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

Ma. del Rosario Martinez-Blanco [a,b,c,d,e], Gerardo Ornelas-Vargas [a,b,c,d,e], Celina Lizeth Castañeda-Miranda [a,b,c,d], Luis Octavio Solís-Sánchez [a,b,c,d,e], Rodrigo Castañeda-Miranada [a,b,c,d,e], Héctor René Vega-Carrillo [c,d,e,f], Jose M Celaya-Padilla [a,b,d], Idalia Garza-Veloz [a,b,c,d,g], Margarita Martínez-Fierro [a,b,c,d,g], José Manuel Ortiz-Rodríguez [a,b,c,d,e,*]

[a] Laboratorio Nacional en Investigación, Desarrollo Tecnológico e Innovación en Sistemas Embebidos, Diseño Electrónico Avanzado y Microsistemas, Universidad Autónoma de Zacatecas, Av. Ramón López Velarde, 801, Col. Centro, 98000, Zacatecas, Mexico
[b] Centro de Investigación e Innovación Tecnológica Industrial (CIITI), Universidad Autónoma de Zacatecas, Av. Ramón López Velarde, 801, Col. Centro, 98000, Zacatecas, Mexico
[c] Grupo de Investigación Regional Emergente (GIRE), Universidad Autónoma de Zacatecas, Av. Ramón López Velarde, 801, Col. Centro, 98000, Zacatecas, Mexico
[d] Laboratorio de Innovación y Desarrollo Tecnológico en Inteligencia Artificial (LIDTIA), Universidad Autónoma de Zacatecas, Av. Ramón López Velarde, 801, Col. Centro, 98000, Zacatecas, Mexico
[e] Unidad Académica de Ingeniería Eléctrica (UAIE), Universidad Autónoma de Zacatecas, Av. Ramón López Velarde, 801, Col. Centro 98000, Zacatecas, Mexico
[f] Unidad Académica de Estudios Nucleares (UAEN), Universidad Autónoma de Zacatecas, C. Cipres 10, Fracc. La Peñuela, 98068, Zacatecas, Mexico
[g] Laboratorio de Medicina Molecular, Unidad Académica de Medicina Humana y Ciencias de la Salud, Universidad Autónoma de Zacatecas, Campus UAZ siglo XXI, Edificio L1, 3er Piso,Carretera Zacatecas-Guadalajara Km 6 Ejido la Escondida, 98160, Zacatecas, Mexico

HIGHLIGHTS

- Main drawback of neutron spectrometry with BPNN is network topology optimization.
- Compared to BPNN, it's usually much faster to train a (GRNN).
- GRNN are often more accurate than BPNN in the prediction. These characteristics make GRNNs to be of great interest.
- This computational code, automates the pre-processing, training and testing stages.

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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 a 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, i.e. 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, provided that the optimal values of spread has been determined and that the dataset adequately represents the problem space. In addition, GRNN are often more accurate than BPNN in the prediction. These characteristics make GRNNs to be of great interest in the neutron spectrometry domain. This work presents a computational tool based on GRNN capable to solve the neutron spectrometry problem. This

Abbreviations: BPNN, back propagation neural networks; GRNN, generalized regression neural network; BSS, Bonner Spheres System; ANN, Artificial neural networks; PNN, Probabilistic neural networks; RBF, Radial Basis Function; IAEA, International Atomic Energy Agency; MSE, mean square error

* Corresponding author at: Laboratorio de Innovación y Desarrollo Tecnológico en Inteligencia Artificial (LIDTIA), Universidad Autónoma de Zacatecas, Av. Ramón López Velarde, 801, Col. Centro, 98000 Zacatecas, Mexico.
E-mail addresses: mrosariomb@yahoo.com.mx (Ma. del Rosario Martinez-Blanco), ornelashlls@gmail.com (G. Ornelas-Vargas), celina.castaneda@utlook.com (C.L. Castañeda-Miranda), l_solis@ymail.com (L.O. Solís-Sánchez), rcastm@gmail.com (R. Castañeda-Miranada), fermineutron@yahoo.com (H.R. Vega-Carrillo), jose.cpadilla@gmail.com (J. Celaya-Padilla), idgarve@gmail.com (I. Garza-Veloz), margaritamf@uaz.edu.mx (M. Martínez-Fierro), morvymm@yahoo.com.mx (J.M. Ortiz-Rodríguez).

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computational code, automates the pre-processing, training and testing stages using a k-fold cross validation of 3 folds, 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.

1. Introduction

Spectrometry and dosimetry of neutron radiation is one of the most complicated tasks in radiation protection (Kardan et al., 2004a, 2004b). The monitoring of radiation exposure of neutron fields is mainly done with passive detection systems, among those systems, track detectors, film dosimeters i.e. albedo dosimeters are the most common type detector (Fehrenbancher et al., 1999). These detector use foil filters to detetect said neutron fields, nevertheless, 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), is also utilized as multi-element system where each element has a particular response to neutrons (Bonner, 1961; Alevra et al., 1992; Awschalom and Sanna, 1985). Usually these dosimeters have better detection efficiency in a wide energy range, allowing a better dose assessment (Fehrenbancher et al., 1999). The detection is achieved using the integral counts obtained by the active detector, said counts are weighted by factors that belong to each element (Alberts et al., 1997), The integral counts can also be used to unfold the neutron spectrum that is multiplied by neutron fluence-to-dose conversion coefficients. With the neutron spectrum information, different dose quantities can be estimated i.e. Hp(10), H*(10) (International Commission on Radiation Units and Measurements, 2001).

Nevertheless, BSS have some drawbacks, the weight computation is a time consuming procedure, low resolution spectrum and the necessity of an unfolding procedure. 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 have been proposed such as Monte Carlo (Lindemann and Zech, 1995), regularization (Routti and Sandberg, 2001), parameterization, iterative methods (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 and Iñiguez, 2002; García-Domínguez et al., 1999). Artificial neural networks (ANN) methods have been proposed (Feherembacher et al., 1999), Braga et al. proposed the "Stuttgart Neural Network Simulator", using a Back Propagation Neuronal Network (BPNN) to unfold the neutron spectra, the methodology was tested in twenty-two spectra with a reported error of 0.0014, however the methodology required 3×10^{5} iterations to achieve said performance. (Braga and Dias, 2002; Kardan et al., 2003). Recently, Suman et al. proposed a new approach using the Monte Carlo methodology to unfold the spectra and as a fitness function, then using a genetic algorithm several Monte Carlo solutions were gathered and merged into the final solution to unveil the spectra, a set of 37 spectra were used to test the system, a reported a 2.32×10^{-3} Chi-square was obtained, after up to 1000 generations (Suman et al., 2014). However, the application of ANN to unfold actual neutron spectra still has some problems. Significant work is still to be done in order to assets the feasibility of the ANN for the spectrum unfolding problem (Braga and Dias, 2002).

ANN are a large structured system of equations (Haykin, 1999). These systems have many degrees of freedom and are able to adapt to the task they are supposed to do (Galushkin, 2007; Apolloni et al., 2009). Generally, the most common type of ANN, falls into two different types: Back Propagation Neuronal Networks (Graupe, 2007; Mohan et al., 1997; Jain et al., 1996) and probabilistic neural networks (PNN) (Chtioui et al., 1997; Huang and Zhao, 2005; Mao et al., 2000; Huang, 1999). BPNN use equations that are connected using the weight factors (Arbib, 2003; Hammer and Vilmann, 2003). The selection of the weighting factors makes these neural networks so powerful. On the other hand, PNN uses a statistical approach to select the equations within the structure and do not weight these functions (Mao et al., 2000; Huang, 1999; Specht, 1998).

Previous research of ANN in neutron spectrum unfolding indicate that BPNN perform well (Braga and Diaz, 2002; Kardan et al., 2004a, 2004b; Fehrenbacher et al., 1999; Hernandez-Davila et al., 2005; Vega-Carrillo et al., 2009). However, BPNN have serious drawbacks in neutron spectrometry; the proper determination of the network architecture, the long training periods, another drawback is the lack of available neutron spectra data to train and test the networks, said BPNN networks usually require huge data to train (Ortiz-Rodríguez et al., 2013). Even that Generalized Regression Neural Network (GRNN) and BPNN are complementary versions of the same ANN architecture, GRNN is usually much faster to train (Chtioui et al., 1997; Mao et al., 2000).

The GRNN may converge even with a fraction of the training samples as a BPNN typically needs (Mao et al., 2000) (Huang, 1999; Specht, 1998). Therefore, the use of a GRNN is especially advantageous due to the ability to converge 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. GRNN only require the spread constant parameter, 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).

A GRNN is a feed forward neural network based on non-linear regression theory consisting of four layers: the input layer, the pattern layer, the summation layer and the output layer. Said GRNN function as an approximation for complex tasks such as system modeling and prediction. The neurons in the first three layers are fully connected, each output neuron of said layer is connected only to some processing units in the summation layer, a schematic ot a GRNN is shown in Fig. 1.

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

The function of the pattern layers of the GRNN is a Radial Basis Function (RBF) (Specht, 1998; Specht and Shapiro, 1991), typically a Gaussian kernel function, as can be seen in Fig. 2, the activation of pattern units characterizes the distance of the center of a RBF to produce; localized, bounded, and rapidly symmetric activations, those activations rapidly decrease with the distance from the