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DETERMINATION OF VOLUMETRIC FRACTION IN ANNULAR THREE-PHASE FLOW USING ARTIFICIAL NEURAL NETWORKS

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Abstract. *A model based on artificial intelligence centered on an artificial neural network (ANN), capable of predicting the volumetric fraction in a three-phase flow, is developed. The study is based on artificial data from the literature, which were obtained with a non-intrusive gamma-ray technique. A simulation was developed with the mathematical code MCNP-X, based on the Montecarlo method that allows the configuration of two gamma radiation emitting sources, formed by the Americo-241* Am^{241} *and the Celsium isotope-137* Cs^{137} *in conjunction with a NaI scintillation detector (TI), which has high sensitivity to radiation. After performing the gamma-ray simulation, the total energy values emitted by* Am^{241} *and* Cs^{137} *through the pipe with a stratified, annular and homogenous flow pattern inside were taken, which were defined as input data in the adaptative neurofuzzy inference system (ANFIS). These data were defined as input data in the ANFIS, in order to obtain predictive values of the volumetric fraction of the phases. The structuring of the ANN was developed with Matlab software, where the inputs were those used by the authors in ANFIS, developing different configurations for the hyperparameters, in order to generate predictive values of the mentioned volumetric fractions. The statistical parameters defined to determine the best predictive behavior of the ANN models were the relative error percentage (MRE%) and the mean absolute error (MAE). When comparing ANN results with those obtained by the author in ANFIS, a difference in the error percentages below 2% was determined. This demonstrates that ANN can predict results with adequate accuracy.*

Keywords: *artificial neural networks, three-phase flow, volumetric fraction, gamma-ray attenuation technique, numerical simulation*

1. INTRODUCTION

Currently, the energy from the oil and gas industry is one of the most important in the world. Taking into account that the demand for energy is currently on the rise and has a global oil consumption forecast for 2022 of 200 thousand barrels per day (Bpd) to 3.3 million Bpd, according to information given by the International Energy Agency (IEA). This is why there is great interest in developing techniques that allow the measurement of interesting data such as the volumetric fraction for each fluid phase that is transported by a pipe. The use of gamma ray sources, has made it possible to determine the fraction of fluids without the need to modify the operating conditions, thus (Abouelwafa and Kendall 1980) presented a novel method for the time with which to mediate component ratios in multiphase systems using gamma ray attenuation. In this way (Åbro and Johansen 1999) says that the gamma ray attenuation depends on the flow composition, photon energy, pipe diameter and pipe wall thickness, thus, he implemented this technique to determine the void fraction in oil-gas two-phase fluid, using two different energy emission sources, one Am^{241} Fonte and the other Cs^{137} Fonte. Several authors use the MCNP-X code which is specific to simulate electrons, the use of this code allows a coherent dispersion and the possibility of fluorescent emission after photoelectric absorption, from this code it was possible to determine the volume fractions for a multiphase flow (Salgado et al. 2009).

In 2009, Salgado also implemented Artificial Neural Networks (ANN) for the prediction of volumetric fraction of Oil-Water-Gas in annular, homogeneous and stratified flow. In 2014 again Salgado implements gamma ray attenuation compose of one source and two Nal(TI) detectors used to predict volume fractions for multiphase Water-Oil-Gas flows with annular flow regime, stratified and also with variations in water salinity, subsequently he implements ANN for volume fraction of each working fluid (Salgado et al. 2014). Similarly, (G. H. Roshani et al. 2014) says that ANN is a method that allows working with modeling, prediction and classification problems, that is why in his study he uses a multilayer perceptron (MLP) neural network to develop his ANN model where he used the volume fraction data obtained with the simulation in MCNP-4C of the gamma ray attenuation technique.

ANN can currently be defined as a numerical system that is composed of processing elements (G. H. Roshani et al. 2014). In addition, an artificial neural network is made up of many individual units, artificial neurons or processing elements, connected with coefficients (weights) that constitute the neural structure (Agatonovic-Kustrin and Beresford 2000). Considering that the application of artificial intelligence techniques with the structuring of a multilayer perceptron ANN based on machine leaning is really interesting due to the flexibility it provides in the adaptation and restructuring of inputs, hidden layers (HL) and their outputs, together with the activation function (Ruiz-Diaz, Hernández-Cely, and González-Estrada 2021b).

This study is based in the volume fraction data shown by (G. Roshani et al. 2020) which were obtained by simulation in the mathematical code MCBP-X, based on the Montecarlo method that allowed them to configure two gamma radiation emitting sources. The total energy values emitted by sources though the pipeline were taken as input data in the Adaptative Neurofuzzy Inference System (ANFIS), these input data were taken as input data to perform the ANN training and subsequently the validation of the results and the measurement of the mean relative error percentage (MRE%) and the mean absolute error (MAE) obtained with ANN.

2. METODOLOGY

This article was carried out based on information shown in the work of (G. Roshani et al. 2020), from a total of 108 data were taken. Selected 36 for each flow pattern (Stratified, Annular and Homogenous) in a three-phase flow, specifically showing the volume fractions of fluid in each of it is phases. These data were used to develop the predictive model in ANN and to validate with the results shown by the author in his ANFIS model.

2.1 ANN Develop

The ANN model is based on the implementation of a neural network, consisting of two hidden layers with a number of neurons determined for each flow regime. These neural networks have as input parameters the total energy values emitted by the gamma ray sources and as output data the volume fraction of water (α_w) and gas (α_g) measured by the Nal (TI) detector. In this case 108 data were used, of which 36 were taken for each flow regime, with 70% for training, 15% for testing and 15% for evaluating respectively of the amount of data of the respective regime. The Fig. 1 shows the design of the behavior of a network with a backpropagation learning rule.

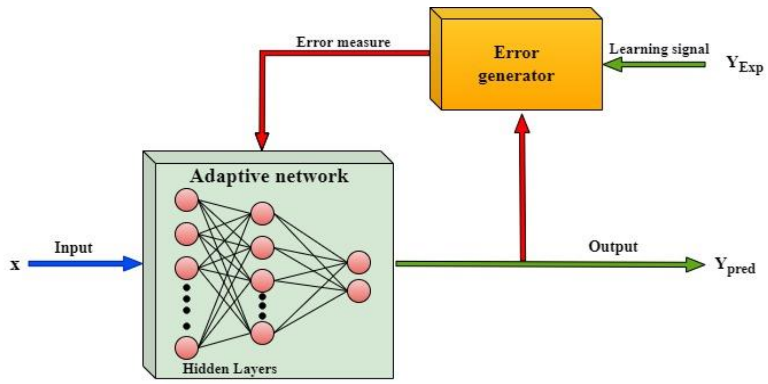

Figure 1. ANN structure developed.

2.2 Volume fraction determination

For the determination of the volume fraction in a three-phase flow, the flow patterns are shown in Fig. 2, which graphically shows the different flow regimes in transverse plane of the pipe. The fractions for the three different flow regimes are defined in precious studies by (G. Roshani et al. 2020) which were determined by simulating a gamma ray system with the mathematical code MCNP-X and subsequently implemented in the Adaptative Neurofuzzy Inference System (ANFIS). The input data defined by the author to implement in ANFIS were the total energy values emitted by each of the Americo-241 (Am^{241}) and Celsium isotope-137 (Cs^{137}) emission sources through the multiphase water-gas-oil flow tube and measured with tow Nal (TI) scintillation detectors each located at different positions, detectors one detected the photon beams emitted directly from the sources and detector two is used to receive the signal from the scattered photon beams. Thus, the output data were measured which were the α_w and α_g taking into account that the total sum of the three volume fractions is 100% and that there is a constraint problem, in ANFIS only two volume fractions are predicted for water-gas and the oil fraction can be found from the constraint relation.

Similarly, in order to compare the prediction results shown by Roshani in ANFIS with those obtained in the present work with an ANN model, 36 data for each of the flow regimes (Stratified, Annular, Homogenous) were taken into consideration to develop the ANN model for each of these regimes. The same input and output considerations were taken into account for the prediction made by the author in ANFIS, but the number of layers and the number of neurons in each of them were caried to achieve a more accurate prediction. In this way, Tab. 1 presents the best architecture of the ANN models proposed to predict the volume fractions in each of the flow regimes under study.

Table 1. Configuration of proposed ANN model for predicting the volume fractions.

ANN Configuration	Regime		
Neural Network	Stratified	Annular	Homogeneous
Inputs/Output	4/2	4/2	4/2
N	36	36	36
First HL composition	13	18	10
second HL composition	16	16	16
Activation function	TanSig		

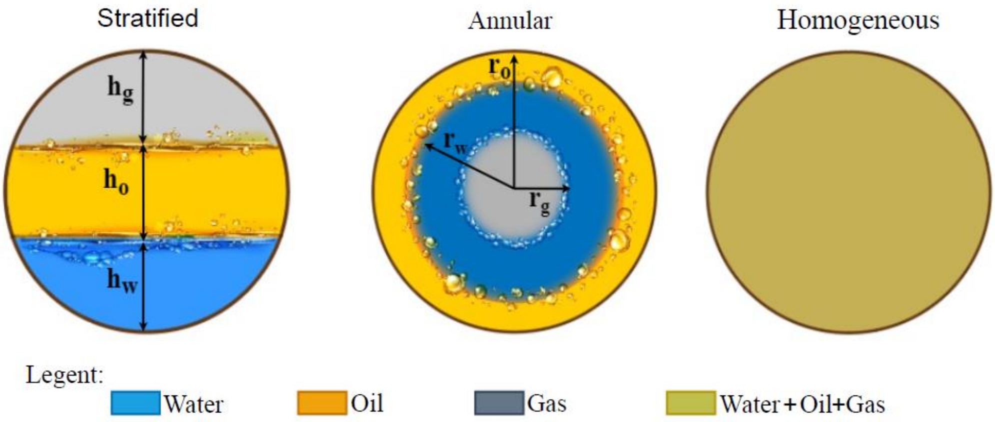

Figure 2. Flow regime in pipe’s transverse plane: a) Stratified, b) Annular and c) Homogeneous.

2.3 Predictive model evaluation

To optimize the selection of the ANN model with the least error, some parameters shown in previous studies were applied by (G. Roshani et al. 2020; Ruiz-Diaz, Gómez-Camperos, and Hernández-Cely 2022; Ruiz-Diaz, Hernández-Cely, and González-Estrada 2021a), these statistical parameters are defined by the mean relative error percentage (MRE%), the mean absolute error (MAE) and the coefficient of determination (R^2). These parameters are shown in Eq. (1), Eq. (2) and Eq. (3).

$$MRE\,(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_{Exp,i} - Y_{Pred,i}}{Y_{Exp,i}}\right| x\,100 \qquad (1)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_{Exp,i} - Y_{Pred,i}\right| \qquad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(Y_{Exp,i} - Y_{Pred,i}\right)^2}{\sum_{i=1}^{N}\left(Y_{Exp,i} - \overline{Y}_{Pred,i}\right)^2} \qquad (3)$$

Where $Y_{Exp,i}$ represent the true experimental value of the output, $Y_{Pred,i}$ is the prediction output value, N is the number of input data in artificial neural network and $\overline{Y}_{Pred,i}$ represent the mean value of the output values.

3. RESULTADOS

The structure of the ANN models has the main objective of determining the volume fractions for each of the fluids that make up the three-phase flow (water-oil-gas), considering that this flow was studied for three flow patterns. These fractions were determined from the numerical values presented by (G. Roshani et al. 2020) and then perform the implementation of an ANFIS model to predict the volume fraction for each fluid in operation. Based in this, the training of the artificial neural networks (ANN) was developed in the Matlab software, from which the results shown in Tab. 2 were obtained, which concretely presents the error percentages of the results obtained in the determination of volume fractions.

Based on the errors shown in Tab. 2 for an ANN model and comparing the errors (MRE% and MAE) of the prediction with the errors shown by the author in his ANFIS model, it was determined that the ANN model for a stratified regime has better error percentages than those shown in the literature. On the other hand, for the annular and homogeneous regimes the author has better error results in his ANFIS model compared to the errors of the ANN model.

Thus, when analyzing the errors of the ANN results for each of the regimes, it is found that, for a Homogeneous regime and the training set, there are better results of MRE% and MAE, since for predicting the water outlet there is an average error of 0.25% and 0.01 respectively, for the gas of 0.14% and 0.07. In addition, for the testing these errors for the water output are 2.14 and 0.47, respectively, and for the gas output are 0.83 and 0.43.

Table 2. Accuracy of ANN models for which 70% of the data was taken for training, 15% for testing and 15% for evaluating.

Pattern		Stratified Regime				Annular Regime				Homogenous Regime			
		α_w		α_g		α_w		α_g		α_w		α_g	
Phase	Value	MRE %	MAE	MRE %	MA E	MRE %	MA E	MRE %	MA E	MRE %	MA E	MRE %	MA E
Training	Max	2,22	0,22	0,62	0,26	0,92	0,27	0,66	0,37	0,99	0,36	0,78	0,15
	Min	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00
	Mean	0,41	0,25	0,19	0,09	0,24	0,08	0,36	0,16	0,25	0,01	0,14	0,07
Testing	Max	10,10	0,10	2,06	0,02	7,50	0,66	2,37	1,66	3,26	0,85	1,44	0,56
	Min	0,82	0,07	0,14	0,46	2,55	1,89	0,87	0,44	1,27	0,12	0,27	0,36
	Mean	2,99	0,03	0,73	0,26	3,13	1,03	1,65	0,85	2,14	0,47	0,83	0,43
Evaluatin g	Max	1,58	3,54	2,22	1,25	4,77	2,21	4,56	2,70	8,25	1,70	4,48	0,46
	Min	0,77	0,56	0,25	0,35	2,86	1,32	2,32	0,96	2,32	0,00	0,02	0,10
	Mean	0,56	1,95	0,62	0,67	3,43	1,65	3,13	1,66	3,99	0,65	1,43	0,20

For the stratified regime, the prediction for the data set used is shown in Fig. 3 it can be seen that ANN could adequately predict the volume fractions, since it has a coefficient of determination of 0.9838 for water and 0.9955 for gas.

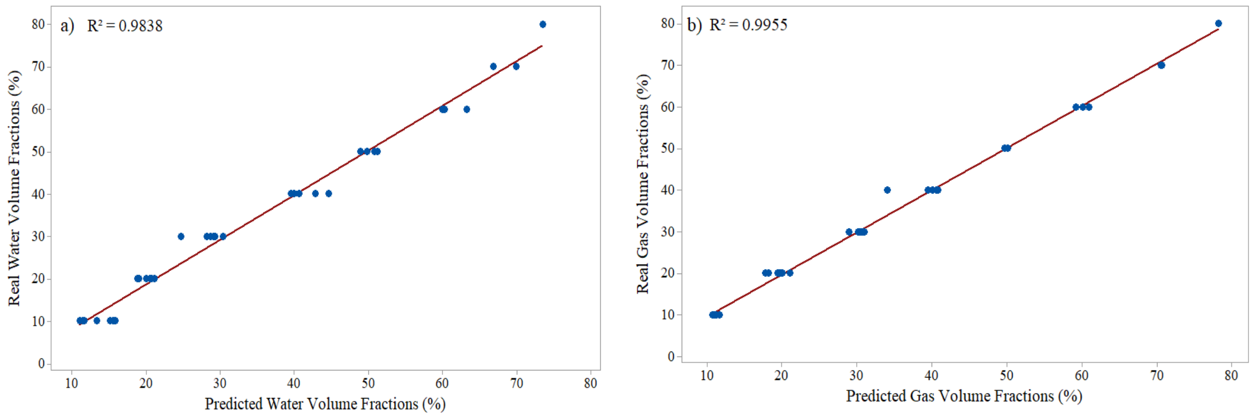

Figure 3. Comparation between ANN and (G. Roshani et al. 2020) models for stratified regime. a) α_w and b) α_g .

Similarly for an annular regime, Fig. 4 shows the prediction for the data set used in the ANN prediction model and shows that the percentage of water and gas predicted is close to real data, obtaining a coefficient of determination of 0.9838 for water and 0.9955 for gas.

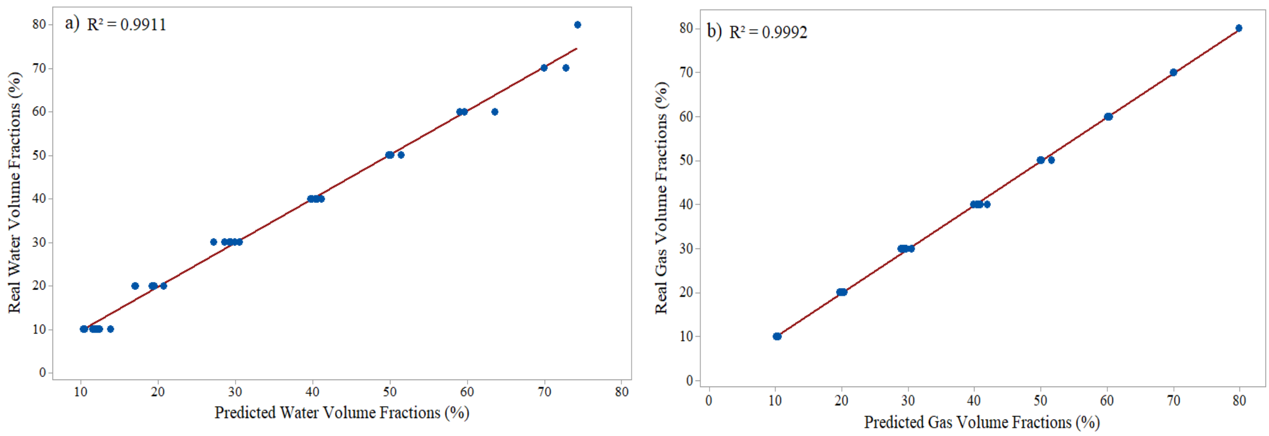

Figure 4. Comparation between ANN and (G. Roshani et al. 2020) models for annular regime a) α_w and b) α_g .

For homogeneous regime, the prediction for the data set used is shown in Fig. 5 where it can be seen that ANN could adequately predict the volume fractions even, since it has a coefficient of determination of 0.9921 for water and 0.9880 for gas.

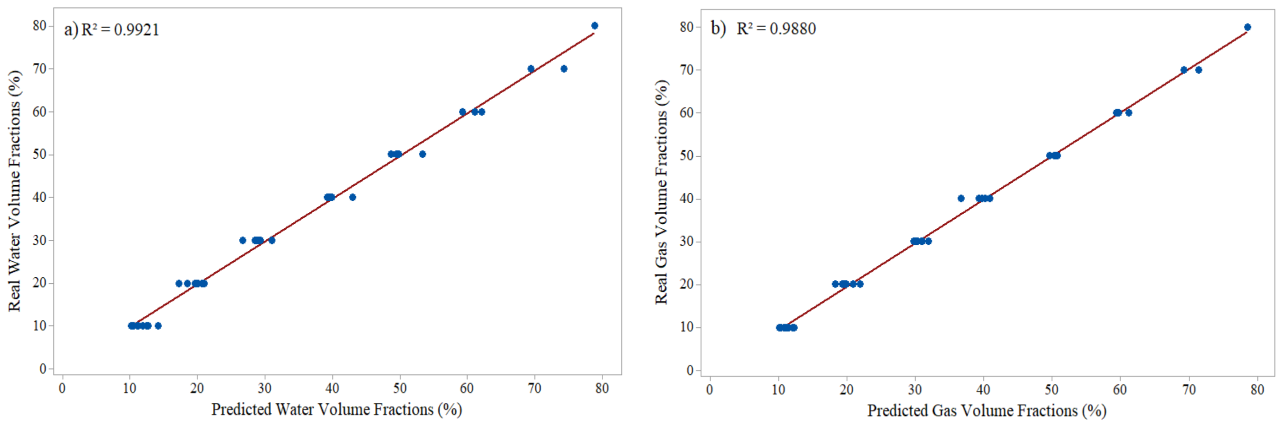

Figure 5. Comparation between ANN and (G. Roshani et al. 2020) models for homogeneous regime a) α_w and b) α_g

Fraction prediction conduct for the data sed is shown in Fig. 6 where it can be seen that for the flow regimes a) stratified, b) annular and c) homogeneous, volume fractions can be predicted with an ANN model. The result shown in Fig. 6 show results that confirm the good performance of the ANN trained in MATLAB with respect to real data taken for training.

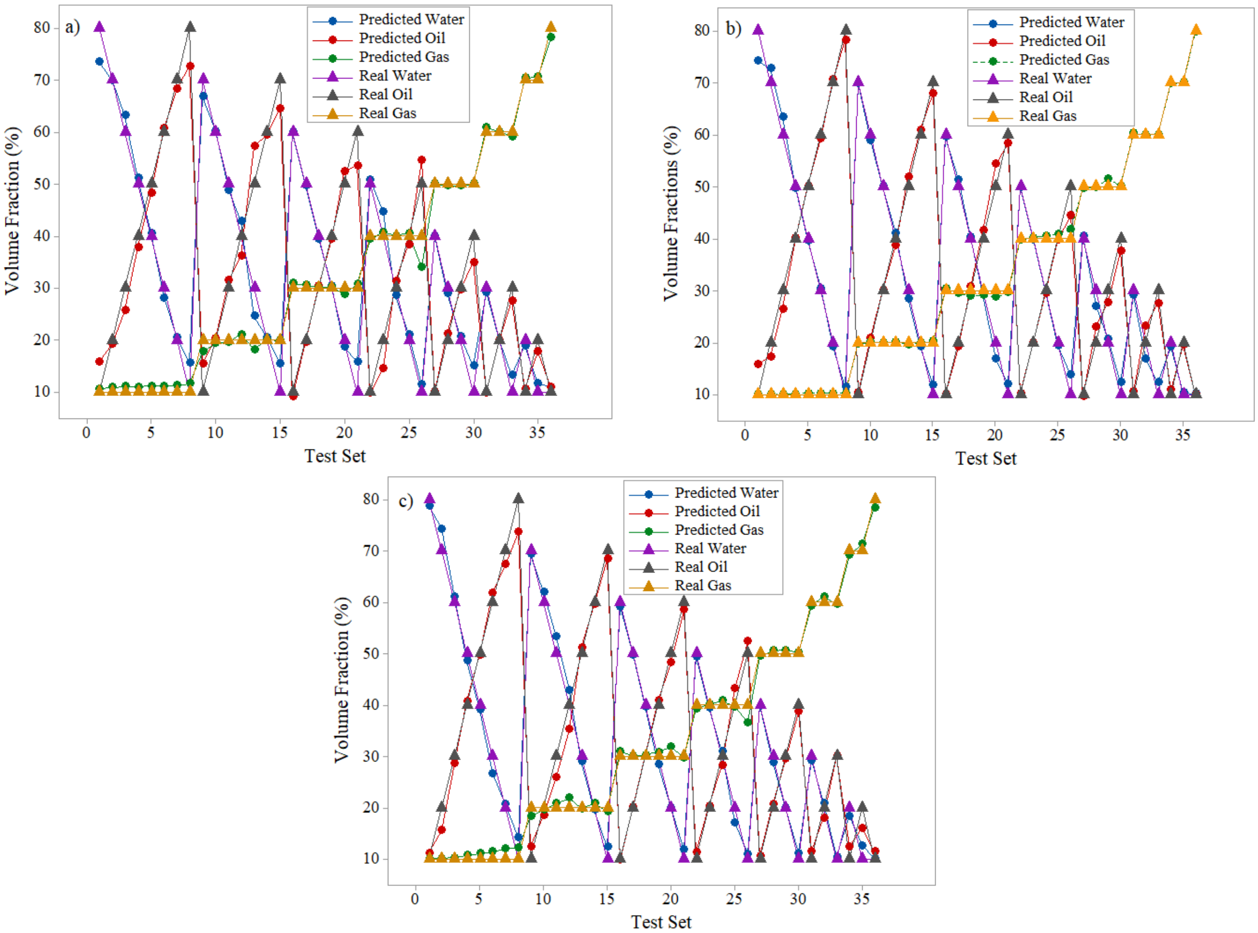

Figure 6. Test validation results on regimes: a) stratified; b) annular; c) homogeneous regime.

4. CONCLUSIONS

In the present work, artificial neural network (ANN) models were developed to obtain predictions of the percentages of water, oil and gas for the stratified, annular and homogeneous flow regimes. the predictive models generated in the structuring were trained with 70% of the data taken from the literature, based on parameters of total energy emitted by the gamma ray sources (input data) and the volumetric fractions (output data) for each of the flow regimes, 15% for Testing and the other 15% for evaluating. For each of these ANN model data, their respective errors (MRE% and MAE) were obtained, from which it can be said that the results obtained show that the proposed models have achieved a good agreement with the data taken for training. These results can be seen in Fig. 3,4 and 5 where a correlation coefficient (R^2) very close to 1 was achieved for the actual volume fraction data versus the predicted volume fractions in ANN.

Fig. 6 shows graphically the actual and predicted volume fractions against the number of simulated data, it can also be seen that the results of the ANN model are optimal for predicting volume fractions. Considering the high computational cost of implementing ANFIS, the results shown by (G. Roshani et al. 2020) are very good, thus, when comparing with the results of the ANN models developed in this work, it can be seen that although ANN has a very low computational cost, the results are very good and precise. Since we obtained an MRE% below 4%, an MAE below 2% and R^2 0.9911 for water and 0.9992 for gas in annular regime.

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