 0″, 1″, 2″, 3.5″, 4.5″, 5″, 6″, −6″, −5″, −4.5″, −3.5″, −2″, −1″ was simulated using MCNP5 Monte Carlo code.

The pair of TLDs, TLD-600 and TLD-700 are used for neutron dosimetry in mixed neutron and gamma fields. TLD-600 chips are enriched of ^{6}Li, and thus sensitive to thermal neutrons. As the photon interactions depend on the atomic number, the sensitivity of TLD-600 is approximately the same as that of TLD-700.

In this study the LiF, TLD pairs were considered as cubical cells with dimensions of 0.32 × 0.32 × 0.09 cm^3, and the density of 2.52 g/cm^3. A disk source of neutron with 6 inch radius was simulated at the distance of 100 cm from the center of the polyethylene sphere. The source was defined as mono-directional beam emitting the neutrons towards the sphere parallel to X axis. Figure 1, shows the simulation geometry obtained by Visual Editor graphical user interface. As shown in the figure, three removable rods which were parallel to X, Y, and Z axes, were simulated in the center of the sphere to accommodate the TLD chips. In real experimental situation, after exposing the spectrometer to neutrons, the rods can be pulled out and the TLDs will be withdrawn, and read out.

Simulations were performed in 1E-08 to 10 Mev with 50 energy intervals with equal logarithmic distances. The values of neutron flux received by TLDs were calculated using Tally type F4 in cells defined as TLD-600 chips. Unlike real experimental measurements, MCNP simulations can discriminate neutron, and photon flux separately. In the simulations performed in this study, the neutron flux is scored only in TLD-600 chips, while TLD-700 chips were only defined to make the simulation geometry and materials similar to the real experimental situations.

[2]GRNN.

2017 JINST 12 T07007

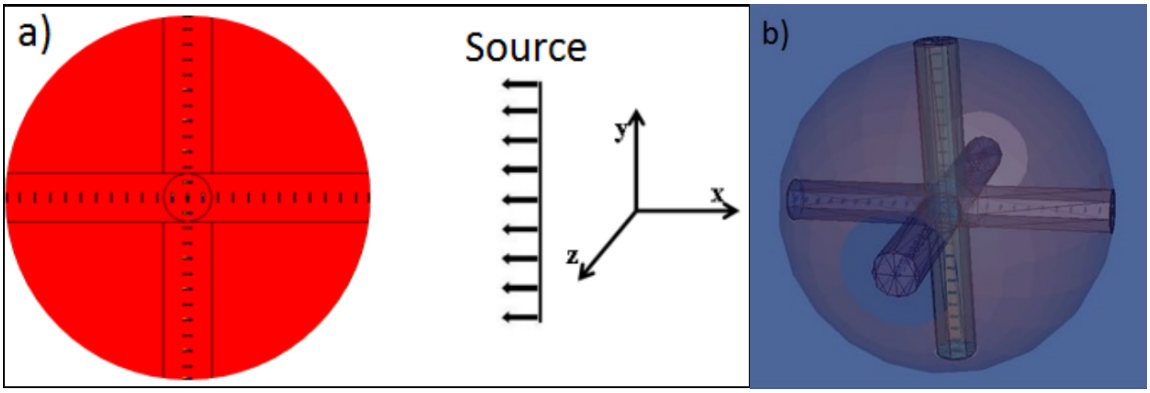

Figure 1. a) 2D simulation geometry, and b) 3D simulation dosimetry of single-sphere spectrometer.

The response matrix of TLD-600 chips was obtained using the reading of TLDs, according to equation (2.1):

$$F_{[1\times1]} = \emptyset_{[1\times n]} \times R_{[n\times1]} \,. \tag{2.1}$$

In which $F_{[1\times1]}$ is the reading of each TLD, $\emptyset_{[1\times n]}$ is the neutron flux, n is the number of energy intervals, and $R_{[n\times1]}$ is the response matrix of each TLD for n energy interval.

2.2 Unfolding neutron spectra

The GRNN artificial neural network in MATLAB was used for unfolding neutron spectra. 251 spectra, given by the IAEA Tec-doc 403,[3] each containing 57 energy intervals, were used in this study.

2.2.1 Kernel spread constant selection

Leave-one-out cross-validation[4] technique was used to find the optimum network. This technique uses a single observation from the original sample as the validation data, while other observations are used as the training data.

Therefore the network was trained with 250 spectra, and one spectrum was predicted, then the mean Sum Square Error[5] value of the predicted spectrum and the real spectrum was calculated. The spread constant values of the network were changed between 0.01 and 2 with interval of 0.01, and the network was trained for all of these values to find out the optimum kernel spread value. Figure 2 shows the schematic of this network.

Finally the mean SSE of different spectra were plotted versus the spread constant values, and the spread constant with minimum value of mean SSE was used as the optimum spread constant.

2.2.2 Data selection for training and testing of GRNN

In the next step the network was trained with the optimum kernel spread value, and 126 spectra of the IAEA Tec-doc 403. Other 125 spectra were used for testing the performance of the GRNN. Finally the mean SSE of the neutron spectra predicted by the GRNN, with the real spectra were obtained. Figure 3, shows the schematic of this network.

[3]Technical report series #403, supplement to Technical report series #318.
[4]LOOCV.
[5]SSE.

2017 JINST 12 T07007

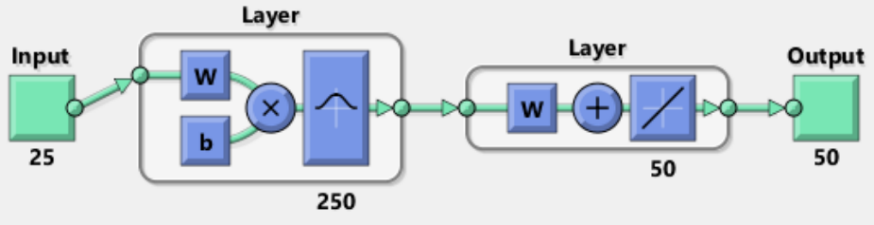

Figure 2. Schematic of GRNN network used for finding the optimum kernel spread constant.

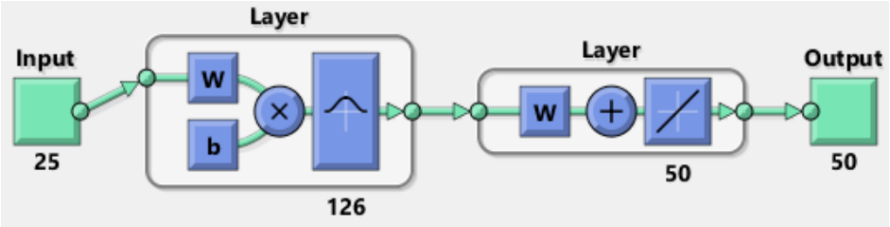

Figure 3. The GRNN network with optimum spread value used for predicting the unknown spectra.

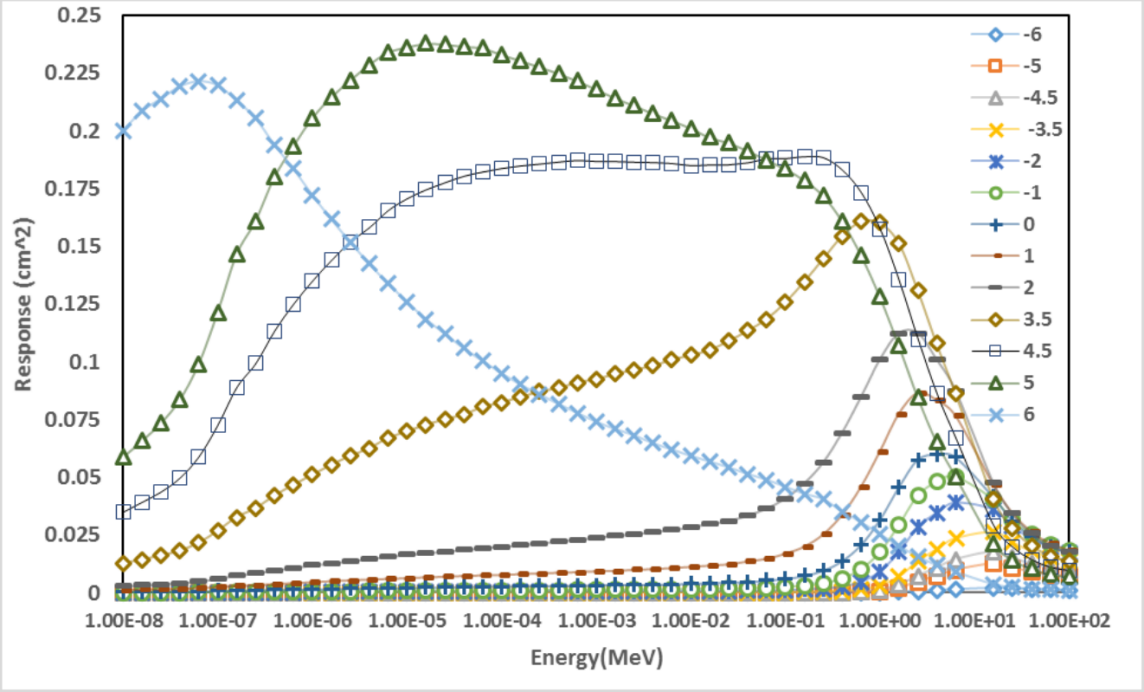

Figure 4. The response function of the TLD-600 chips located on X axis at different radial distances.

3 Results

3.1 The response functions

The response functions $R_{[n\times1]}$ of TLD-600 chips located at different distances from the center of the sphere on X, and Y axes are shown in figures 4, and 5. According to figure 4, by moving from 6 cm to −6 cm, the TLDs see more polyethylene and their responses decrease.

2017 JINST 12 T07007

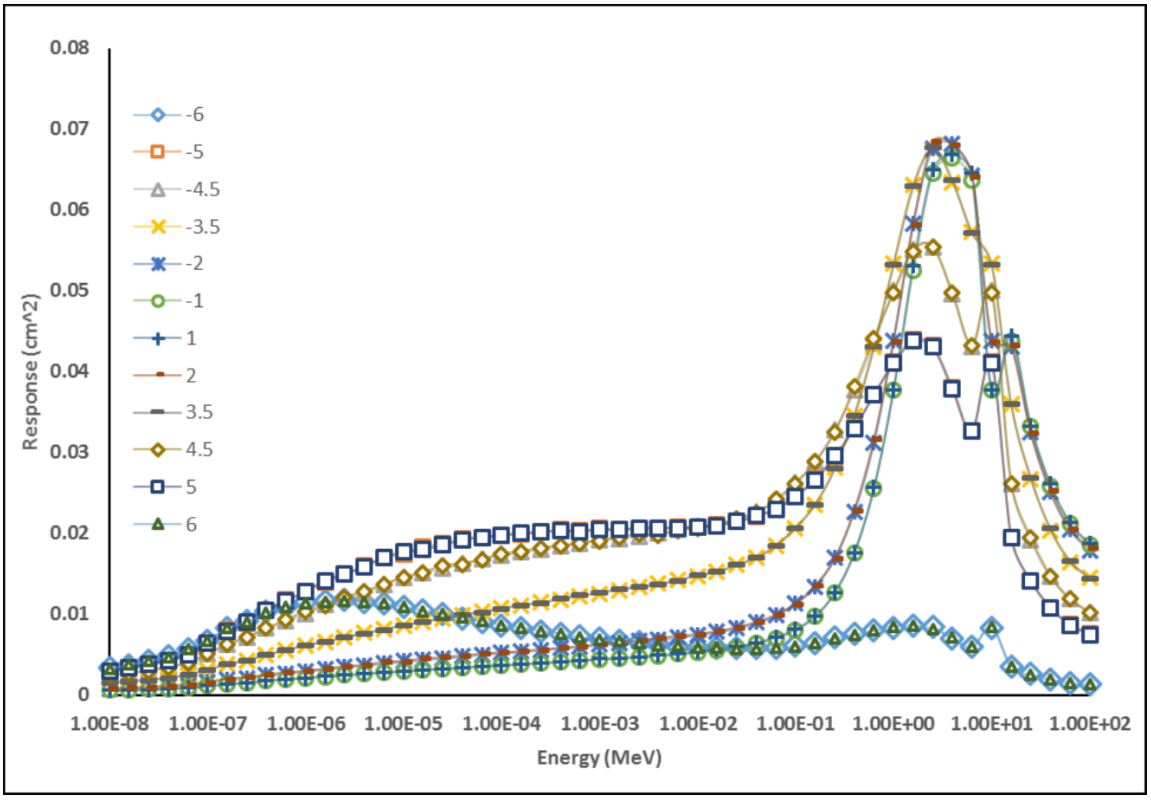

Figure 5. The response function of the TLD-600 chips located on Y axis at different radial distances.

Figure 5 shows that the radiation reaching the TLDs located at the center of the sphere experience a thicker layer of polyethylene therefore the TLD responses decrease in comparison with other neighboring TLDs.

It should be mentioned that the response of the TLDs with the minimum polyethylene moderator, i.e. TLDs located at x=6 (see figure 4), and y=−6 cm, and y=6 cm (see figure 5), are completely different from the other TLDs.

3.2 Kernel spread constant optimization

Figure 6 show the mean SSE values of predicted spectra and real ones for different spread constants. According to the figure, the optimum spread constant is 0.09.

3.3 Unfolding neutron spectra using GRNN neural network

To unfold the neutron spectra, the GRNN artificial neural network with optimum kernel spread constant, 0.09, was used. Figure 7 shows the mean SSE for 125 predicted spectra relative to the real ones. According to the figure, the network is able to predict the neutron spectra with low errors. Three predicted spectra are compared with real ones in figure 8.

4 Discussions

The results of this study indicates that the neutron spectra predicted by GRNN are close to the real spectra. According to the results, the GRNN can be effectively used for predicting the neutron

2017 JINST 12 T07007

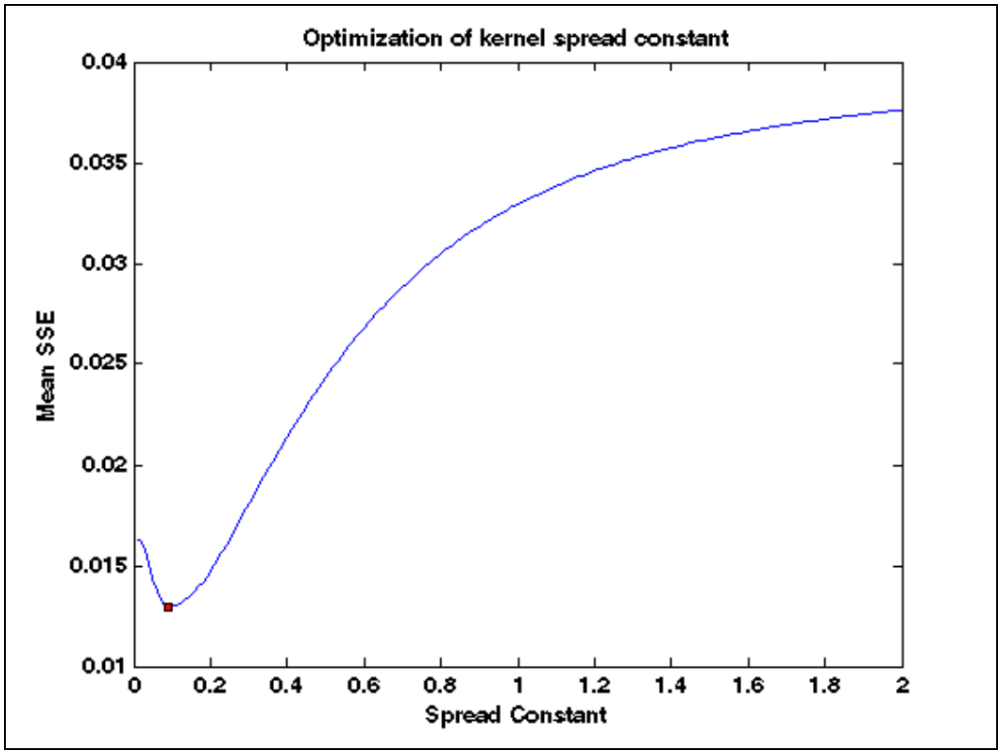

Figure 6. The mean SSE values of predicted spectra relative to the real ones for different spread constants.

spectra from the readings of Thermoluminescence dosimeters located at different radial distances inside a single-sphere spectrometer.

GRNN has several advantages over BPNN. GRNN has a relatively simple and static structure with 2 layers, named pattern and summation layers. The only free parameter in the network, is the spread constant value. GRNN estimation is never trapped by a local minimum, and always converges to a global solution. The use of GRNN from the readings of TLD pairs inside the single sphere spectrometer is shown to be a promising alternative procedure for unfolding the neutron spectra successfully.

5 Conclusions

Artificial neural networks, (ANN) has been proved to be an effective tool in predicting neutron spectra. GRNN is a fast neural network, with simple learning algorithm, and network architecture. In this study, GRNN was applied to predict the neutron spectrum using the readings of the TLDs located at different positions inside a single sphere neutron spectrometer. The network was trained with the optimum kernel spread value, and 126 spectra of the IAEA Tec-doc 403. 125 spectra were used for testing the performance of the GRNN.

Comparison of the predicted spectra with the real spectra shows that the trained GRNN has high performance. It is concluded that ANN technology could be used as a powerful and accurate tool in neutron spectrum unfolding techniques.

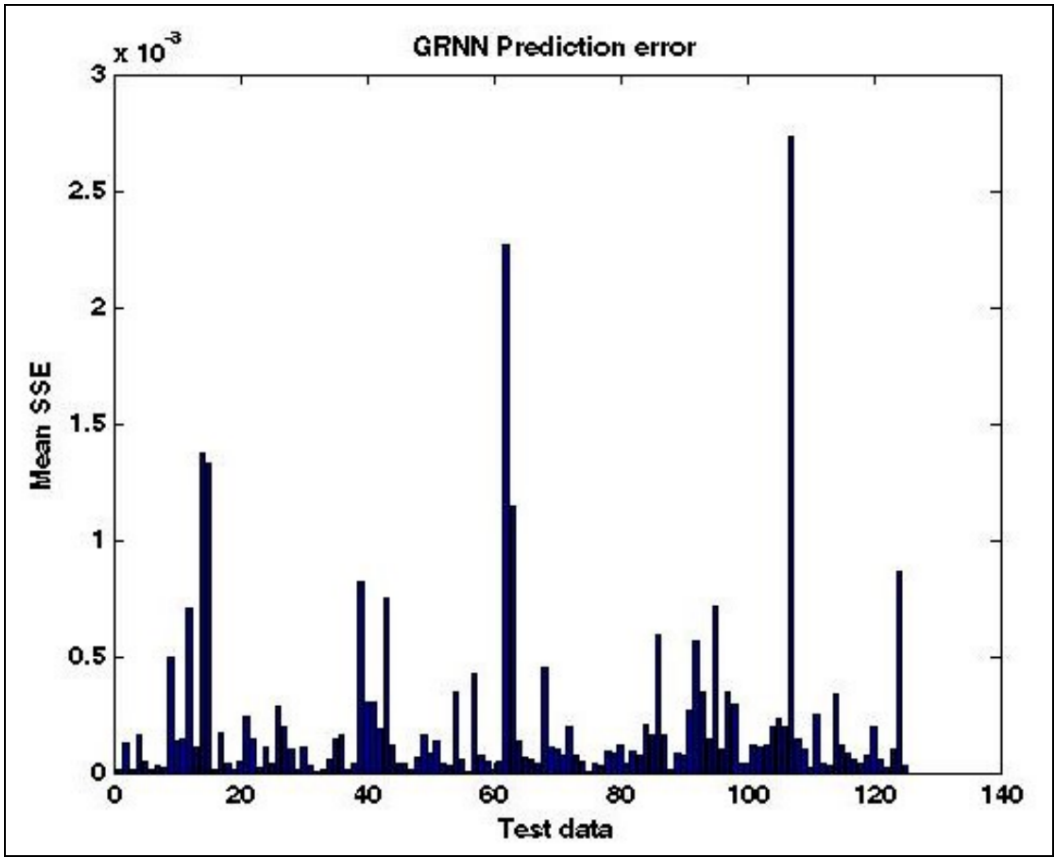

Figure 7. The mean SSE for 125 predicted spectra relative to the real ones.

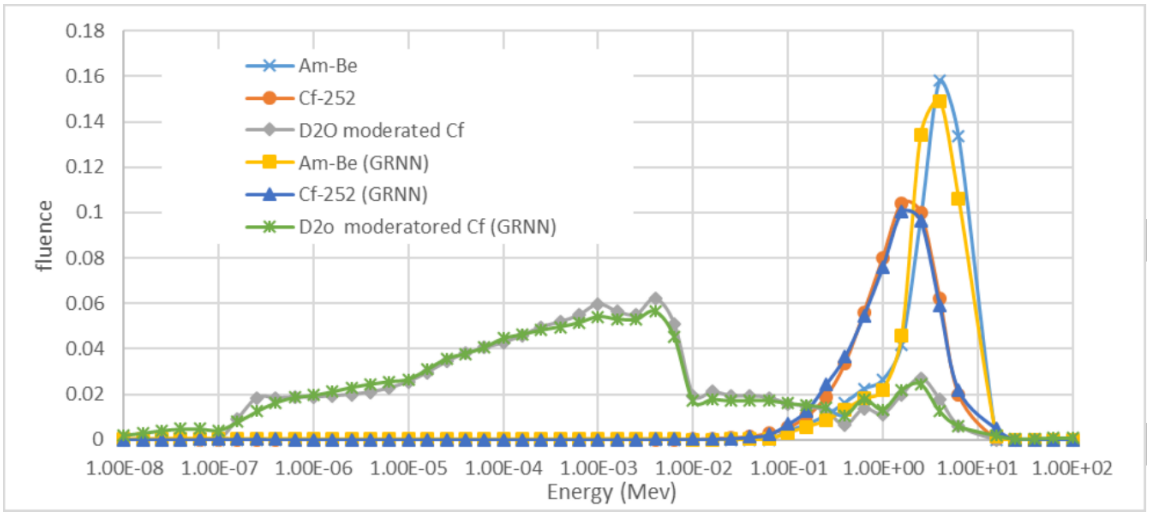

Figure 8. Comparison of spectra predicted using GRNN with real energy spectra given by IAEA report 403.

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2017 JINST 12 T07007