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GAMMA RAY DENSITOMETRY TECHNIQUES FOR MEASURING OF VOLUME FRACTIONS

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ABSTRACT

Knowledge of the volume fraction in a multiphase flow is of key importance in predicting the performance of many systems and processes. It is therefore an important parameter to characterize such flows. In the context of nuclear techniques, the gamma ray densitometry is promising and this is due to its non-invasive characteristics and very reliable results. It is used in several applications for multiphase flows (water-oil-air), which are employed tools such as: computational fluid dynamics, artificial neural networks and statistical methods of radiation transport, such as the Monte Carlo method. Based on the gamma radiation techniques for measurements of volume fractions, the aim of this paper is to present several techniques developed for this purpose.

1. INTRODUCTION

The volume fraction is one of the most important parameters used to characterize multiphase flow and consequently on system performance prediction.

Considered one of the options for the measurement of volume fractions in multiphase flows, the gamma-ray densitometry is a noninvasive technique and has been investigated and developed by many researches and professionals [1]. Some of the other advantages of the gamma-ray attenuation technique are listed below:

1. Relatively inexpensive
2. Relatively simple
3. Generally reliable
4. Usually portable
5. May be used with two-phase and three-phase flows
6. Applicable to a wide range of systems due to availability of different gamma-ray energies suitable for different test section material and test fluids

For the material volume fractions (MVF) prediction [2], artificial intelligence techniques, especially artificial neural network (ANN) [3] have been applied. The main characteristic of ANN is the ability of learning by examples (training set).

The aim of this paper is to present some gamma-ray densitometry techniques for volume fraction measurements. For this, differences in the type of experiment (tube vertically or horizontally, for example) were not considered, so the focus was on technical analysis itself, from the following elements: experimental, artificial intelligence, Monte Carlo N-Particle (MCNP) [4] and dual modality densitometry (DMD). One criterion was that the articles had to have at least two of these elements.

2. GAMMA-RAY DENSITOMETRY TECHNIQUES

Each section will be devoted to an article, comprising the elements, in the scope of the techniques which is the object of this work.

2.1 Experiment and artificial intelligence

The elements discussed in this section are from the article “Void fraction prediction in two-phase flows independent of the liquid phase density changes” from E. Nazemi et al [5].

In this work, all the experiments were carried out in static conditions. The experiments were conducted with pipe vertically. As main pipe, a pyrex-glass pipe was used. For modeling the annular regime, two phase separator pipes (PVC films with thickness of 0.40 mm) with various diameters were used. A 2 mCi Cs-137(6 62 keV) source, collimated in order to make a narrow beam passing through the center of the pipe, and a measurement time of 600 s were chosen because of the static nature of the experiment. Two NaI detectors were used, one as transmission detector and another as the scattering detector. The experimental setup is shown in Figure 1.

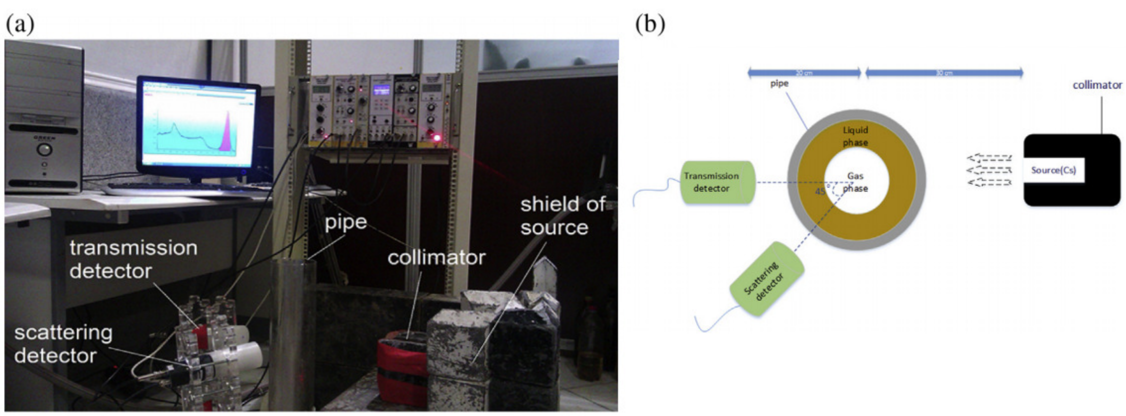

Figure 1: (a) Experimental setup [5]. (b) Schematic view of experimental setup [5].

They were used as liquid phases, at the temperature of 20 ^{o}C, gasoline, kerosene, gasoil, lubricant oil, and water with the densities of 0.735, 0.795, 0.826, 0.852, and 0.980 gcm^{-3}, respectively. The air was used as the material of the gas phase. The void fractions of 0, 20, 30, 40, 50, 60, and 70 percentages, were tested for each liquid phase (totally 35 tests).

In this paper, the authors also use multi-layer perceptron (MLP) networks [6]. The simplified overview of the proposed MLP model is shown in Figure 2, where the inputs are registered counts in transmission and scattering detectors and the output is air percentage independent of the liquid phase density change.

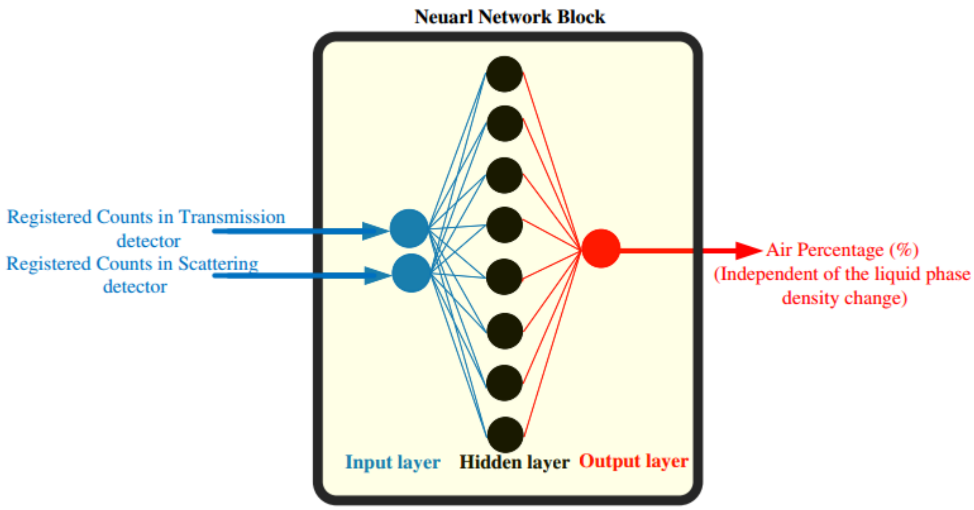

Figure 2: Architecture for the proposed MLP model [5].

The data set required for training the network is achieved using the experimental. The number of samples for training and testing data are 25 (about 72%) and 10 (about 28%) respectively. MATLAB 8.1.0.604 software was used for training the ANN model. Table 1 shows the specification of the suggested ANN model being used in this study.

Table 1: Specification of the proposed ANN model [5]

Neural network	MLP
Number of neurons in the input layer	2
Number of neurons in the first hidden layer	8
Number of neurons in the output layer	1
Number of epochs	225
Activation function	tansig

The Table 2 and the Table 3 show the predicted air percentage by ANN model. It can be seen that the ANN model is close to the experimental result.

Table 2: The data used for training the network and predicted percentage [5]

Density (g/cm^3)	Counts in transmitted detector	Counts in scattering detector	Air percentage	Predicted air percentage
0.98	339200	146567	60	56.8631
0.98	322149	159154	50	49.7742
0.98	290976	184201	30	29.7153
0.98	266872	200261	20	19.9502
0.98	191683	237383	0	0.18095
0.852	364038	131045	70	69.0559
0.852	329262	156929	50	46.1148
0.852	316302	166498	40	37.7872
0.852	300659	176123	30	29.2368
0.852	212708	231156	0	−0.6417
0.826	364760	130824	70	70.4174
0.826	333148	151958	50	52.3969
0.826	318259	164689	40	40.3028
0.826	305599	173082	30	30.7214
0.826	287582	188160	20	20.2779
0.826	220991	225237	0	0.4197
0.795	354267	138826	60	61.1803
0.795	340337	149266	50	50.5215
0.795	323798	162757	40	38.9792
0.795	291953	185501	20	20.1550
0.795	227173	219663	0	0.3549
0.735	357239	133409	60	58.4560
0.735	332939	153640	40	47.9398
0.735	298566	179741	20	20.2767
0.735	237058	208642	0	−0.3123

Table 3: The data used for testing the network and predicted percentage [5]

Density (g/cm^3)	Counts in transmitted detector	Counts in scattering detector	Air percentage	Predicted air percentage
0.98	357357	138767	70	69.8306
0.98	306051	170367	40	38.1361
0.852	342689	142971	60	58.4539
0.826	351272	140760	60	57.7951
0.795	364762	130597	70	69.8743
0.735	367109	128762	70	71.3576
0.735	315381	168194	30	34.3287
0.735	346396	145322	50	55.0055
0.852	279868	190960	20	18.6121
0.795	310504	171719	30	29.7965

2.2 Neural networks based on dual modality densitometry (DMD)

The elements discussed in this section are from the article "Determination of Gas and Water Volume Fraction in Oil Water Gas Pipe Flow Using Neural Networks Based on Dual Modality Densitometry," from C. Jing et al [7].

In this paper, the authors developed models of dual modality densitometry (DMD) that can be used for measuring the gas volume fraction (GVF) and water volume fraction (WVF) in oil water gas pipe flow.

For this, the computer simulation models were defined by using GEANT4 software [8]. A simulation geometry constructed by Geant4 shows in Figure 3.

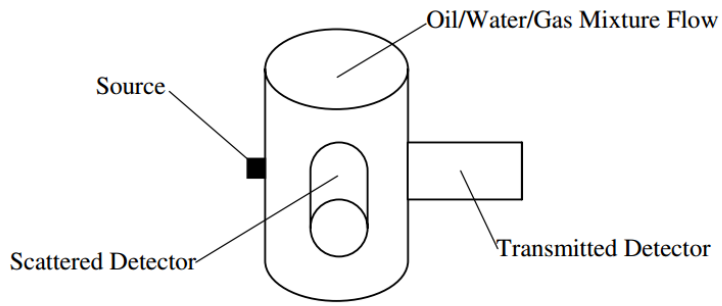

Figure 3: A simplified measurement geometry [7].

40mm x 40mm NaI detectors were used. Oil is cetene (molecular formula $C_{16}H_{34}$) instead of crude oil, gas is methane (molecular formula CH_4) instead of natural gas. Source energy of 59.5keV of radiation were used. The numbers of simulation event are 100,000. The flow in pipe is the mixture of oil, water and gas. The intensities of transmitted radiation and scattered radiation decayed by different mixture matter were recorded by Geant4. The simulation data was used to train and test the radial basis function neural networks.

In this paper radial basis function (RBF) neural network was used, since it can be trained very quickly because the algorithm uses a fixed Gaussian function. A RBF neural network architecture used for predicting GVF and WVF is shown in Figure 4. The input layer consists of registered counts in transmission and scattering detectors. The output layer is the GVF and WVF predicted. The hidden layer nodes are called RBF units.

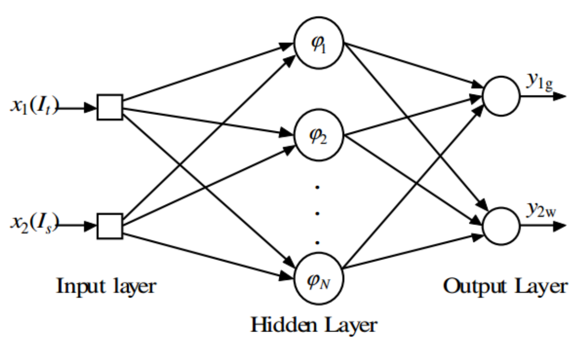

Figure 4: A architecture of a RBF neural network [7].

The Figure 5 is the comparison of the predicting GVF to true GVF and the predicting WVF to true WVF. It can be seen that the predicting GVF fit true GVF well and the predicting WVF has some errors to true WVF. This is because of the linear attenuation coefficient of gas is small, so when GVF changes, the detected transmitted and scattered radiation intensities change too. The Table 4 shows the statistical results in the course of trying to predict GVF and WVF. Although the errors between true WVF and the predicting WVF emerge, the mean square error (MSE) is lower.

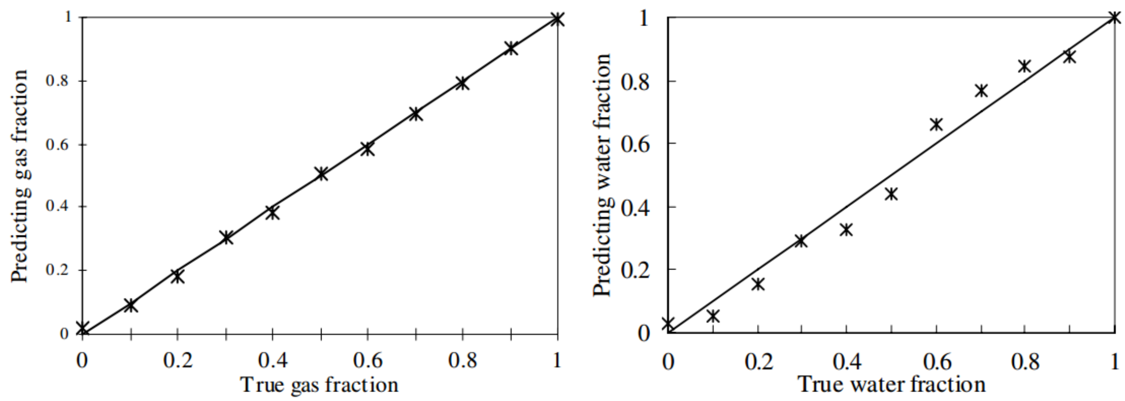

Figure 5 The comparison of the predicting GVF to true GVF and WVF to true WVF [7].

Table 4: The statistical results of predicting GVF and WVF [7]

Performance	WVF	GVF
MSE	0.001850085	0.000130955
Min Abs Error	0.000539245	0.001850492
Max Abs Error	0.071016457	0.019572849

2.3 Artificial intelligence and MCNP

The elements discussed in this section are from the article "Prediction of volume fractions in three-phase flows using nuclear tachnique and artificial neural network," from C. M. Salgado et al [9].

In this work, the Monte Carlo N-Particle eXtended (MCNP-X) [4], has been used. MCNP-X code was used to simulate gamma-rays scattering and absorption from a radiation source in annular, stratified and homogeneous regimes in an oil-water-gas pipeline. By the use of MCNP-X simulations, it was possible to generate a data set for training the ANN.

A fan bean geometry has been used for de source and three different NaI(Tl) detectors, in all simulations. It were used two collimated (angle bean 6.7^{o}) gamma-rays point sources (121 keV – ^{152}Eu; 356 keV – ^{133}Ba). A steel tube ANSI316 composes a test section with 1 mm thickness and 18 cm of internal diameter. The measurement system is shown in Figure 6.

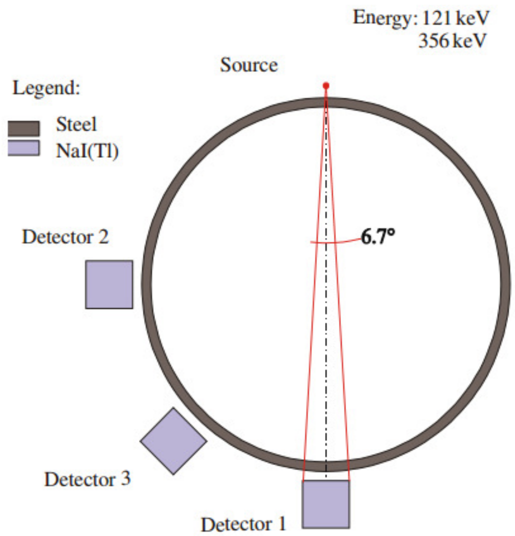

Figure 6: Simulated system [9].

In all studies, salty water was used (4% of NaCl); the gaseous phase was substitute by air and the patrol was assumed as hydrocarbon (C_5H_{10}).

The models for the different flow regimes are shown in Figure 7.

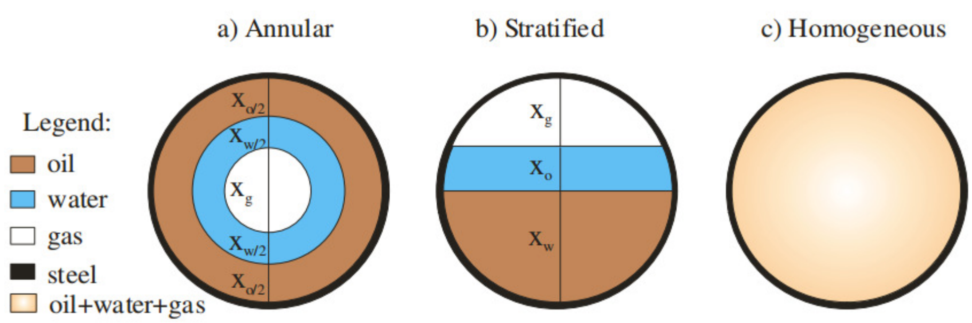

Figure 7: Regime models [9].

For the ANN, 3-layer feed-forward multilayer perceptron [3] has been used. To training the algorithm, it was used the back-propagation algorithm [10]. So, MCNP-X [11] has been used in order to generate the training set, in the training phase.

For different combinations of volume fractions were made 64 simulations, in order to generate the ANN training (52 simulations), test (6 simulations) and production (6 simulations) sets. The test set was used to evaluate the neural network generalization; the production set was used for a final test, after ANN training in order to test the ANN in the working phase.

The prediction for the test set of the annular, stratified and homogeneous regimes are shown in Figure 8, Figure 9 and Figure 10, respectively, indicating that the ANN could adequately predict volume fractions. Note that only two phases are used as ANN output. The third phase is obtained by complement.

The results obtained for the production set on annular, stratified and homogeneous regimes are presented in Table 5, Table 6 and Table 7, respectively.

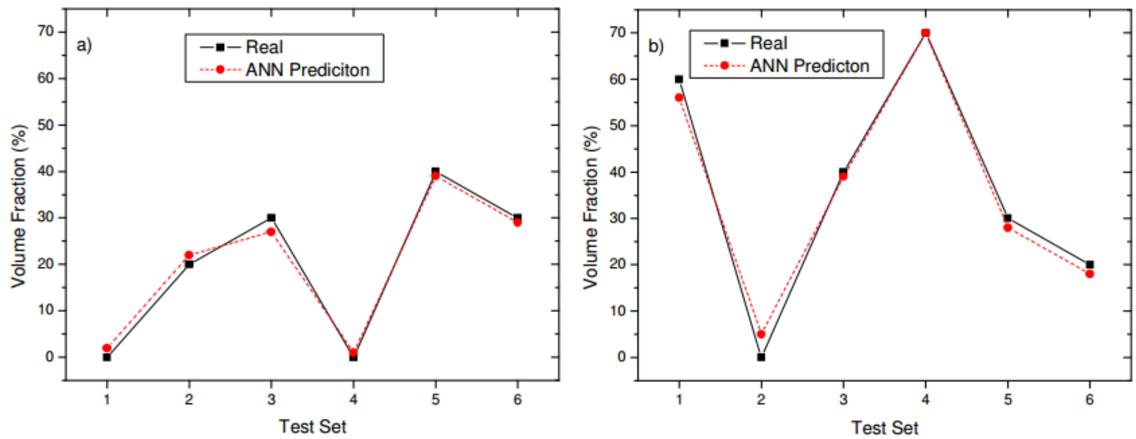

Figure 8: Results obtained for the test set on annular regime [9]: a) air; b) water.

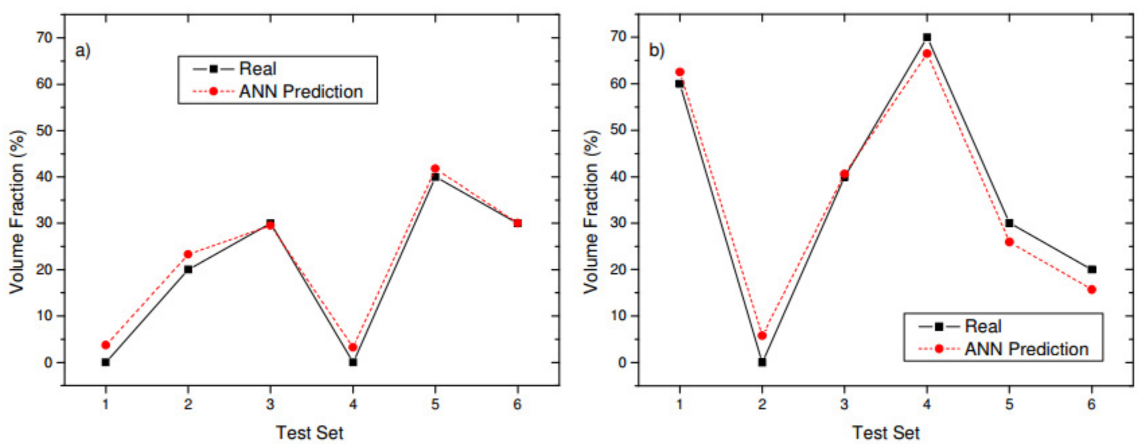

Figure 9: Results obtained for the test set on stratified regime [9]: a) air; b) water.

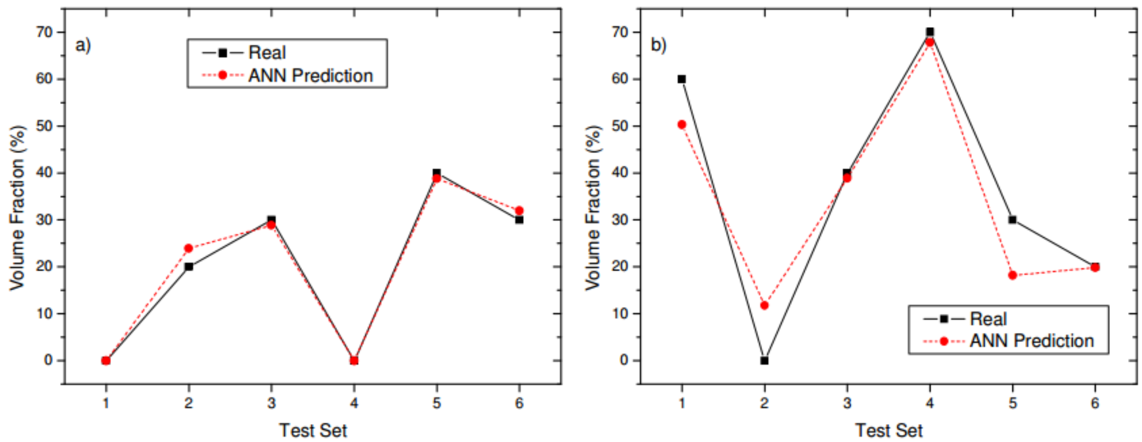

Figure 10: Results obtained for the test set on homogeneous regime [9]: a) air; b) water.

Table 5: ANN prediction for the production set on annular regime [9]

Data Set	Air (%)		Water (%)	
	Real	ANN	Real	ANN
1	70	73.85	0	5.10
2	80	79.44	10	7.41
3	60	63.79	0	3.05
4	68	70.60	16	16.77
5	10	10.46	70	69.72
6	30	30.38	0	5.45

Table 6: ANN prediction for the production set on stratified regime [9]

Data Set	Air (%)		Water (%)	
	Real	ANN	Real	ANN
1	70	67.89	0	4.47
2	80	77.82	10	10.48
3	60	59.19	0	1.18
4	68	62.37	16	15.33
5	10	11.51	70	68.65
6	30	32.96	0	3.70

Table 7: ANN prediction for the production set on homogeneous regime

Data Set	Air (%)		Water (%)	
	Real	ANN	Real	ANN
1	30	32.36	0	16.95
2	70	71.19	0	7.67
3	80	81.47	10	10.18
4	60	63.47	0	14.51
5	68	64.43	16	18.65
6	10	11.68	70	76.83

Note that some larger errors can be observed. The use of a more adequate (more complete) training and test sets, as well as other detection schemes should be investigated, in order to increase the performance, minimizing such errors.

3. CONCLUSIONS

The techniques presented are of great value because they are not invasive. However, we can see some intrinsic characteristics of each technique, i.e. when dealing with complexity, models of DMD stands out and their predicting results show that WVF has some errors.

To improve the results, in second technique presented, a continuous recalibration during the measuring of void fraction, to eliminate the errors caused by the variations of fluid properties, is necessary. Therefore, this is a disadvantage of the technique used.

An advantage on the use of MCNP is that it plays a very important role in data generation for ANN training. The ANN can eliminate problems associated with availability of radioactive sources, detectors and representative test section of each flow regime, in the initial phase of the project.

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