A neutron spectrum unfolding code based on generalized regression artificial neural networks

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Abstract

The most delicate part of neutron spectrometry, is the unfolding process. The derivation of the spectral information is not simple because the unknown is not given directly as result of the measurements. Novel methods based on Artificial Neural Networks have been widely investigated. In prior works, back propagation neural networks (BPNN) have been used to solve the neutron spectrometry problem, however, some drawbacks still exist using this kind of neural nets, as the optimum selection of the network topology and the long training time. Compared to BPNN, it's usually much faster to train a generalized regression neural network (GRNN). That's mainly because spread constant is the only parameter used in GRNN. Another feature is that the network will converge to a global minimum. In addition, often are more accurate than BPNN in prediction. These characteristics make GRNN be of great interest in the neutron spectrometry domain. In this work is presented a computational tool based on GRNN, capable to solve the neutron spectrometry problem. This computational code, automates the pre-processing, training and testing stages, the statistical analysis and the post-processing of the information, using 7 Bonner spheres rate counts as only entrance data. The code was designed for a Bonner Spheres System based on a ^{6}LiI(Eu) neutron detector and a response matrix expressed in 60 energy bins taken from an International Atomic Energy Agency compilation.

Keywords: Artificial neural networks, neutron spectrometry, Bonner spheres, unfolding

1. INTRODUCTION

Spectrometry and dosimetry of neutron radiation is one of the most complicated tasks in radiation protection (Kardan, et al., 2004). The monitoring of radiation exposure in neutron fields is mainly done with passive detection systems like track detectors, albedo dosimeters of film dosimeters with foil filters (Feherembacher, et al., 1999). These dosimetric systems have a response that strongly depends upon neutron energy.

A special type of neutron dosimeters, commonly known as Bonner Spheres System (BSS), are also utilized as multi-element systems where each element has a particular response to neutrons (Bonner, 1961) (Alevra, et al., 1992) (Awschalom & Sanna, 1985). Usually these dosimeters have better detection efficiency in a wider energy range allowing a better dose assessment. (Feherembacher, et al., 1999) This is achieved using the integral counts, obtained by the active detector, that are weighted by factors that belong to each element (Alberts, et al., 1997) or using the integral counts to unfold the neutron spectrum that is multiplied by neutron fluence-to-dose conversion coefficients. With the neutron spectrum information different dose quantities, like Hp(10), H*(10), can be estimated. (International Commission on Radiation Units and Measurements, 2001)

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 discrete version of the Fredholm integro-differential equation, which is an ill-conditioned system with an infinite number of solutions. (Vega-Carrillo, et al., 2002)

To unfold the neutron spectrum, several methods are used such as Monte Carlo (Lindemann & Zech, 1995), regularization (Routti & Sandberg, 2001), parameterization, iterative (International Commission on Radiation units and Measurements, 2001) and maximum entropy (Reginatto, et al., 2002) procedures. Each of them has difficulties that have motivated the development of complementary procedures (Vega-Carrillo, et al., 2002), (Vega-Carrillo & Iñiguez, 2002), (García-Domínguez, et al., 1999) . Methods based

upon artificial neural networks (ANN), have been utilized (Feherembacher, et al., 1999), (Braga & Dias, 2002), (Kardan, et al., 2003). However, the application of ANN to unfold actual neutron spectra still has some problems and the need of more investigation has been suggested (Braga & Dias, 2002).

ANN are large structured system of equations (Haykin, 1999). These system have many degrees of freedom and are able to adapt to the task they are supposed to do (A.I., 2007) (Apolloni, et al., 2009) (Bassis, et al., 2009). Two very different of types of neural networks exist: Back Propagation (BPNN) (G.D., 2007) (M. C.K., et al., 1997) (J. A.K., et al., 1996) and Probabilistic (PNN) neural networks (Chtioui, et al., 1997) (Huang & Zhao, 2005) (Mao, et al., 2000) (Huang, 1999). BPNN use equations that are connected using weight factors (Arbib, 2003) (Hammer & Vilmann, 2003). The selection of the weighting factors makes these neural networks so powerful. PNN use statistical methods to select the equations within the structure and do not weight these functions differently (Mao, et al., 2000) (Huang, 1999) (Specht, 1990) (Specht, 1992) (Specht, 1998).

Previous researches on neutron spectrum unfolding with ANN indicate that BPNN perform well (Braga & Diaz, 2002) (Kardan, et al., 2004) (Fehrenbacher, et al., 1999) (Hernandez-Davila, et al., 2005) (Vega-Carrillo, et al., 2006) (Vega-Carrillo, et al., 2009). However, serious drawbacks when using BPNN in neutron spectrometry are the proper determination of the network architecture, the long training periods and the lack of available data, neutron spectra, to train the networks which is generally never enough for BPNN (Ortiz-Rodríguez, et al., 2013). Comparing to BPNN, it is usually much faster to train a Generalized Regression Neural Network (GRNN), which falls into the category of PNN (Chtioui, et al., 1997) (Mao, et al., 2000).

GRNN like other PNN need only a fraction of the training samples a BPNN would need (Mao, et al., 2000) (Huang, 1999) (Specht, 1992) (Specht, 1998) (Specht, 1990). Therefore the use of a GRNN is especially advantageous due to its ability to converge to the underlying function of the data with only few training samples available. The additional knowledge needed to get the fit in a satisfying way is relatively small and can be done

without additional input by the user. That is mainly because the spread constant is the only parameter used in GRNN opposite to BPNN in which before the training stage, it is necessary to determine many learning and architectural parameters of the network (Ortiz-Rodríguez, et al., 2013).

Another characteristic of GRNN, which makes it fast in training, is that there is only the linear output layer beyond the first hidden layer; this guarantees that the network will converge to a global minimum opposite to BPNN. In addition, GRNN often are more accurate than BPNN in prediction. These characteristics make GRNN be of great interest in the neutron spectrometry research area. However, due this is an emergent research area, one drawback is the lack of scientific knowledge and technological tools to train ant test GRNN in the neutron spectrometry field.

The aim of this work was to train a GRNN capable to solve with high efficiency the neutron spectrum unfolding problem. To achieve the before mentioned, a neutron spectrum unfolding computational tool based on GRNN technology was designed. This computer code, developed under the Matlab programming environment, automates the stages of pre-processing the information used to train and test the network, the selection of the spread constant, the training and testing stages of the network, the analysis of the performance of the trained network and the storing of information produced before, during and after training and testing stages, for further analysis. The anterior saves a lot of time and let's to use the saved time in other related research activities.

To determine the optimum spread constant value, around 2000 neural networks were trained in 157 seconds average. The final GRNN was trained and tested in 0.058 seconds average in only one epoch, using the calculated optimum spread constant. After training, the performance of the network was analyzed by comparing the output of the trained network with the expected value. In this work, the best and the worst cases are showed. Results obtained show that GRNN in neutron spectrometry shows high efficiency and generalization capability.

2. MATERIALS AND METHODS

In this work, a GRNN was trained in order to solve the neutron spectrometry problem by using a customized technological tool designed with this purpose. As is showed in figure 1, a GRNN is a feed forward neural network based on non-linear regression theory consisting on four layers: the input layer, the pattern layer, the summation layer and the output layer. It is suited to function approximation tasks such as system modeling and prediction. While the neurons in the first three layers are fully connected, each output neuron is connected only to some processing units in the summation layer.

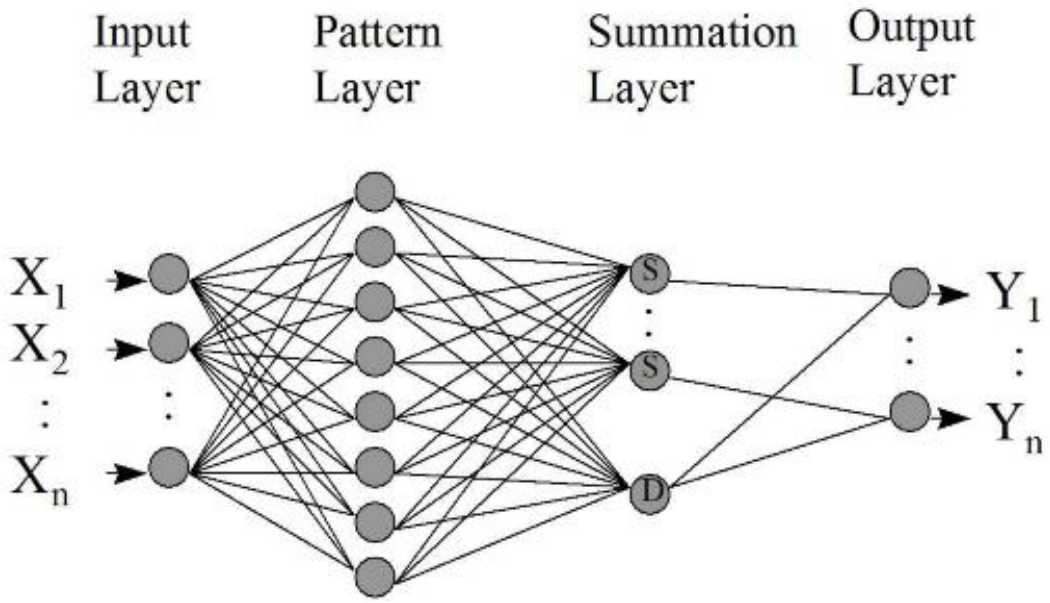

Figure 1. General structure of GRNN

As can be seen from figure 1, the first layer is the input layer and is fully connected to the pattern layer. The second layers is the pattern layer and has one neuron for each input pattern. The neuron stores the values of the predictor variables for the case along with the target value.

The function of the pattern layers of the GRNN is a Radial Basis Function (RBF) (Specht, 1990) (Specht, 1998) (Specht & Romsdahl, 1994) (Specht & Shapiro, 1991), typically the

Gaussian kernel function. As can be seen from figure 2, the activation of pattern units essentially characterize the distances of centers of RBF to produce localized, bounded, and rapidly symmetric activations, that is, activations rapidly decreasing with the distance from the function´s centers. The RBF is so named because the radius distance is the argument to the function, as seen in figure 2.

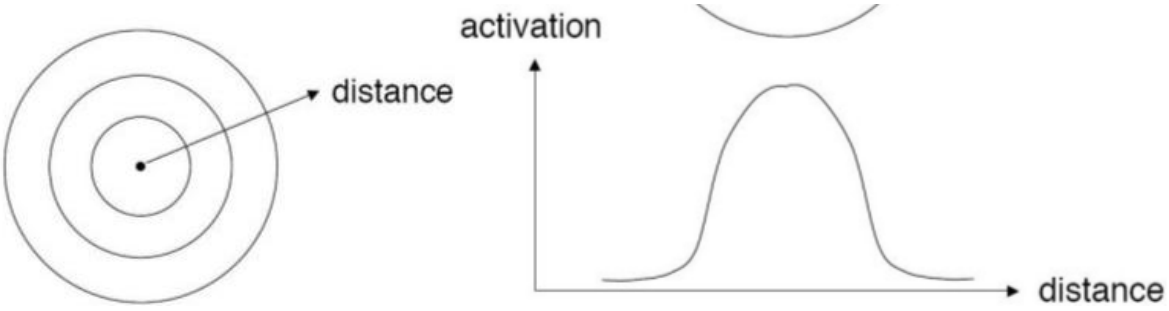

Figure 2. Radial Basis Function (RBF)

The width of RBF of the pattern units, also known as the spread constant σ, is an important parameter allowing the user to influence generalization capabilities of the GRNN. In general, larger values of the spread constant results in a smoother interpolation of the output vectors values among the values corresponding to the centers of RBF of the individual pattern units.

The summation layer has two different types of processing units: the summation units and the single division unit. The number of the summation units is always the same as the number of the GRNN output units. The summation unit adds up the weight values coming from each of the pattern neurons. The division unit only sums the weighted activations of the pattern units without using any activation function.

As before mentioned, due GRNN applied in neutron spectrometry is an emergent research area, in which one drawback is the lack of scientific knowledge and technological tools to train, test and to evaluate the performance of the knowledge acquired by the networks trained.

In this work, a neutron spectrum unfolding computer tool based on neural nets technology was designed to train a GRNN capable to solve the neutron spectrum unfolding problem with high performance and generalization capabilities. The code automates the preprocessing, training, testing, validation and post processing stages of the information regarded with GRNN. The code, showed in figure 3, is capable to train, to test and to validate GRNN. After training and testing the neural net, the code analyze, graph and stores the results obtained.

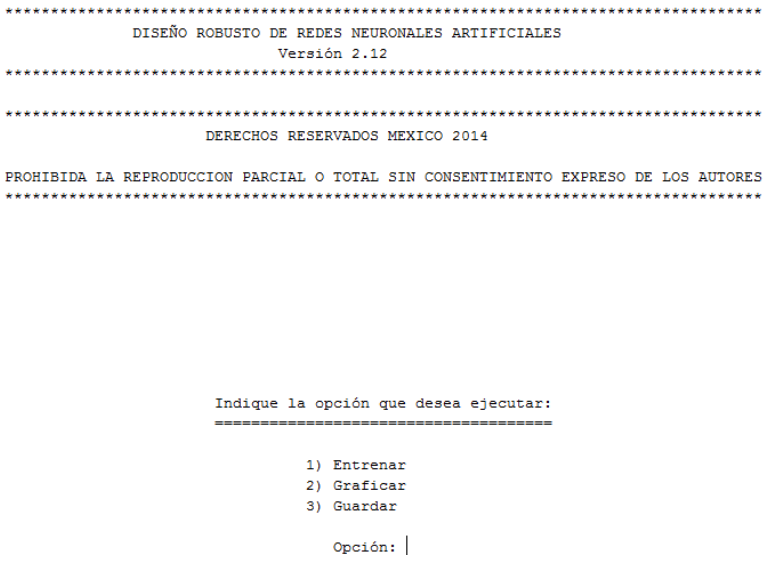

Figure 3. First screen of program designed to train GRNN in neutron spectrometry

In order to train GRNNs, the code uses 251 neutron spectra extracted by the International Atomic Energy Agency (IAEA) compilation (IEAE, 2001). The IAEA's compendium contains a large collection of detector responses and spectra. The report was made with the aim to provide specific technical information that could be used by radiation protection specialists for proper selection of dosimeters and survey instruments, and for interpretation of data obtained with these detectors.

At this stage of development, the customized technological tool designed to train GRNNs for neutron spectrometry uses 251 neutron spectra and three response matrix from IAEA´s compilation. The designed technological tool automates the following activities:

- Read the neutron spectra data set coming from IAEA´s compendium, which are expressed in 60 energy bins.
- Read a response matrix used to train the neural network.
- Because the neutron spectra coming from IAEA´s compendium are expressed in lethargy units, the code converts these spectra in energy units.
- The neutrons expressed in energy units are multiplied by the selected response matrix in order to calculate the count rates.
- To train the GRNN, the code uses the 251 calculated count rates as entrance data and their corresponding neutron spectra expressed in energy units as the output data. Figure 4.

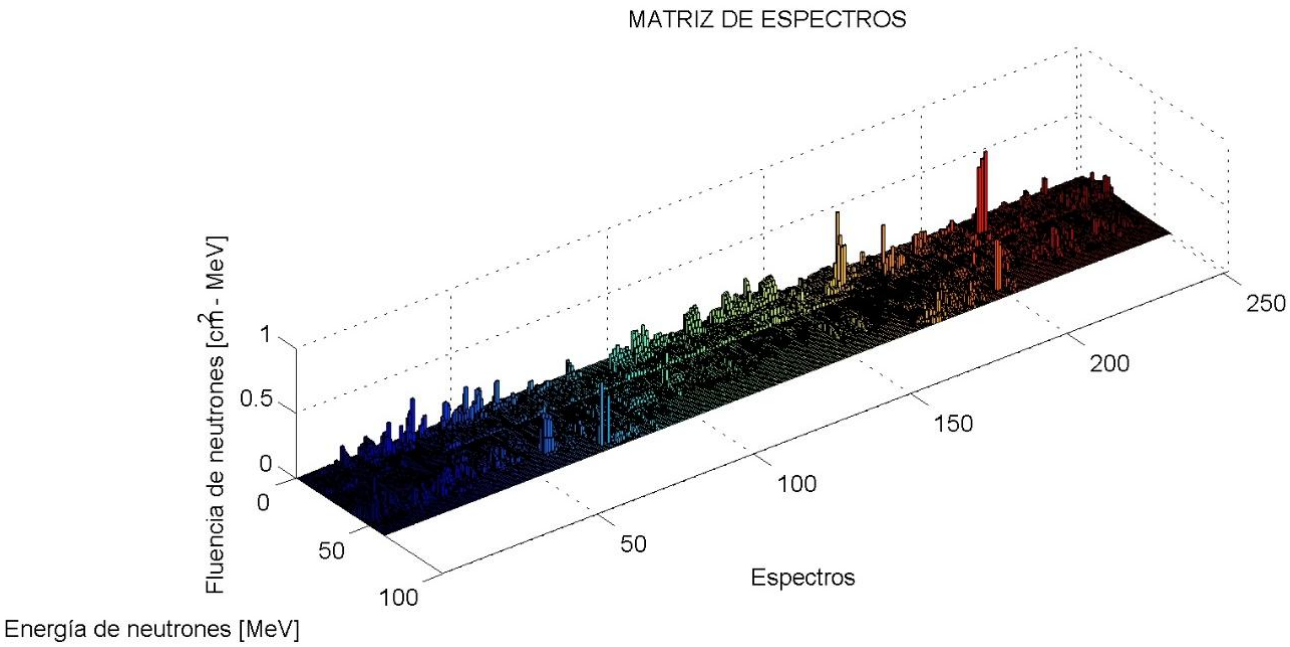

Figure 4. Neutron spectra data set, expressed in energy units, used to train the GRNN

- Randomly the code generates the training data set, 80% of the whole data set, and the testing data set, remaining 20%, as is showed in figure 5.
- Using the before calculated information, the following stage was to determine the spread constant value. To calculate this value, the computer tool trains several neural networks varying this value from 0 in increments of 0.01 through 2 and compare the mean square error (mse) which is used to determine the performance of

the network. The minimum value obtained is selected as the spread constant value. 2000 GRNN were trained in 157 seconds average, to determine an optimum value equal to 0.2711, as is showed in figure 6.

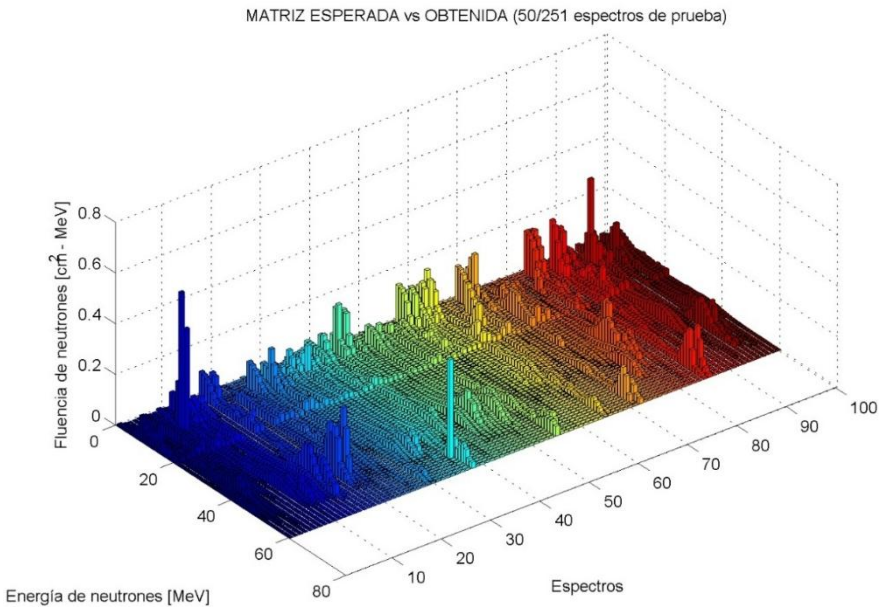

Figure 5. Neutron spectra data set used at testing stage, compared with target spectra

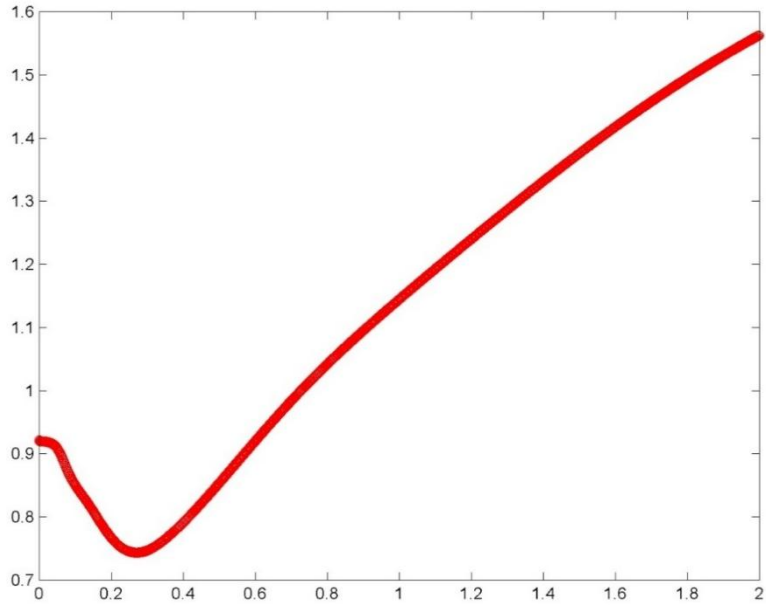

Figure 6. Optimum spread constant value, sigma, determination

- Using the calculated spread constant value, a final GRNN was trained and tested in 0.058 seconds average in only one epoch. At testing stage the code compare and analyze the output of the trained neural network with the expected spectrum, showed in figure 5. At testing stage 50 neutron spectrum, randomly selected, were used to analyze the performance of the trained network, performing chi square and correlation tests. In this work, the best and the worst cases are showed from figures 7 through 10.

At testing stage, 50 counts rates, randomly selected in the preprocessing stage, are used to test the performance and generalization capabilities of the trained network, no target output is proportionated to the network. The designed code analyze and compare the output of the network whit the neutron spectrum expected as is showed in figures 7-10.

3. RESULTS

As mentioned, after selecting the spread constant value, a final GRNN was trained in 0.058 seconds average. After training, a testing stage was performed in order to analyze the performance and generalization capabilities of the trained network. At testing stage only the input was proportionated to the network. Figure 7 shows the best spectrum observed at testing stage, compared with the expected output. The values showed in figures 7 through 10 were calculated and graphed with the customized technological computer code which saves a lot of time if the calculations had been executed by hand by the researcher.

As can be seen from figure 7, due the proper selection of the spread constant value, the GRNN calculated values, each one of the 60 energy bins of the spectrum, are around the target value (the spectrum from IAEA´s compendium). Opposite to BPNN, non-negative values and oscillations around the target value are generated when GRNN are used.

As can be appreciated in figure 7, the performance of the trained network was 2E-4. The chi square test was 0.049, near to the optimum value and far from the statistical margin.

The correlation test was 0.99 which means that the calculated and expected spectra are very similar and the network performance is high.

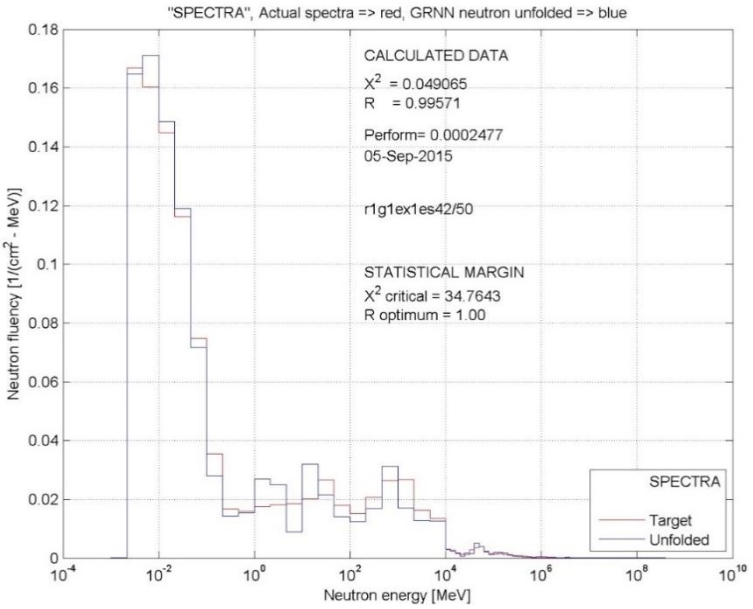

Figure 7. Best spectrum obtained at testing stage compared with target spectrum

Figure 8 shows the chi square and correlation test of the best spectrum at testing stage. From this figure can be seen that the predicted and expected values, 60 energy bins of the neutron spectrum, are very near because the values obtained, 0.049 for the chi square test and 0.99 for the correlation test, the calculated and target spectrum are very similar and have a high performance and generalization capabilities.

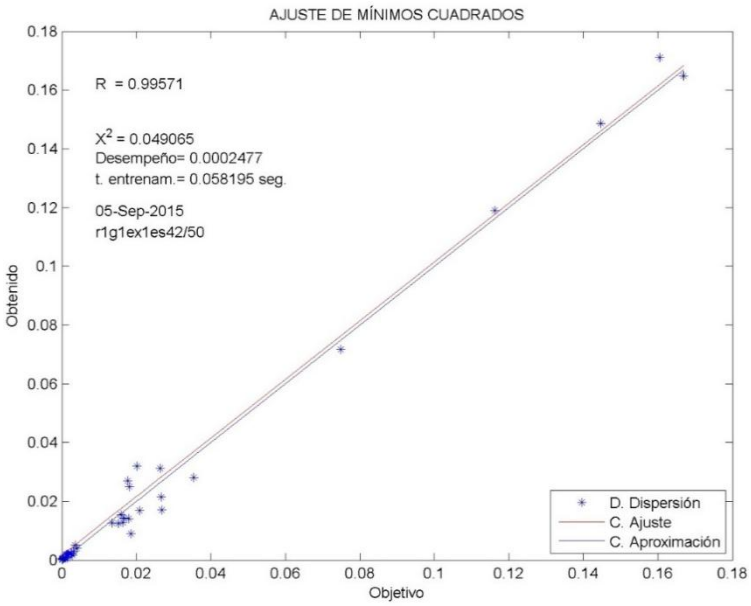

Figure 8. Best correlation test obtained at testing stage

Figure 9 shows the worst spectrum observed at testing stage. From this figure can be seen that 59 of the 60 energy bins of the calculated spectrum by GRNN are around of the target value. Only one value from the 60 energy bins present's differences with regard to expected value which affects significantly the chi square and correlation tests, 0.32 and 0.46 respectively. Remaining 48 cases used at testing stage are above the values here showed.

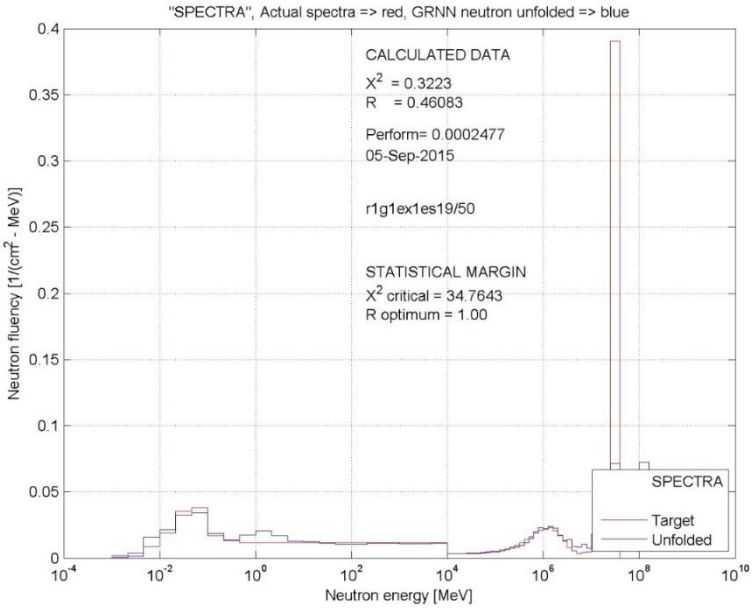

Figure 9. Worst spectrum obtained at testing stage compared with target spectrum

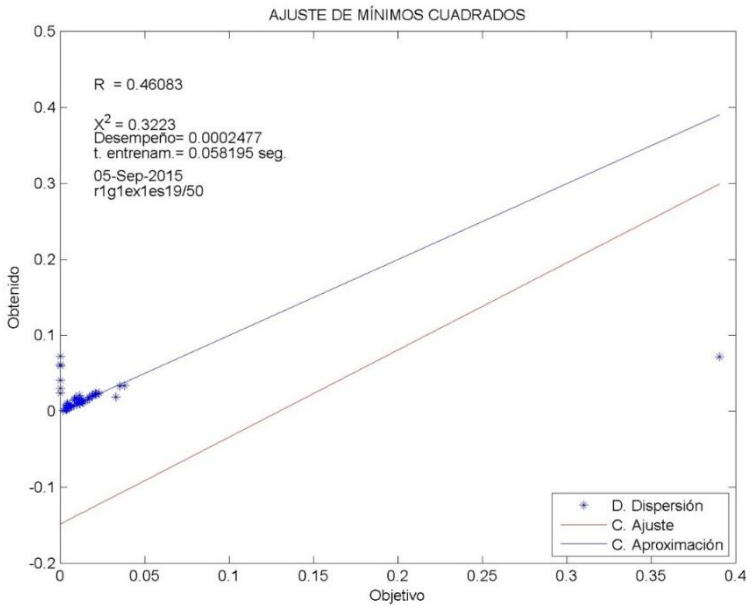

Figure 10. Worst correlation test obtained at testing stage

Figure 10 show the correlation test of the worst spectrum. As can be seen from this figure, the only one value of the neutron spectrum that is far from the expected value, the point on the right side of the graph, affects significantly the statistical tests, however, as can be seen from figure 9 and 10, the remaining 59 values are very near from expected values, which demonstrates the power of GRNN in the solution of the neutron spectrum unfolding problem, which uses a limited amount of information extracted from IAEA´s compendium.

4. DISCUSSION

ANN technology is widely recognized as a powerful modeling tool. An ANN is a massively parallel distributed processor that trough a learning process acquires experiential knowledge, making available for use. In general, an ANN is a set of input nodes that links directly to a series of output nodes or indirectly through one or more hidden layers. The use of an ANN requires the training of the network and the testing of the trained network. During training a set of synaptic weights is obtained, where the knowledge is stored.

GRNN is a special case of PNN. Compared with its competitor, e.g. BPNN, GRNN has several advantages: First of all, the structure of a GRNN is relatively simple and static with 2 layers, namely pattern and summation layers. Once the input goes through each unit in the pattern layer, the relationship between the input and the response would be "memorized" and stored in the unit. As a result, # of units in the pattern layer is equal to # of observations in the training sample. This type of network is able to learning from the training data by "1-pass" training in a fraction of the time it takes to train BPNN. The spread constant value, is the only free parameter in the network. Unlike standard BPNN, GRNN estimation is always able to converge to a global solution and won't be trapped by a local minimum.

The use of GRNN to unfold the neutron spectra from the count rates measured with the BSS is a promising alternative procedure, which has been applied with success in this work. However, one of the main drawbacks was the lack of scientific and technological tools based on this technology. Because the anterior, a scientific computational tool was designed to train, to test, to analyze and to validate GRNN in this research domain.

5. CONCLUSIONS

An ANN simulates a highly interconnected, parallel computational structure with many individual processing elements or neurons. It learns trough 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.

GRNN is one of the simplest neural network, in term of network architecture and learning algorithm. The training pattern can be considered as the center of Gaussian function and the target output could be considered as multiplier of the probability density function. Another advantage is that the learning is instantaneous, which mean require no time for training. In this work, around 2000 neural networks were trained in 154 seconds average to

determine that with the best performance. Each network was trained in 0.058 seconds average.

The purpose of this work was to apply GRNN to predict the neutron spectrum using the count rates data from a BSS. Two hundred and fifty one different types of neutron spectra, a limited amount of information, were used as training data set obtained from IAEA´s compilation. 80% of the whole data set was used at training stage and remaining 20% at testing stage. In order to realize the training and testing of GRNN a customized computer tool designed in Matlab environment was designed, which automates the preprocessing, and post processing of the whole information regarded with the training and testing stages.

In the GRNN testing stage fifty predicted spectra were obtained as outputs of the GRNN. Comparison with standard spectra shows that the trained GRNN has high performance and generalization capabilities, indicating that ANN technology could be used as a promising alternative with high accuracy in neutron spectrum unfolding techniques.

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