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VOLUME FRACTION PREDICTION IN BIPHASIC FLOW USING NUCLEAR TECHNIQUE AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The volume fraction is one of the most important parameters used to characterize air-liquid two-phase flows. It is a physical value to determine other parameters, such as the phase's densities and to determine the flow rate of each phase. These parameters are important to predict the flow pattern and to determine a mathematical model for the system. To study, for example, heat transfer and pressure drop. This work presents a methodology for volume fractions prediction in water-gas stratified flow regime using the nuclear technique and artificial intelligence. The volume fractions calculate in biphasic flow systems is complex and the analysis by means of analytical equations becomes very difficult. The approach is based on gamma-ray pulse height distributions pattern recognition by means of the artificial neural network. The detection system uses appropriate broad beam geometry, comprised of a (^{137}Cs) energy gamma-ray source and a NaI(Tl) scintillation detector in order measure transmitted beam whose the counts rates are influenced by the phases composition. These distributions are directly used by the network without any parameterization of the measured signal. The ideal and static theoretical models for stratified regime have been developed using MCNP-X code, which was used to provide training, test and validation data for the network. The detector also was modeled with this code and the results were compared to experimental photopeak efficiency measurements of radiation sources. The proposed network could obtain with satisfactory prediction of the volume fraction in water-gas system, demonstrating to be a promising approach for this purpose.

1. INTRODUCTION

Multiphase flow measurement is a very important issue in offshore petroleum industries. One of the procedures normally employed in biphasic flows measuring of gas-liquid is to obtain the volume fraction and the superficial velocity of the fluid. The use of techniques for determination volume fractions with adequate precision is required. Commonly, such techniques are invasive, and involves in high cost associated to installation and maintenance. On the other hand, non-invasive techniques tend to be less accurate. Due to this fact, many investigations on non-invasive techniques are found in literature with the aim of improving accuracy and reducing costs.

By using of gamma-ray sources it is possible to perform these measurements without modifying the operational conditions, allowing accomplishment of the entire monitoring process [1-6]. Therefore, a non-invasive system that can provide material volume fraction predictions is a great contribution.
The artificial neural network (ANN) [7] has been used in order to interpret the pulse height distributions (PHDs) obtained by gamma-ray radiation detector to predict the volume fractions [6][8][9][10][22][23]. ANNs are mathematical models inspired in the human brain, which has the ability of learning by examples. ANNs are able to discover behaviors and

patterns from a finite set of data (called the “training set” or “training patterns”). If an adequate training set is provided, the ANN is able to generalize the knowledge acquired during (learning) process, responding adequately to new situations (not comprised in the training set). The training and test patterns (different volume fractions) were obtained by means of static and ideal mathematical models for stratified regimes.

These models were developed by mathematical simulation using the Monte Carlo N-Particle eXtended (MCNP-X) computer code [11] based on the method of Monte Carlo (MC) [5][6]. The MC technique is a widely used simulation tool for radiation transport, mainly in situations where physical measurements are inconvenient or impracticable. In this work the MCNP-X code, which is specific for simulating electron and photon transport through materials with various geometries, has been used. The model developed in the MCNP-X code considers the main effects of radiation with the matter involved and the PHDs from the NaI(Tl) detector. The energy resolution, dimensions and characteristics of a real detector are also considered; in general, the model presented tends to approach the realistic case.

In this work, the whole gamma-ray PHDs obtained by detector are directly used to feed the ANNs without any parameterization of the signal, the detector is positioned at 180° diametrically opposed to sources of ^{241}Am and ^{137}Cs.

An evaluation of the quality training of ANN was made from 25 patterns not used during the training phase, also generated by mathematical code. In this study, the training patterns (combination of the volume fractions of each material) were distributed uniformly throughout the search space; moreover, the choice of each data set was performed manually. Another important enhancement over the mathematical model used in previous work (Salgado et al, 2009) is the use of a more realistic model of the NaI(Tl) detector, considering the real dimensions and materials compositions, as well as its energy resolution.

Thus, this work provides a new methodology, able to calculate volume fractions of biphasic flows (gas-water) based on interpretation of gamma-ray PHDs by means of the ANN.

2. GENERAL

2.1. Physical Model and Monte Carlo

The Monte Carlo (MC) technique is a widely used simulation tool for radiation transport. In this work, the Monte Carlo N-Particle eXtended (MCNP-X) code, which is specific for simulating electron and photon transport through materials with various geometries, has been used. Gamma-rays simulation in MCNP-X comprises: i) incoherent and coherent scattering; ii) the possibility of fluorescent emission after photoelectric absorption; iii) pair production with local emission of annihilation radiation and bremsstrahlung [11]. This technique is applied in the radiological protection, modeling nuclear installations, shielding of radiation and to calculate efficiency of detectors. In this work, MCNP-X code was used to simulate gamma-rays scattering and absorption from a radiation source in stratified regimes in a water-gas tube. It consists of following many “particles”, one to one, since the source, where its “birth” occurs, throughout its “life”, until its “death” (escape, cut-off energy, absorption, etc.). The probability distributions are randomly showed using transport data to calculate the result in each step of its “life”. In this work MCNP-X code was used in the elaboration of mathematical models. By the use of this code, it was possible to generate of an adequate data set for training the ANN too.

Using transmission radiation from gamma-rays source with a narrow beam it is possible to increase the measurement area on the cross section of the pipe [3][12] and make the volume fraction estimation less dependent on the flow regime. The mathematical model considered scintillator detector as a homogeneous equilateral cylinder 1" x 1" [13-17]. The mathematical modeling considered sodium iodide homogeneous detectors activated with thallium - NaI(Tl) [15]. The experimental validation of mathematical model of this detector was performed in previous works [18-19].

In all simulations a narrow beam geometry has been used for the source and a scintillator NaI(Tl) detector. The detector was located aligned diametrically to the source (180°). Two collimated (angle beam 8.84°) gamma-rays point sources (59.45keV: ^{241}Am and 662 keV: ^{137}Cs) have been used. A PolyVinyl Chloride (PVC) tube composes a test section with 0.3175 cm thickness and 25.0 cm of external diameter was used. The simulated measurement system is shown is Fig. 1.

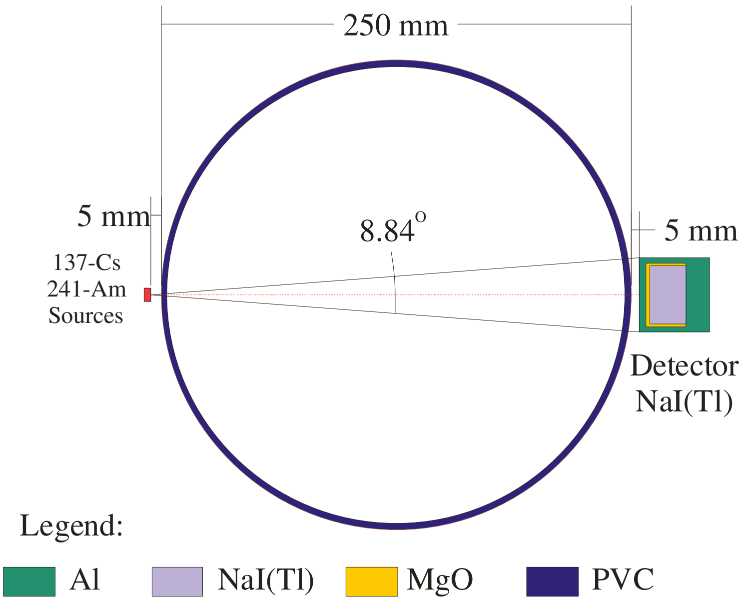

Figure 1: System modeling of MVF calculation.

In our studies, pure water was used (H_2O) with a mass density of 1.0 g.cm^{-3}; the gaseous phase was substituted by air with a mass density of 1.205x10^{-3} [20].

The model of stratified flow regime presented in Fig. 2 had been used to get a data in order to train the ANN. As a result, the values of the thickness (h_w) of water fluid has been varied, in the simulation, getting different combinations of volume fractions. For each one of these combinations relative counts to transmission beams had been gotten.

The simulated data had been used to train an AAN aiming to match them with the values for each volume fraction pre established. The pulse height distribution (PHD) is obtained from the measured transmission beam achieved by detector which is wholly used for network training.

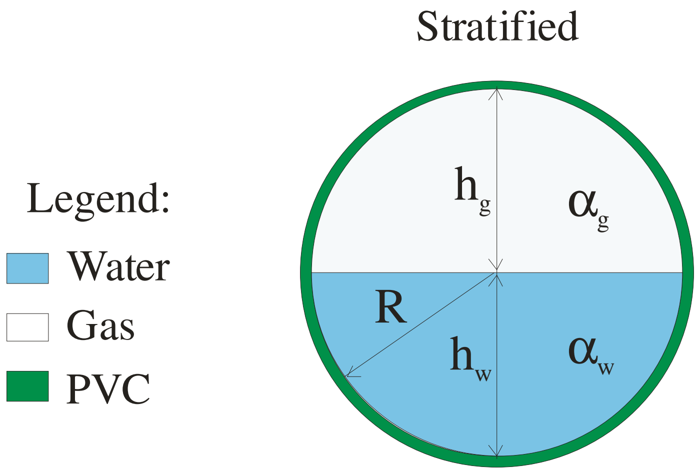

Figure 2: Stratified flow regime.

The gas (α_g) or water (α_w) volume fraction is obtained by taking the ratio of the circular segment area filled with each material (gas or water), and the cross sectional area of the pipe from Equation 1.

$$\alpha_{g,w} = \frac{S_S}{S} = \left[\frac{arcCos}{180^0}\left(\frac{R-h}{R}\right)\right] - \left[\left(\sqrt{h(2R-h)}\right)\times\frac{(R-h))}{\pi R^2}\right] \tag{1}$$

where:
α_m: volume fraction, m: material;
R: internal radius of the pipe;
h_m: circular segment height.

2.2. Artificial Neural Network

ANN is mathematical models inspired in the human brain [7]. The main characteristic of this technique is the ability of learning by examples. ANNs are able to discover behaviors and patterns from a finite set of data (called the "training set" of the ANN). If an adequate training set is provided, the ANN is able to generalize the knowledge acquired during training (learning) process and the ANN may respond adequately to new situations (not comprised in the training set). The two phases of the ANN are:

i) The training phase, in which, by using a learning (training) algorithm, the ANN is supposed to learn features (behavior, patterns, etc) from a previously provided finite set of examples (the training set). This is often an off-line phase and training set may be carefully generated;

ii) The working phase (or the use of the ANN), in which the trained ANN is used to respond to new (real-world) situations. This is an on-line phase and the ANN doesn't need the training set any more.

There are different types of ANN. In this work, a 3-layer feed-forward multilayer perceptron [7] has been used. The learning/training algorithm was the well-known (supervised) back-propagation algorithm [21] and the stop criterion is cross-validation which uses part of the data, so called test set, to decide the breakpoint of the training of the network avoiding, therefore, in such a way, a super training and consequence of loss in the generalization.

In the learning phase, MCNP-X has been used in order to generate the training set. The models for the stratified flow regimes had been used to get a data set in order to feed the ANN. The values of the thickness (h_w) of water material has been varied, in the MCNP-X code, getting diverse combinations of volume fraction. For each one of these combinations, which had been varied of 0% to 100%, relative counts from transmitted beam had been calculated.

2.3. Method Application and Results

The first step in this investigation was the Monte Carlo simulations by means of MCNP-X, in order to generate the training set for the ANN. Data for testing the ANN have also been generated. For illustration, the simulated measurement of transmitted beam, which supplied the PHD are presented in Fig 3. The PHD had been classified in energy range of 20 to 720 keV.

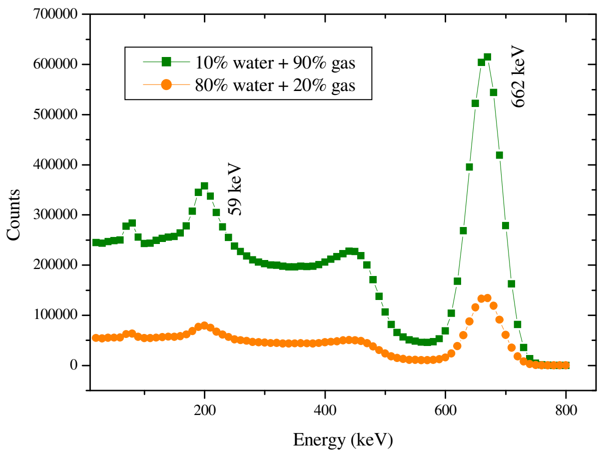

Figure 3: PHD generated by the MCNP-X for transmitted beam.

A set of 26 simulations, for different combinations of volume fractions were made, in order to generate the ANN training (15 simulations), test (6 simulations) and production (5 simulations) sets. The test set was used to evaluate the neural network generalization (for stopping criteria, see [7]). The production set is used for a final test, after ANN training in order to test the ANN in the working phase.

The ANN training patterns are composed by the following data:

i) ANN Inputs:
   Detector: counts from channel 2 to 72 (C_{20}, C_{20}, …, C_{710}), (20 to 710 keV, with steps of 10 keV).

ii) ANN Outputs:
   H_2O volume fraction.

Note that only 1 phase is used as ANN output. The second phase is obtained by complement.

3. RESULTS AND DISCUSSION

3.1. Stratified Regime

Fig. 4 shows the correlation between the volume fractions predicted by the ANN and the real one for all patterns.

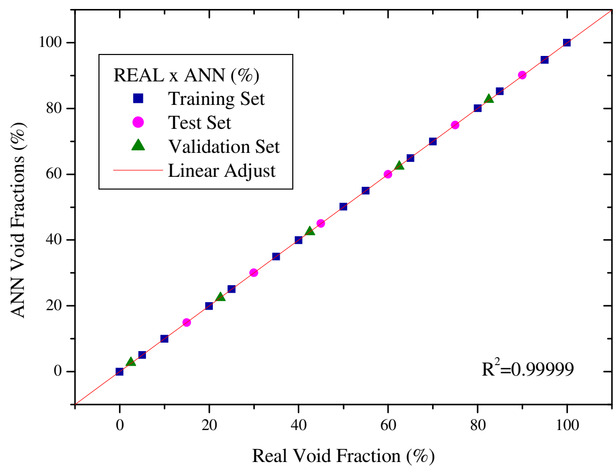

Figure 4: Volume fraction obtained for all the used data.

Linear model was fit to the data of Fig. 4 using a least-squares procedure and linear correlation coefficient of 0.99999 was obtained for water demonstrating an excellent convergence of neural network about all data set. The prediction for the Test Set of the stratified regime is shown in Fig. 5 indicating that the ANN could adequately predict volume fractions.

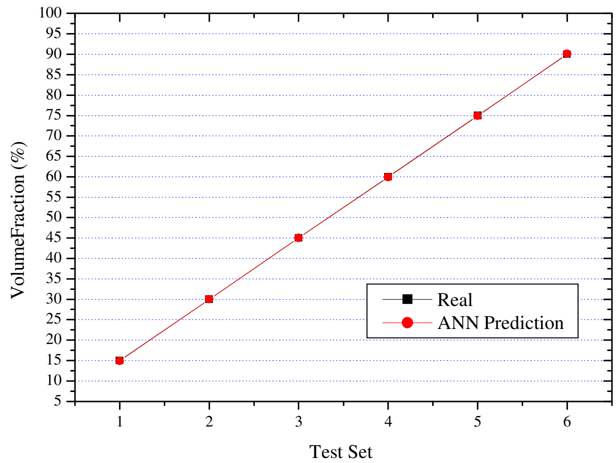

Figure 5: ANN Prediction for the Test Set on annular regime.

In Table 1, results obtained for the production set of outputs ANN on stratified regime are presented.

Table 1: ANN prediction for the production set on stratified regimes

Data Validation	water (α_w) (%)	
	Real	ANN
1	2.5	2.7
2	22.5	22.5
3	42.5	42.5
4	62.5	62.4
5	82.5	82.7

The training parameters that had presented the lesser relative error in the production set are presented in Table 2.

Table 2: Parameters of the network that presented better outputs set

Rate Learning η = 0.001 e Momentum = 0.01					
PARAMETERS	LAYERS				
	Input	Hidden			Out
Activation Function	Linear [-1,1]	Gaussian	tanh	Gaussian Complement	Logistic
Neurons	71	13	13	13	2

The ANN performance of the volume fraction predictions is summarized in Table 3. As can be seen in Table 3, the ANN could predict more than 92% of all patterns with errors less than 5% for water volume fractions. The volume fractions predictions presented very good results, with maximum relative errors below 0.53%.

Table 3: Summary of pattern recognition for the prediction results

Error Relative	Number of Patterns (%)
≤ 5%	92.308
5% - 10%	3.846
10% - 20%	0
20% - 30%	0
> 30%	0

The result in general are good, pointing to the feasibility of using this methodology to adequately correlate measurements obtained from NaI(Tl) detectors to volume fractions in stratified regime with ANN.

4. CONCLUSIONS

For the investigated stratified regime, ANN could satisfactorily correlate the measurements simulated by MCNP-X code with the volume fraction of each material of a biphasic (gas-water) system, indicating that the methodology can be applied with such purpose. The results for all validation tests presented maximum average relative errors of 0.53% for volume fraction demonstrating good agreement between the real and ANN predict values of volume fractions. More than 92% of the all data were predicted with relative error within ±5%. The results are encouraging and indicate that the methodology can be used for measuring the volume fraction or the water level.

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