falls into the category of Probabilistic Neural Networks (PNN) a subclass of Statistical Neural Networks (SNN) [59–61].

GRANNs have been successfully applied in other optimization and classification problems. Due to the intrinsic nature of this kind of network, is capable to solve the parameter optimization problems of FFBPNN architectures, since only one parameter is required to be optimized.

The learning of FFBPNN can be described as trial and error while GRANN use a statistical approach in their prediction algorithm, which is capable of working with only few training samples. Unlike FFBPNN, GRANN use a statistical approach in their prediction algorithm which is based on the Bayes strategy for pattern recognition [59–61]. In this sense, the experience is learned not by trial but by experience others made for the neural network.

Opposite to FFBPNN, GRANN are very flexible and new information can be added immediately with almost no retraining. The biggest advantage is the fact that the probabilistic approach of GRANN works with one-step-only learning and uses a single common radial basis function kernel bandwidth, σ, that is tuned to achieve an optimal ANN learning [59–61].

In addition to the above mentioned, the time required for training GRANNs, is significantly reduced from hours to milliseconds, compared to the FFBPNNs training process, since only one iteration is required to train GRANNs.

In preliminary works, FFBPNN and GRANN were trained and tested and the performance of both architectures was compared in the solution of the neutron spectrun unfolding problem. The results obtained showed that GRANNs solve the parameter optimization problems of FFBPNN, have a better performance and solve the neutron spectrum unfolding problem with greater efficiency.

However, scientific and technological tools have not been developed that allow applying this type of technology with efficiency in real experimental places [64, 65].

In consequence, scientific computational tools are needed in order to train, to test, to analyze, and to validate GRANN technology in this research domain and to use it in real experimental places.

In collaboration agreement with the OMADS company, an enterprise dedicated to the research, innovation and technological development [66], the aim of this research work was to study, to analyze, to design and to implement *Synapse*, a neutron spectrum unfolding code based on GRANN technology, which is capable to unfold the neutron spectrum and to calculate 15 different dosimetric quantities using the count rates, coming from a BSS, as the only entrance information.

The code solves the neutron spectrometry and dosimetry problems with high performance and generalization capacity. The results obtained show that the Synapse code is a promising alternative which can be used for solving the neutron spectromtery and dosimetry problems and can be applied in real experimental places.

2. Materials and methods

2.1. Generalized regression artificial neural networks

GRANN is a type of supervised Feed Forward Neural Network (FFNN) introduced by Donald F. Specht in 1991 [62]. Opposite to FFBPNN, where data may be propagated forward and backward many times until an acceptable error is found, the training of GRANN is very fast because the training data set propagates forward only once [59–63].

The structure of the calculations for the probabilistic density function in GRANN has striking similarities to FFBPNN, however, inside the neurons, GRANN use functions based on knowledge resulting from the Bayes strategy for pattern classification. The strength of a GRANN lies in the function that is used inside the neuron. The regression performed by GRANN is given by eq. 4:

$$E[Y/x] = \int_{\infty}^{\infty} Y.f(Y/x)dy = \frac{\int_{\infty}^{\infty} Y.f(x,Y)dy}{\int_{\infty}^{\infty}(x,Y)dy} \quad (4)$$

For a non-parametric estimate of $f(x,y)$, one consistent estimator is the Gaussian function which is a good choice for estimating the probability density function, f. The probability estimator $\hat{f}(x,y)$ is based on sample values x_i and y_i of the random variables X and Y given by eq. 5:

$$\hat{f}(x,y) = \frac{1}{\frac{2\pi^{(p+1)}}{2.\sigma^{(p+1)}}}. \cdot \frac{1}{n}\sum_{i=1}^{n}\left\{\exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]\exp\left[\frac{(Y-Y_i)^2}{2\sigma^2}\right]\right\} \quad (5)$$

Were p is the dimension of the vector variable; n is the number of training pairs $x_i \rightarrow y_i$; σ is the single learning or smoothing parameter chosen during the network training; Y_i is a desired scalar output given by the observed input x_i.

The topology of GRANN consist of four layers. The first layer is the input layer that is fully connected with second layer. The input neurons are distribution units which provide all the measurement variables X to all neurons of second layer also known as pattern layer.

The second layer is the first hidden layer and consists of N processing elements or nodes, where N is the number of sample within a training data set and each node represents the input vector, X_i, associated with the vector assigned with the j^{th} sample in training data.

In each node, each input vector is subtracted from the vector assigned to the node X_j. This difference es then squared by the node and the result is feed into a nonlinear kernel which is usually an exponential function. The pattern unit output are passed to the summation units of third layer which is called summation layer.

The summation layer is the second hidden layer and has two nodes. The input to the first node, as shows eq. 6, is the sum of the pattern layer outputs, each weighted by the observed output yj corresponding to Xj. The input of the second node is the summation of the pattern layer activation.

$$\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2\sigma^2}\right) \tag{6}$$

The fourth layer also known as output layer, receives the two outputs from the summation layer and divides them to yield an estimate of Y, the prediction result.

$$\hat{Y}(\chi) = \frac{\sum_{i=1}^{n} Y_i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \tag{7}$$

Opposite to FFBPNN, in GRANN architecture there are no learning and architectural parameters to be determined such as the number of hidden layers, the training algorithm, learning rate, momentum, among others. The only one parameter that must be determined is the smoothing factor, σ, which is applied after the training stage.

The choice of this parameter is very important because affects the smoothing of the training samples. In this sense, small values of σ tend to make each training point distinct whereas large values force a greater degree of interpolation between the training samples [59–63].

In prior works, GRANN were used to solve the neutron spectrum unfolding problem from the count rates measured with the BSS.

The results obtained showed that the use of GRANN to unfold the neutron spectra is a promising alternative approach, however, one of the main drawbacks was the lack of scientific and technological tools based on this emerging technology, capable to be used in real experimental places with high efficency. For this reason, in this research work, the synapse code was developed.

2.2. Synapse code development

The Synapse code is composed of three main stages as showed in Figure 1: The the GRANN methodology, the neutron spectra unfolding code based on GRANN and the rates count comming from BSS.

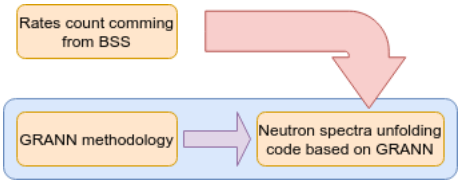

Figure 1. General view of the main stages for implementing the Synapse code

2.3. Stage one: GRANN methodology

The GRANN methodology is a set of computer algorithms programmed for training several GRANNs in order to create the network architecture capable to solve the neutron spectrometry and dosimetry problems and for calculating the optimized value of the smoothing factor, σ, which is used in a final GRANN, programmed at the second stage, in order to unfold the neutron spectrum based on the rates count measured with a BBS in experimental places.

The GRANN methodology is composed by three stages as illustrated in Figure 2: the pre-processing of the information of trainig data, the training of several GRANNs and the determination of the critical value of the GRANN, the smoothing factor, σ.

Figure 2. Stage one, automatization process of GRANN methodology

Pre-processing of the training information. Because GRANN is a kind of FFNN with supervised training, a data set with both, inputs and outputs, was required to perform the GRANN training and testing. The data set was obtained from the IAEA's neutron spectrum compendium [67].

The neutron spectrum reported on the IAEA compendium, are defined in lethargy units, and are expressed in 60 energy groups, ranging from thermal neutrons to 630 MeV. As mentioned, the IAEA report also contains information regarded with 15 dosimetric quantities and several survey instruments.

The pre processing stage of the GRANN methodology, showed in Figure 3, was implemented for building the input-output data sets used for training the

GRANNs. The rate counts were used as entrance data and the neutron spectrum, dosimetric quantities and instrument survey readings are used as output data.

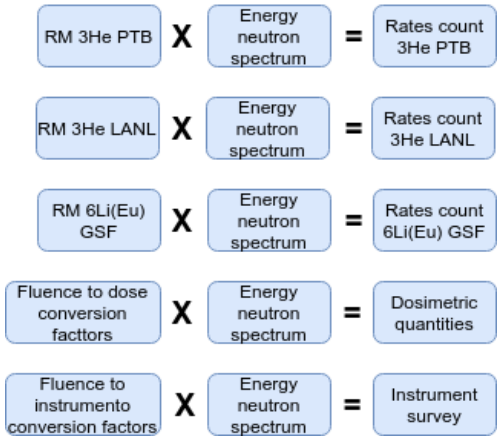

Figure 3. IAEA's information extraction procedure and calculation of GRANN training data set

Each neutron spectrum was converted from lethargy to energy units using equation 8, and with this information, the BS rates count were calculated.

$$\phi_E(E) = \phi_E(u) * ln\left(\frac{E_{sup}}{E_{inf}}\right) \tag{8}$$

Where $\phi_E(u)$ is the neutron spectrum expressed in energy lethargy units, E_{sup} is the superior energy interval and E_{inf} is the inferior energy interval.

As is showed in Figure 3, for calculating the rates count, the neutron spectrum expressed in energy units, extracted from the IAEA compilation, were multiplied with each response matrix (RM).

The RM taken from the IAEA compilation were: the RM for a ^3He neutron detector, calculated by the PTB; the RM for a ^3He neutron detector, calculated by LALN; and the RM for a $^6LiI(Eu)$ neutron detector, calculated by GSF.

As can be seen on Figure 3, by multiplying the neutron spectrum data set with the fluence to dose and instrument conversion factors, the values of 15 dosimetric quantities and 7 survey instruments were calculated.

After performing the calculations, the rates count for each neutron detector, the equivalent doses and the instruments readings were obtained.

This information was embedded on the Synapse code, and is used for unfolding the experimental neutron spectrum, based on the rates count measured experimentally, using the GRANN technology in which the code is based.

GRANN training and smoothing factor, σ, determination. Each time the Synapse code is used for unfolding a real experimental neutron spectrum, the three general stages are executed. These stages were automated designing computer programming routines, under the Matlab programming environment.

In order to train and test a GRANN capable to solve the neutron spectrum unfolding problem, a data-set with 251 neutron spectra, 15 dosimetric quantities and 7 measurement instruments, extracted from the IAEA's compilation, were used. 80 % of the whole data-set was used at GRANN training stage and the remaining 20 % was used at testing stage.

For calculating the spread value, the programmed algorithms train and test 2000 GRANN, using the data set calculated at pre-processing stage, with the aim to calculate and to choose the optimized value of the smoothing factor, σ.

Opposite to FFBPNN, GRANNs have a fixed network architecture and the only one parameter to be optimized is the smoothing factor. This feature lets to add new information to the whole database in order to extend the training examples by retraining the network for increasing the knowledge.

The feature of retraining GRANNs, lets to experiment by varying the features of the entrance and output data, i.e., the measured rates count, and the spectrum, equivalent doses and survey instruments respectively, with the aim to reduce the number of BS used at experimental measurements.

By reducing the number of BS in experimental places, the time spent making experimental measurements, and the weight of the whole BSS could be reduced.

To do a retraining using FFBPNNs, is very difficult, mainly because each new training, requires to optimize new learning and architectural parameters of the network, whis is the more serious drawback.

As mentioned, the most important parameter for training GRANNs, is the optimum selection of the spread value, σ. A very large spread value could cause over fit, while a very small value may cause a sub adjustment of the trained network. Therefore, the value of the spread constant is a parameter that has to be selected optimally.

To make a very close adjustment of the data, a spread value smaller than the typical distance between the input vectors is used. To adjust more smoothly, a higher spread value is used.

However, a very large spread value could cause an over adjustment, while a very small value could cause a sub adjustment. Therefore, the constant propagation value can be considered as a regularization parameter that has to be selected optimally.

In this research work, the cross validation technique Leave-one-out [68], was automated as a programming routine on the Synapse code, in order to choose the optimum value of the spread constant.

The designed computer programming routine selects a single observation from the original sample, maintaining it as the data to validate, and uses the remaining observations as training data. The kernel spread constant is selected in the range of 0 to 2 in steps of 0.01.

For training the GRANNs, 80 % of the whole data set was used at training stage and the remaining 20 % at testing stage. The average time to calculate the optimum value of σ after trainig 2000 GRANNs, is 154 seconds approximately.

As showed on Figure 4, the sum of the mean square error (MSE), is calculated at training and testing stages. After calculating all the testing MSE, the average value is selected as the kernel spread constant or smoothing factor σ.

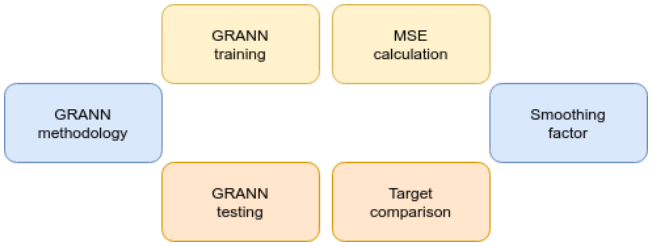

Figure 4. GRANN training and determination of the smoothing factor

Once each individual neural net is trained using the calculated training data set, the sum of the MSE between each spectrum calculated by the network and the expected one is calculated. As soon as all the MSEs are calculated, the mean is selected as the corresponding value for the specific smoothing factor, σ.

After calculating the optimized spread value, the next stage involves training a final GRANN, as is showed in Figure 5. After creating a final network, based on the 2000 GRANNs previously trained, the code is ready to perform the unfolding of neutron spectrum measured in experimental environments, using the rates count of a BSS as the only entrance data.

Figure 5. Final GRANN used to unfold the experimental neutron spectrum

The training time of the final GRANN is in the order of milliseconds, with an average value 0.058 seconds, which compared to the time used for training FFBPNN is significantly lower.

2.4. Stage two: neutron spectra unfolding code based on GRANN

Similarly to the stage one, the second stage is a set of computer algorithms programmed for unfolding the neutron spectrum based on an optimized GRANN which uses as the only entrance data, the rates count measured with a BBS, in real experimental places.

In this stage, as is showed in Figure 6, a final GRANN is trained, using the smoothing factor calculated at stage one, for unfolding neutron spectrum by using the rates count measured in real experimental places with a BSS as the only entrance data.

Figure 6. Stage two, neutron spectra unfolding code based on GRANN methodology

It is important to mention that, in addition to the neutron spectrum, the code was programmed for calculating 15 dosimetric quantities and/or 7 survey instruments values.

The Synapse code was fully automated designing computer programming routines. A Graphical User Interface (GUI) for the end user was also designed with the aim to unfold neutron spectrum in real experimental, work and research places.

2.5. Neutron spectrum unfolding with the Synapse code

The unfolding of neutron spectrum in real experimental environments using the Synapse code is done as follows. Figure 7, shows the main window of the Synapse code, where can be seen that the only piece of entrance information, on the part of the end user, are the rates count measured with a BSS with a neutron detector based on ^{3}He or $^{6}LiI(Eu)$.

The first step to operate the Synapse code is the selection of a working directory, for storing the calculations made during the unfolding of the neutron spectrum.

The selection or creation of the working directory is done by clicking the button labeled as *"Folder"*, located on the upper left corner of the main window (Figure 7).

After clicking on the *"Folder"* button, a window like the shown in Figure 8 will open. This window lets to select a working folder or, alternatively, create a new one.

The main window of the Synapse code also has a text box labeled as "Network Id" that allows assigning

an identifier to the neutron spectrum unfolding that is being carried out. This information will be stored on a text file, to identify the training carried out, for performing posterior analysis.

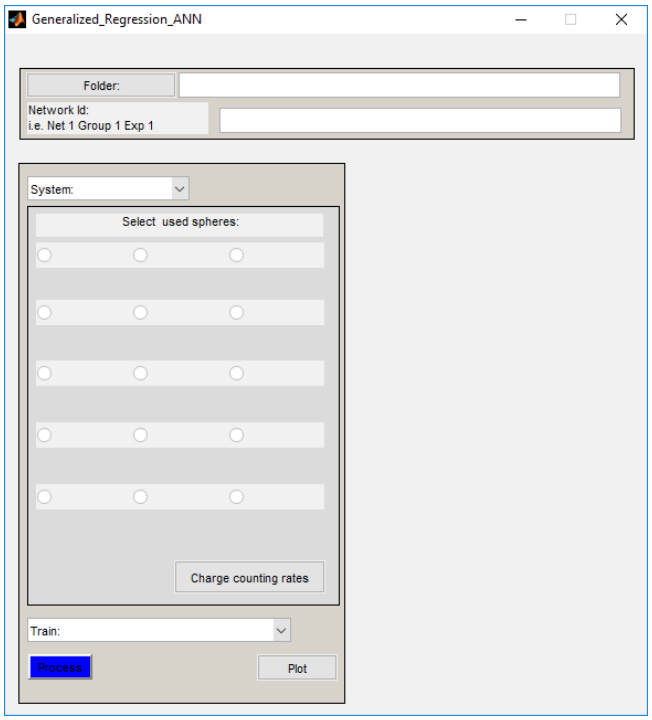

Figure 7. Main window of the Synapse unfolding code

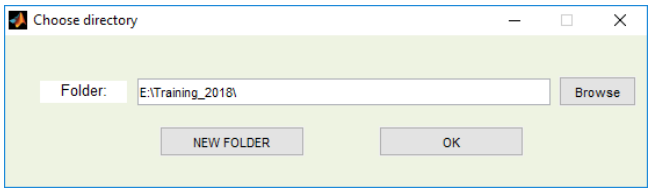

Figure 8. Window for selecting the working folder in order to store the generated information

The code is able to perform the unfolding of neutron spectrum, from experimental environments, using one of three RM extracted from the IAEA's compendium, which are embedded on the code: $^{6}Li(Eu) - GSF$, $^{3}He - PTB$ and $^{3}He - LANL$.

The main window has a drop-down selection menu, labeled as *"System"*, for selecting the desired RM which will be used to train the embedded GRANN. According to the selected RM, a different configuration of Bonner spheres will be showed as shown on Figure 9.

An important feature of the Synapse code, that demonstrates the prediction and classification power of this technological tool, based on GRANNs, is the fact that the end user does not have to use all the BS shown in Figure 9. The code has the flexibility to allow to the end user to make a selection of specific BS.

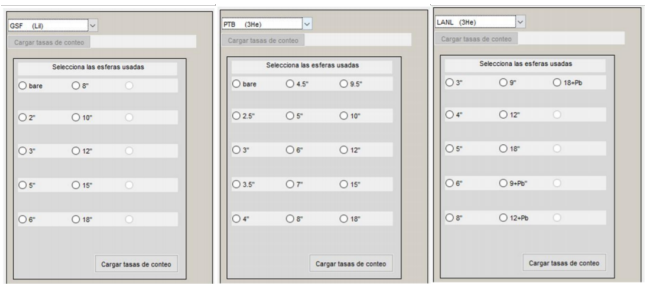

Figure 9. Drop-down selection menu for selecting different RM

Unlike the classical techniques, based on traditional numerical methods, GRANNs use statistical methods to perform the classification and prediction of the output data in a single iteration, using the information contained in the training databases.

Because of this, it has been observed that this type of technology has the ability to classify spectra and calculate equivalent doses using less information in the entrance data, that is, fewer Bonner spheres.

At present, experiments are being carried out that show that this type of technology is capable of performing the unfolding of the spectrum using less Bonner spheres as input data.

After selecting the desired BS of the chosen RM, a text box under the BS labels is generated that allows to write the readings taken experimentally with the corresponding BSS, as is showed in Figure 10.

As can be noticed on Figure 10, prior to the training of the GRANNs, in the right side of the main window, there is no information about any trained neural network. After performing the training, a graph appears on the right side of the main window, as is showed in Figure 12.

This graph shows the 2000 GRANN trained in order to choose the smoothing factor that will be used in the final GRANN.

Once the RM was selected, the appropriate number of Bonner Spheres was chosen and the experimental values measured with the BSS were entered, the end user should click on the drop-down menu labeled as "Train", shown in Figure 11, which has the possibility to train GRANNs with the following options: single spectra, single doses, single instruments, spectra and doses, spectra and instruments, doses and instruments and spectra, doses and instruments.

At present, because of difficulty of the programming procedure, only the options single spectra, single doses, single instruments and spectra and doses were programmed on the code.

Finally, the GRANNs of the Synapse code are ready to be trained by clicking on the button labeled as "Process".

After pressing this button, as is showed in Figure 12, the GRANN is trained and the neutron spectra, equivalent doses or instrument survey, are calculated, according to the selection made in previous stages.

As mentioned, on the right side of the main window (Figure 12), a graph appears that shows the smoothing factors calculated after training the 2000 GRANNs.

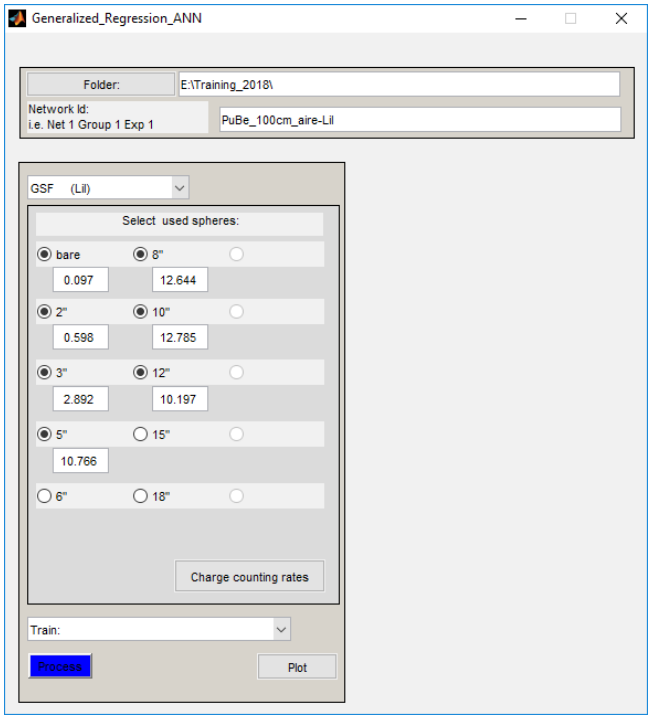

Figure 10. Entering the experimental values measured with BSS

As can be seen, the whole process on the part of the end user, in order to unfold neutron spectrum based on BSS measurements, is to create a working folder, to select the RM of the desired neutron detector, to enter the experimental measured rate counts and to select the desired GRANN training.

After the GRANN training is done, the code generates a text file with the information regarded to the training performed.

2.6. Testing and validation of the Synapse code

The final stage of this research work was to apply the designed Synapse neutron spectrum unfolding code, in real experimental environments, with the aim of testing and validating the results obtained with the trained GRANN.

In order to validate the results obtained with the Synapse code in experimental environments, the

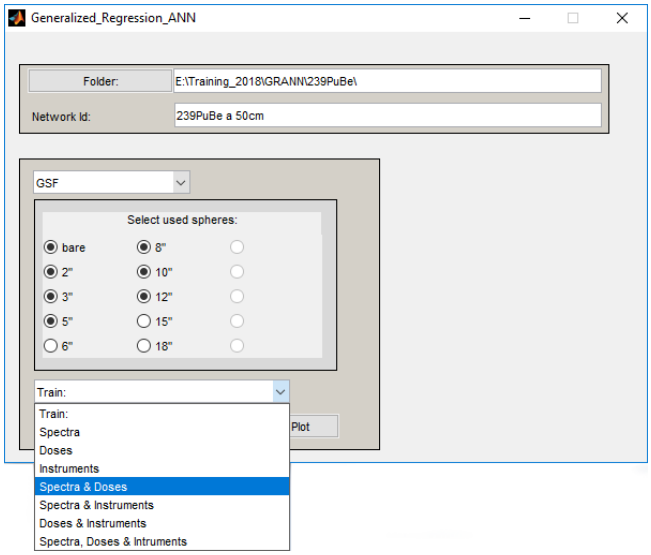

Figure 11. Selection window for training a GRANN with several options

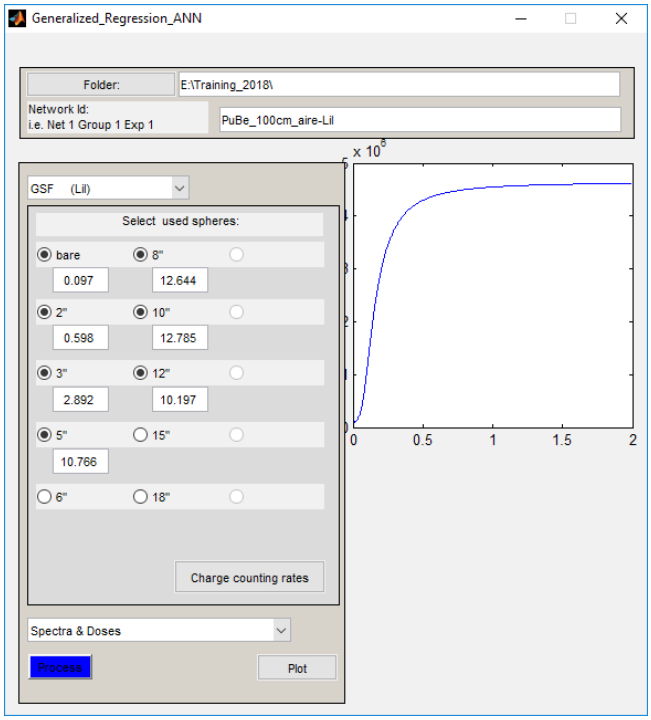

Figure 12. Text boxes for writing the measured experimental rates count

unfolded spectrum of both, a $^{239}PuBe$ and a ^{252}Cf neutron sources were calculated and compared with the reference neutron sources taken from the IAEA compendium.

Following the procedure previously described, the RM of a $^{6}Li(Eu) - GSF$ neutron detector was selected as is showed in Figure 12.

After selecting the RM, the experimental rate counts measured with a BSS with a $^{6}Li(Eu)$ neutron detector, property of the Unidad Académica de Estudios Nucleares from the Universidad Autónoma de Zacatecas, México, were introduced to the Synapse code as is showed in Figure 12.

It is important to mention that this neutron detector has 7 Bonner spheres with 0, 2, 3, 5, 8, 10 and 12 inches of diameter. For this reason, only these Bonner spheres were elected from the RM-GSF.

Finally, the GRANNs were trained, and the neutron spectrum were calculated by the code.

3. Results

Figures 13 and 14 show the neutron spectrum unfolded of a $^{239}PuBe$ and ^{252}Cf neutron sources respectively.

As mentioned, the rates count were measured with the BSS property of the Unidad Académica de Estudios Nucleares, México.

In Figure 13, the $^{239}PuBe$ reference neutron spectrum, taken from the IAEA compendium, is showed on red line. The spectrum unfolded with the Synapse code is showed in blue line.

The results obtained by using the Synapse code, were compared with the $^{239}PuBe$ reference neutron spectrum, taken from the IAEA compendium. As can be seen, the calculated neutron spectrum agrees with the shape and the peak of the maximum energy, when compared with the target one.

Figure 14, shows the ^{252}Cf reference neutron spectrum, taken from the IAEA compendium on red line, compared with the neutron spectrum, calculated by the Synapse code, showed in blue line.

As can be seen, the neutron spectrum unfolded with the Synapse code also agrees with the shape and the peak of the maximum energy of the reference neutron spectrum.

This demonstrates that the Synapse code, solves with high efficiency and generalization capability the neutron spectrum unfolding problem, by using AI technology based on GRANNs.

The code can be applied with success for unfolding neutron spectrum in real experimental places.

It is important to mention that, although the Synapse code is an innovative and a highly technological tool, based on complex technology, the code is easy, friendly and intuitive for the end user, if compared with other codes used nowadays.

From the results obtained after unfolding the neutron spectrum of both, a $^{239}PuBe$ and a ^{252}Cf neutron sources, can be seen that the Synapse neutron spectrum unfolding code, based on GRANN technology is a promising and innovative technological alternative for solving the neutron spectrometry and dosimetry problems, in high energy physics, for radiation protection purposes, and that can be applied with success in real experimental places.

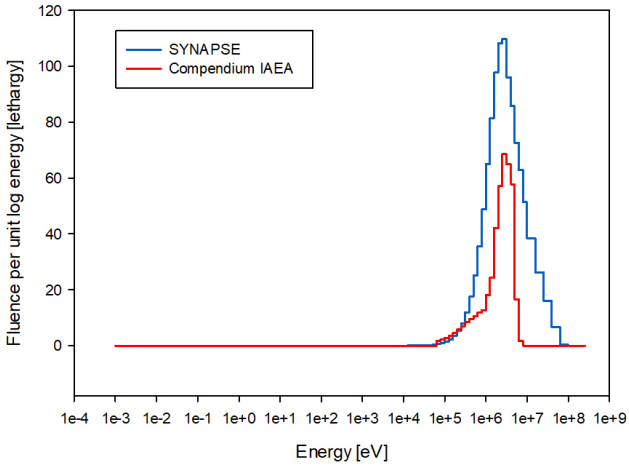

Figure 13. Neutron spectrum unfolding of a $^{239}PuBe$ neutron source

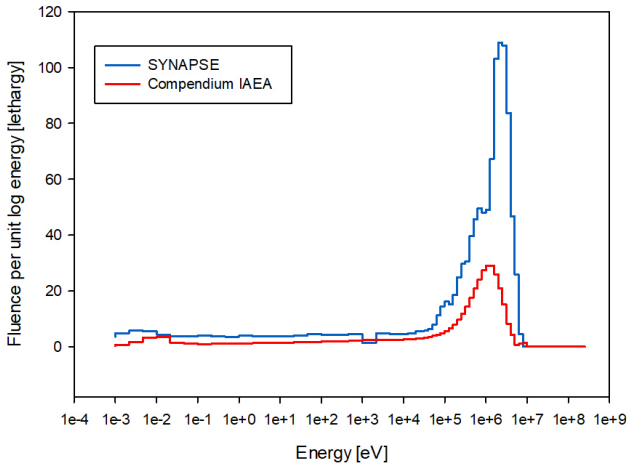

Figure 14. Neutron spectrum unfolding of a ^{252}Cf neutron source

4. Discussion and conclusions

The use of AI technology in the neutron spectrometry and dosimetry research domain, is a new solution proposal. Previous researches indicate that FFBPNN perform well and this kind of network has been the most popular approach used in this research area.

The neutron spectra unfolding and calculation of equivalent doses, starting from the rates count coming from a BSS, using FFBPNN technology, has received much attention in recent years due the successful results observed.

However, the intrinsic difficulties, associated with the optimization of the learning and architectural parameters of the networks, make difficult to apply the theories of IA in the field of neutron spectrometry.

The anterior, has motivated the study and development of alternative methodologies with the aim to explore different types of ANN architectures such as GRANNs, that have the characteristics of being non-parametric, that is, unlike FFBPNN, in GRANN is not required to determine and to optimize the entire set of parameters that FFBPNN requires.

Opposite to FFBPNN, GRANN are very flexible and new information can be added immediately with almost no retraining. The biggest advantage is the fact that the probabilistic approach of GRANN works with one-step-only learning and uses a single common radial basis function kernel bandwidth, σ, that is tuned to achieve an optimal ANN learning.

Given the novelty of the approach, it was observed the need of developing scientific and technological tools for the end user, able to solve with high performance and efficiency the problems associated with neutron spectrometry and dosimetry.

Because the technology based on AI is an emerging research domain, specifically using GRANNs, there is a lack of scientific and technological tools to implement it in work, experimental and laboratory environments, in a flexible and efficient way.

In collaboration agreement with the OMADS company the *Synapse* neutron spectrum unfolding code, based on GRANN technology, was developed.

The code is capable to unfold the neutron spectrum and to calculate 15 different dosimetric quantities using the count rates, coming from a BSS, as the only entrance information.

The code solves the neutron spectrometry and dosimetry problems with high performance and generalization capacity, and the results obtained show that is a promising alternative which can be applied in the solution of these problems.

The Synapse code was fully automated with the aim to unfold neutron spectrum in real experimental, work and research places.

Each time the Synapse code is executed, three general stages are performed. At stage one, in order to calculate an optimized spread value, σ, 2000 GRANN are trained and tested in an average time of 154 seconds approximately.

Once the the optimized spread value is calculated, at stage two and three, the code is ready to perform the unfolding of neutron spectrum measured in experimental environments, using the rates count of a BSS, as entrance data. The training time of the final GRANN is in 0.058 seconds average.

In order to use the Synapse code, which is fully automated, the whole process is to create a working folder, to select the RM of the desired neutron detector, to enter the experimental measured rates count and to select the desired GRANN training. After the GRANN training is done, the code generates a text file with the information regarded to the training performed.

In order to validate the results obtained with the Synapse code in experimental environments, the unfolded spectrum of both, a $^{239}PuBe$ and a ^{252}Cf neutron sources were calculated and compared with the reference neutron sources taken from the IAEA compendium.

The neutron spectrum unfolded with the Synapse code agree with the shape and the peak of the maximum energy of the two reference neutron spectrum.

This demonstrates that the code, solves with high efficiency and generalization capability the neutron spectrum unfolding problem, by using AI technology based on GRANNs, and can be applied with success for unfolding neutron spectrum in real experimental places.

Unlike the classical techniques, based on traditional numerical methods, GRANNs use statistical methods to perform the classification and prediction of the output data in a single iteration, using the information contained in the training databases.

Because of this, it has been observed that this type of technology has the ability to classify spectra and calculate equivalent doses using less information in the entrance data, that is, fewer Bonner spheres.

By reducing the number of BS in experimental places, the time spent for making experimental measurements could be reduced and in consequence, the weight of the whole BSS.

Despite the success of the results obtained with code, some drawbacks were observed. The first one is that the code was developed using the Matlab programming environment.

The main drawback is that it is a private tool, and the source code of AI technology is not available to modify as one wish or need.

Another problem using this environment, is that is not possible to create executable files with the developed ANN technology.

This makes difficult to distribute copies of the code to work-centers or laboratories. In this sense, for executing the Synapse code, the end user must have a Matlab licence which is very expensive.

One more drawback is that the Synapse code cannot be executed using the new technologies of information and communication such as cloud

computing environments, which is a very promising technological alternative.

The synapse code is executed on a standard laptop computer with an i7 processor and 16 GB of RAM. These features are fixed and cannot be modified. Using cloud computing technology to execute the code, the needs of hardware can be changed on the cloud.

Looking for a solution to the mentioned problems, at present, in collaboration agreement wit the OMADS company, work is being done in order to migrate the Synapse code to open-source programming environments, in such a way it can be executed in a cloud computing environment, using new technologies of information and communication tools of the fourth industrial revolution known as Industry 4.0.

Funding

This work was supported by OMADS Co., a research, innovation and technological development enterprise. This work was partially supported by "Fondo Sectorial de Investigación para la Eduación" under contract 241771.

Acknowledgments

Second author thanks the Master scholarship received by CONACYT through the PNPC Master in Engineering and Applied Technology of the Electrical Engineering Unit from the Autonomous University of Zacatecas, México

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