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COMPARING DIFFERENTE FEED-FORWARD PERCEPTRON ARCHITECTURES IN RADIOACTIVE PARTICLE TRACKING TECHNIQUE

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Abstract.*Nuclear techniques based on attenuation of gamma radiation are widley used in the industry to calculate volume fractions, to predict fluid density and track radioactive particle to evaluate industrial units. This work presents a method based on the principles of the radioactive particle tracking (RPT) technique where counts obtained by an array of detectors properly positioned around the unit will be correlated to predict the instantaneous positions occupied by the radioactive particle by means of an appropriate mathematical search location algorithm. Detection geometry developed employs an array of eight NaI(Tl) scintillator detectors, a* ^{137}Cs *point source with isotropic emission of gamma-rays and a polyvinyl chloride test section filled with air that represents an industrial mixer. The modeling of the detection system is performed by MCNPX code. The aim of this work is to compare multilayer perceptron neural network as a location algorithm in the RPT technique to predict the position of a radioactive particle to evaluate a concrete mixer.*

Keywords:*Radioactive particle tracking, MCNPX code, Artificial neural network, Multilayer perceptron, Industrial mixer.*

1. INTRODUCTION

In the industrial field, nuclear techniques based on attenuation of gamma radiation are used to calculate volume fractions (Salgado et al., 2009), to predict fluid density (Salgado et al., 2016) and track radioactive particle to evaluate industrial units (Dam and Salgado, 2017). Radioactive particle tracking (RPT) is a nuclear non-invasive technique that is used to investigate multiphase systems (Moslemian et al., 1992; Azizi et al., 2017), to visualize profile of fluid velocity fields (Godfroy et al., 1997; Bhusarapu et al., 2005) among others.

RPT consists of monitoring a radioactive particle inside a volume of interest, in this work this volume is represented by an industrial mixer. The radioactive particle should have physical properties similar to those of the investigated flux.The detection system employed depends on some aspects that affect the interaction of the gamma-rays with the detectors materials (Chaouki et al., 1997). The most important aspects are the characteristics of the radioactive particle such as gamma-ray energy and activity; the types of gamma-rays interaction with matter (in this work: photoelectric effect and Compton scattering); the solid angle at which the irradiated surface of the detector is subjected, as seen by the particle; the detection efficiency; the photopeak fraction; and the dead-time of the acquisition system.

The determination of the coordinates (x, y, z) of the radioactive particle is given by algorithms based on phenomenological or empirical approaches, which consider the relation between the number of photons recorded by each of the detectors and the location of the particle. The counts registered in each detector during a time interval is expressed by Eq.(1) (Tsoulfanidis, 1983).

$$C_i = \frac{T\nu A\phi\varepsilon_i(\mathbf{p},t)}{1+T\nu\tau A\phi\varepsilon_i(\mathbf{p},t)}, i = 1, \dots, n \tag{1}$$

Where T is the dwell time, τ is the dead-time of the detectors, A is the source activity, ν is the number of photons emitted by disintegration, ϕ is thephotopeak-to-total ratio and ε_i $(\boldsymbol{p},t)$ is the efficiency of ith detector with respect to a position $\boldsymbol{p}$ in a time t. Besides the distance to the particle, the number of photons recorded depends on the attenuation properties of the materials disposed between the particle and the detector, and on the properties of the detector (Chaouki et al., 1997).

Many reconstruction algorithms have been developed, such as a weighted regression scheme (Devanathan et al., 1990), a modified weighted regression scheme (Luo et al., 2003), the cross correlation technique (Bhusarapu et al., 2005); the Monte Carlo approach (Blet et al., 2000; Doucet et al., 2008; Larachi et al., 1994; Roy et al., 2002; Mosorov and Abdullah, 2011) and feedforward artificial neural network (Godfroy et al., 1997).

Artificial neural networks (ANN) (Rumelhart and Mcclelland, 1986; Haykin, 1999) have been used for some decades in different fields of study. With an ANN it is possible to study and reconstruct online flow visualization in multiphase reactors (Godfroy et al., 1997), predict volume fractions in multiphase flows (Salgado et al., 2009; Salgado et al., 2010), identify flow regime (Salgado et al., 2010), prediction of cement elements percentages (Zadeh et al., 2016) and predict density for petroleum and derivates (Salgado et al., 2016).

The detection system is modeled using the Monte Carlo method by means of the MCNPX code (Pelowitz et al., 2005). It consists of an array with eight NaI(Tl) scintillator detectors placed in two plans, a ^{137}Cs (662 keV) point source with isotropic gamma-ray emission and a polyvinyl chloride tube filled with air. The instantaneous position of the radioactive particle is given by an ANN. The aim of this work is to compare multilayer perceptron architectures as reconstruction algorithm in the RPT technique.

2. METHODOLOGY

2.1 Development of the mathematical model

Detection geometry of this work was developed by means of a mathematical model using MCNPX code. The geometry represents a polyvinyl chloride (PVC) tube with 9.5 cm of inner radius, 0.5 cm thickness and 100 cm length. Outside the tube is an array of eight 2"x2" NaI(Tl) detectors (D_1, D_2, …, D_8) positioned with 90° angle in two planes of the tube: P1 (z = 0 cm) and P2 (z = -25 cm). The distance between the detectors and the tube is 20 cm. The PVC tube is filled with air (density = 1.205^{-3} $g.cm^{-1}$). Radioactive particle is a ^{137}Cs (662 keV) point source with isotrpic emission of gamma rays. In Fig. 1 is represented the simulated geometry.

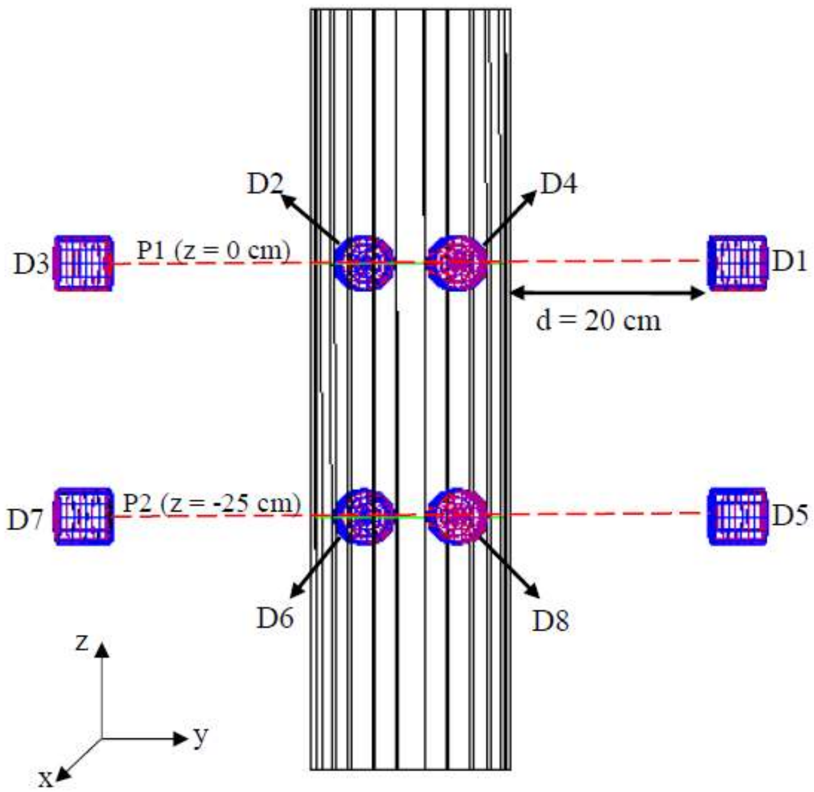

Figure 1 – Detection geometry simulated with MCNPX code.

NaI(Tl) detectors have a reflective layer of magnesium oxide (MgO) and an aluminium layer casing. Cristal dimension is 2"x2" (2" = 5.08 cm), reflective layer and casing have 0.1 cm of front and side thickness. It is important to highlight that the photomultiplier is not simulated in this work because its most contribution is in the region outside the total absorption.

In the MCNPX code output file is the response of the simulation that is the pulse height distribution (PHD) registred in the detector by means of the tally F8. The number of history (NPS) was 1E7 to ensure that the relative error corresponding to the region of photoelectric absorptionis less than 7% in all detectors, although in most cases the error is below 5%. All the detectors were considered the same therefore the photopeak absolut efficiency was considered the same in all detectors.

2.2 Reconstruction algorithm

Radioactive particle position is calculated by means of a reconstruction algorithm that, in this work, is given by a feed-forward multilayer perceptron neural network. Three architectures of these networks were compared in this paper: 2 Hidden Slabs with Different Activation Functions; 3 Hidden Slabs with Different Activation Functions; and 2 Hidden Slabs, Different Activation Functions + Jump Connection.

Feed-forward multilayer perceptron neural network. The feed-forward multilayer perceptron (FFMLP) network architecture was developed by Rumelhart et al. (1986), it is versatile and can be apllied in finances, business, medical, industry and many others applications (Widrow et al., 1994). FFMLP network is formed by k layers of perceptron neurons: the input layer represents the n input signals, the k^{th} layer represents the output layer that has the response of the data set. The amount of neurons in the output layer can be unitary or have multiple outputs, in which case a neuron is associated with each output. The hidden layers are the intermediate layers and its main characteristic is the fact that its neurons have non-linear activation functions.

That said, the three networks that are used in this work are:

a) 2 Hidden Slabs with Different Activation Functions: This is a regular three-layer Backpropagation network with two slabs in the hidden layer. It is possible to use a different activation function for each slab in the hidden layer.

b) 3 Hidden Slabs with Different Activation Functions: It is a Backpropagation network that adds a third slab to the hidden layer. When each slab in the hidden layer has a different activation function, it offers three ways of viewing the data.

c) 2 Hidden Slabs, Different Activation Functions + Jump Connection: This is a regular three-layer Backpropagation network with two slabs in the hidden layer and a jump connection between the input layer and output layer. The output layer receives two different views of the data's features as detected in the hidden slabs plus the original inputs.

Artificial neural network training. To train the artificial neural network (ANN), the data set was distributed approximately in the following proportion: 60% Training, 30% Test, 10% Validation (Zadeh et al., 2016). The radioactive particle was positioned in 108 diferent positions (cases).

ANN training patterns are composed by inputs and outputs. Inputs are the counts registred in the detectors (D_1, D_2, …, D_8, where 8 is the total number of detectors) and the outputs are the positions (x_i, y_j, z_k) of the radioactive particle.

Only the counts registred in the photopeak area were used to train the ANN. PHD was divided in 800 channels and each channel has 10 keV of energy. Photopeak counts were at 670 channel, which represents 662 keV energy of the ^{137}Cs radioisotope. In Fig. 2 is shown the PHD of four detectors of the plane P1 (z = 0 cm) with the photopeak area highlighted in red to the position (0,9,0) of the radioactive particle. It is important to emphasize that the energy resolution was not considered in this work.

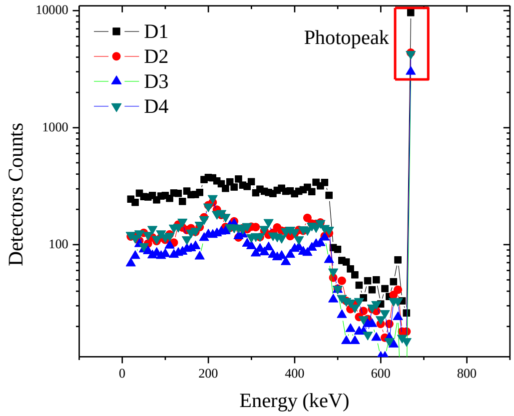

Figure 2 – PHD of four detectors highlighting the photopeak area used to train the ANN.

3. RESULTS AND DISCUSSION

The radioactive particle was positioned in 108 different positions inside the PVC tube that represents an industrial mixer. Then, the counts registred in the eight detectors were used as inputs of the ANN. The results of the three different FFMLP networks are presented: 2 Hidden Slabs with Different Activation Functions (network 1); 3 Hidden Slabs with Different Activation Functions and 2 Hidden Slabs (network 2), Different Activation Functions + Jump Connection (network 3).

Various activation functions (such as Gaussian, Logistic and Tanh) and number of neurons were used to train the networks. Learning rate is 0.001 and the momentum is 0.1 for all networks. The computer used to run the ANN was an Intel Core i5-4690 CPU @ 3.50 GHz and 16.0 GB of RAM.

Relative error, relative mean error (RME) and the correlation coefficient are good parameters to evaluate the ANN. The processed data from Training, Test and Validation sets generated by the three ANN are shown in Table 1, Table 2 and Table 3.

Table 1 – Processed data from the network 1.

Error	x	y	z
≤ 5%	60.18	54.63	59.26
5% - 10%	11.11	12.93	6.48
10% - 20%	12.04	6.48	0.93
20% - 30%	0	1.85	0
> 30%	0	4.63	0
RME (%)	1.56	7.73	-0.23
r^2	0.996	0.990	0.999

In network 1, over 54% of the results for y and z coordinates were below 5% of relative error. Meanwhile, for x coordinate, over 60% were below 5% of relative error. For y coordinate only 4.6% of cases are above 30% of relative error. The training time of this network was 42’68”.

Table 2 – Processed data from the network 2.

Error	x	y	z
≤ 5%	53.70	55.56	63.89
5% - 10%	14.81	13.89	1.85
10% - 20%	12.04	1.85	0.93
20% - 30%	1.85	4.63	0
> 30%	0.93	4.63	0
RME (%)	1.32	6.60	-0.19
r^2	0.992	0.993	0.999

In network 2, over 53% of the results for x and y coordinates were below 5% of relative error. For x coordinate, over 63% were below 5% of relative error. The training time of this network was 1’41”.

Table 3 – Processed data from the network 3.

Error	x	y	z
≤ 5%	62.04	57.41	63.89
5% - 10%	16.67	12.04	1.85
10% - 20%	3.70	2.78	0.93
20% - 30%	0.93	2.78	0
> 30%	0	5.56	0
RME (%)	0.96	7.74	-0.13
r^2	0.998	0.993	0.999

In network 3, over 60% of the results for x and z coordinates were below 5% of relative error. For y coordinate, over 57% were below 5% of relative error and less than 6% of the cases are above 30% of relative error. The training time of this network was 8’43”. For all three networks, the correlation coefficient is 0.99 for the three coordinates (x,y,z) which shows a good convergence of the ANN.

An epoch is a complete pass through the entire set of training patterns of the network, that is a lower epoch may be a parameter for choosing the network. The epoch is 9851606, 369099 and 1899396 for network 1, 2 and 3 respectively.

The Validation set is an important step in the evaluation of the network because there is where the ANN shows its potential to recognize new patterns that were not used in the learning phase. For network 1, the x coordinate presents $r^2 = 0.987$ and $r^2 = 0.983$ for the y coordinate. For network 2, the x coordinate presents $r^2 = 0.975$ and $r^2 = 0.988$ for the y coordinate. For network 3, the x coordinate presents $r^2 = 0.995$ and $r^2 = 0.988$ for the y coordinate. These results of the ANN presents good convergence and it can be used as a reconstruction algorithm of the RPT technique.

4. CONCLUSIONS

This work presents a methodology developed of a radioactive particle tracking (RPT) technique applied in the industry. The reconstruction algorithm is given by a Feed-Forward

Multilayer Perceptron (FFMLP) network. The aim of this paper is to compare three architectures of FFMLP as a reconstruction algorithm of the RPT technique.

The correlation coefficient is 0.99 for all three networks, which indicate the convergence of the ANN. These results points that the ANN is a good algorithm to predict the position the radioactive particle. Comparing all the networks, the results are very similar. However, when analizyng the ANN training time and the epoch, the best results are from the 3 Hidden Slabs with Different Activation Functions (network 2) and these can be good parameters for choosing network 2 instead of the networks 1 and 3.

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