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A high performance gas–liquid two-phase flow meter based on gamma-ray attenuation and scattering

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Abstract The ability to precisely estimate the void fraction of multiphase flow in a pipe is very important in the petroleum industry. In this paper, an approach based on our previous works is proposed for predicting the void fraction independent of flow regime and liquid phase density changes in gas–liquid two-phase flows. Implemented technique is a combination of dual modality densitometry and multi-beam gamma-ray attenuation techniques. The detection system is comprised of a single energy fan beam, two transmission detectors, and one scattering detector. In this work, artificial neural network (ANN) was also implemented to predict the void fraction percentage independent of the flow regime and liquid phase density changes. Registered counts in three detectors and void fraction percentage were utilized as the inputs and output of ANN, respectively. By applying the proposed methodology, the void fraction was estimated with a mean relative error of less than just 1.2480%.

Keywords Gamma-ray · Transmission and scattering · Artificial neural network · Density independent · Flow regime independent · Void fraction

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1 Introduction

Void fraction is a key parameter characterizing multiphase flows in the oil industry. For estimating the performance of a multiphase system operating with more than a single phase, the only way is determining the void fraction. In recent years, different methods such as volumetric, optical, electrical, ultrasonic, and radiation techniques have been introduced to determine void fraction [1]. Among these methods, the gamma radiation attenuation technique has been widely utilized for void fraction measurements. Utilizing the gamma radiation technique has some advantages such as being non intrusive, relatively inexpensive, and portable [1].

In recent years, several investigations have been carried out on measuring the void fraction in multiphase flows. Abro et al. measured the gas volume fraction of a two-phase liquid–gas flow using a multi-beam gamma-ray technique [2]. The system consisted of an Am-241 source and 3 detectors (two detectors for registering transmitted photons and one for registering scattered photons). The void fraction percentage was measured independent of flow regime type. El Abd proposed a methodology based on gamma scattering to measure void fraction in stratified regime of a gas–liquid two-phase flow in pipe using the Compton–Compton scattering peak [3]. He indicated that precision of the proposed method is more than traditional Compton scattering and also transmission method. Faghihi et al. determined void fraction of a two-phase flow in three typical flow regimes of annular, homogenous, and stratified [4]. Polyethylene phantoms in a vertical pipe were implemented in order to model various flow regimes. They registered transmitted and scattered photons in all directions around the pipe. They also utilized MCNP code to simulate the experimental setup and validate the obtained results. Lastly, they presented correlations to estimate the gas volume fraction in two-phase flow. Nazemi et al. measured the void fraction percentage of gas–liquid two-phase flows independent of the flow regime type utilizing a broad beam gamma radiation attenuation technique and ANN [5]. Their system is comprised of one single energy source, a fan beam collimator, and two NaI detectors. A multilayer perceptron neural network with one hidden layer, two inputs, and one output was used to estimate the void fraction. The registered counts in two transmitted detectors and void fraction percentage were considered as the inputs and output of ANN, respectively. They could estimate the void fraction independent of flow regime type with a mean relative error of less than 1.4%. Nazemi et al. proposed a methodology based on a dual modality densitometry technique and ANN for online determination of the void fraction independent of liquid phase density changes in annular regime of two-phase flows [6]. In their system, a narrow single energy beam and two detectors were utilized (one detector for registering scattered photons and the other one for transmitted photons). The experimental registered counts in both detectors and the void fraction percentage were chosen as the inputs and output of ANN, respectively. The proposed ANN model estimated void fraction in the range of 0–70% in a density variations range of 0.735–0.98 g/cm^3. They also used the same technique for estimating the void fraction in stratified regime of gas–liquid flows independent of liquid phase density changes [7]. Using this method, they could estimate the void fraction with root mean square error of less than 1.4%. More researches about radiation-based multiphase flow meters and also some applications of ANN in nuclear engineering problems can be found in references [9–28].

Changes of void fraction, flow regime, and density of liquid phase are typical phenomenon when transporting oil products in pipelines because of fluctuations of temperature, pressure, and other parameters. In this work, an approach based on our previous works [5–8] is proposed for predicting the void fraction independent of flow regime and liquid phase density changes in gas–liquid two-phase flows. Because three parameters including void fraction, flow regime, and liquid density could be changed, at least three types of information are required from the flow in order to predict the void fraction. For this purpose, a combination of dual modality densitometry and multi-beam gamma-ray attenuation techniques was utilized to predict the void fraction. The system is comprised of a single energy fan beam, two transmission detectors, and one scattering detector. Registered counts in three detectors were utilized as the inputs of one ANN, and void fraction was used as the output of the ANN. The procedure of predicting void fraction independent of flow regime and liquid phase density changes in gas–liquid two-phase flows is described completely in the following.

2 Methodology

2.1 Detection system

A combination of dual modality densitometry and a multi-beam gamma-ray attenuation technique was implemented to provide the required data for testing and training the ANN. The experimental setup is shown in Fig. 1, and the experimental equipment and material are shown in Table 1.

Experimental geometry is comprised of two transmission detectors, one scattering detector, and a fan beam source. A collimator with the opening of 36° was utilized in order to make a broad beam. The distance between two transmission detectors and the source was chosen to be 25 cm. The first detector was positioned in direction of 0°, and the second one was positioned in direction of 13°, respectively, to the source.

The output signal of transmission detectors was fed to the preamplifier then to the amplifier (model IAP-3600) and finally to the Multi-Channel Analyzers (model IAP-4110), which was installed on PC for data acquisition and analysis. In both transmission detectors only the transmitted photons (photo peaks) were registered (those within an energy interval of 650–670 keV). The Compton-scattered gamma-rays were counted using the scattering detector (third detector), which was positioned in the angle of 90° with respect to the main pipe. The output signal of the scattering detector was fed to the preamplifier then to the amplifier (model IAP-3600) and finally to the counter (model IAP-2612). It should be noted that all the experiments were conducted in static conditions, and a measurement time of 600 s was used for each test. Three main

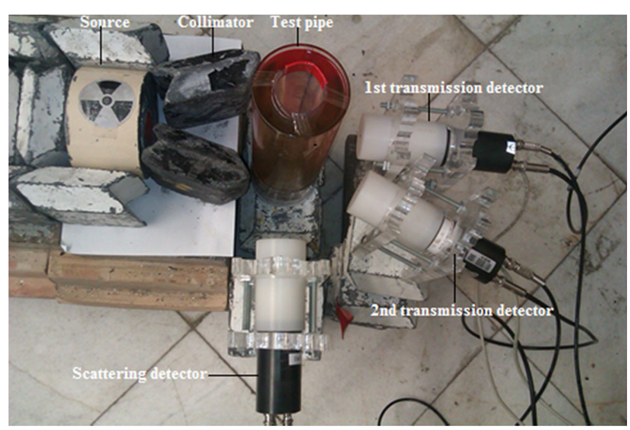

Fig. 1 Experimental setup

Table 1 Experimental equipment and material

Experimental equipment and material	Specification	Quantity/description
Source	Type of radionuclide	^{137}Cs
	Activity	2 mCi
	Energy of emitted gamma-rays (keV)	662
Main pipe	Thickness (mm)	2.5
	Inner diameter (mm)	95
	Material	Pyrex glass
	Density (g/cm^3)	2.35
Liquid phase	Density of gasoline (g/cm^3)	0.735
	Density of kerosene (g/cm^3)	0.795
	Density of gasoil (g/cm^3)	0.826
	Density of lubricant oil (g/cm^3)	0.852
	Density of water (g/cm^3)	0.988
Gas phase	Density of air (g/cm^3)	0.00125
Detector	Type	Sodium Iodide (NaI)
	Size (inch)	1 × 1

flow regimes of stratified, annular, and bubbly with void fractions of 10, 20, 30, 40, 50, 60, and 70% and liquid phase density in the range of 0.735–0.988 g/cm^3 were modeled in the experiments (three different flow regimes × 7 different void fractions × 5 different liquid phase densities = 105 tests). As shown in Table 1, five various liquids have been used instead of one liquid with different densities. Since the high energy gamma-rays (usually with energy more than 100 keV) interact with material through Compton scattering rather than photo-electric, it can be said that density of liquid phase has a dominant effect on the probability of interaction rather than its composition. Besides, since the effective atomic numbers of implemented liquids are close to each other, it could be supposed that all of them are one liquid phase with various densities.

For calculating different void fractions in annular regime, we used Eq. (1) [2]:

$$\alpha_a = \frac{\pi r^2}{\pi R^2} = \frac{r^2}{R^2} \tag{1}$$

where α_a, R, and r are void fraction in annular regime, radius of the pipe, and radius of the gas phase, respectively. These parameters are shown in Fig. 2. Since the radius of the pipe (R) is constant, different void fractions would be calculated just by changing the radius of the gas phase (r).

The void fractions in the range of 10–70%, which was made in the laboratory for annular regime, are shown in Fig. 3 from topside view.

Also for stratified regime, different void fractions could be calculated from Eq. (2) [2]:

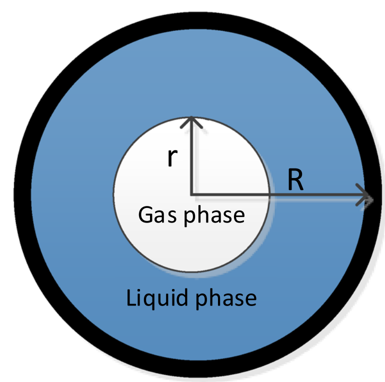

Fig. 2 Defined parameters in annular regime

$$\alpha_s = 1 - \frac{1}{\pi}\left[\arccos\left(\frac{R-L_0}{R}\right) - \frac{1}{2}\sin\left(2\arccos\left(\frac{R-L_0}{R}\right)\right)\right], \tag{2}$$

where α_s, L_0, and R are the void fraction percentage in stratified regime, the level of the liquid in the pipe, and the radius of the pipe, respectively. These parameters are shown in Fig. 4.

Various void fractions made for stratified regime are shown in Fig. 5.

For making various void fractions in static conditions for bubbly regime, an arrangement with 80 cubic plastic straws distributed over the whole pipe cross section was utilized. This was done systematically, so for each of the two straws covered by the measurement volume between the first detector and source, a corresponding number of straws (6 straws) over the total pipe cross section are treated the same way. A schematic cross-sectional view of

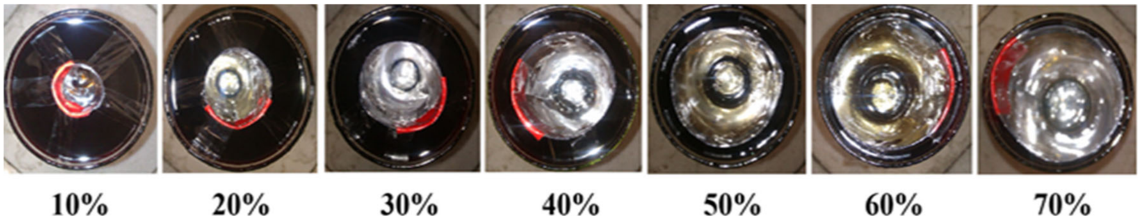

Fig. 3 Void fractions in the range of 10–70% for annular regime

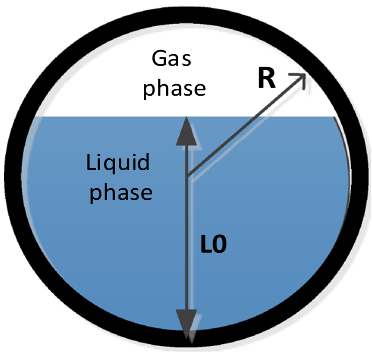

Fig. 4 Defined parameters in stratified regime

the different void fractions in the range of 10–70% is shown in Fig. 6. The white and blue cells are related to the gas phase and liquid phase, respectively. This idea was also utilized by Johnson and Jackson to make the bubbly regime, because it is difficult to model ideal bubbly regime with various void fractions in static conditions [29].

For instance, the registered counts in detectors versus void fractions for gasoline with a density of 0.735 g/cm^3 are shown in Fig. 7. For other four liquid phases, the response of detectors is the same as the gasoline. As it can be seen from these figures, by increasing the void fraction, the registered count in both two transmission detectors would be increased, while it would be decreased in the scattering detector. According to the experimental setup, the first detector is more sensitive than the second one (especially for void fractions in the range from 0 to 40% in the annular flow), since the chance to record transmitted gamma-rays is more. Detector sensitivities depend on the flow regime, and it is the best for the bubbly regime. Additionally, it is directly evident from Fig. 7 that the scattering detector is more sensitive than both detectors in the transmission arrangements for the investigated regimes.

2.2 Artificial neural network

One of the most applicable neural networks is multilayer perceptron (MLP). They include some processing elements called neurons. Neurons are the basic processing elements of neural networks. The synapses of the biological neurons are modeled as weights which are adjusted based on the back-propagation rule in the networks. In this paper, an accurate and precise model based on the MLP neural network in order to predict the void fraction independent of flow regime and liquid phase density changes was presented. The proposed model was shown in Fig. 8. In this figure, the input parameters are the full energy peak in both

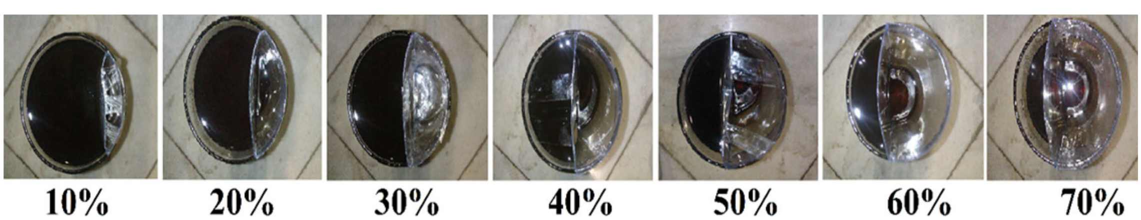

Fig. 5 Void fractions in the range of 10–70% for stratified regime

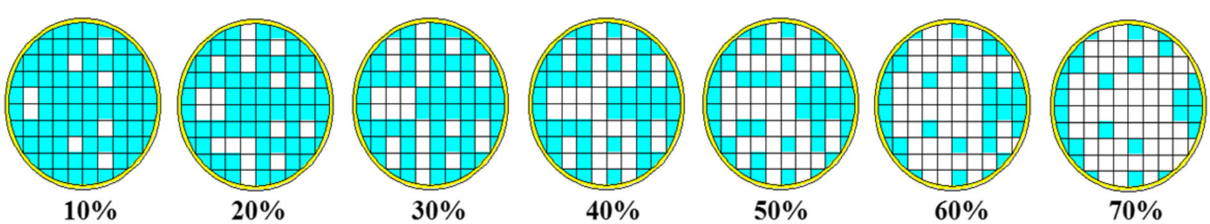

Fig. 6 A schematic cross-sectional view of the made void fractions for bubbly regime in the range of 10–70%

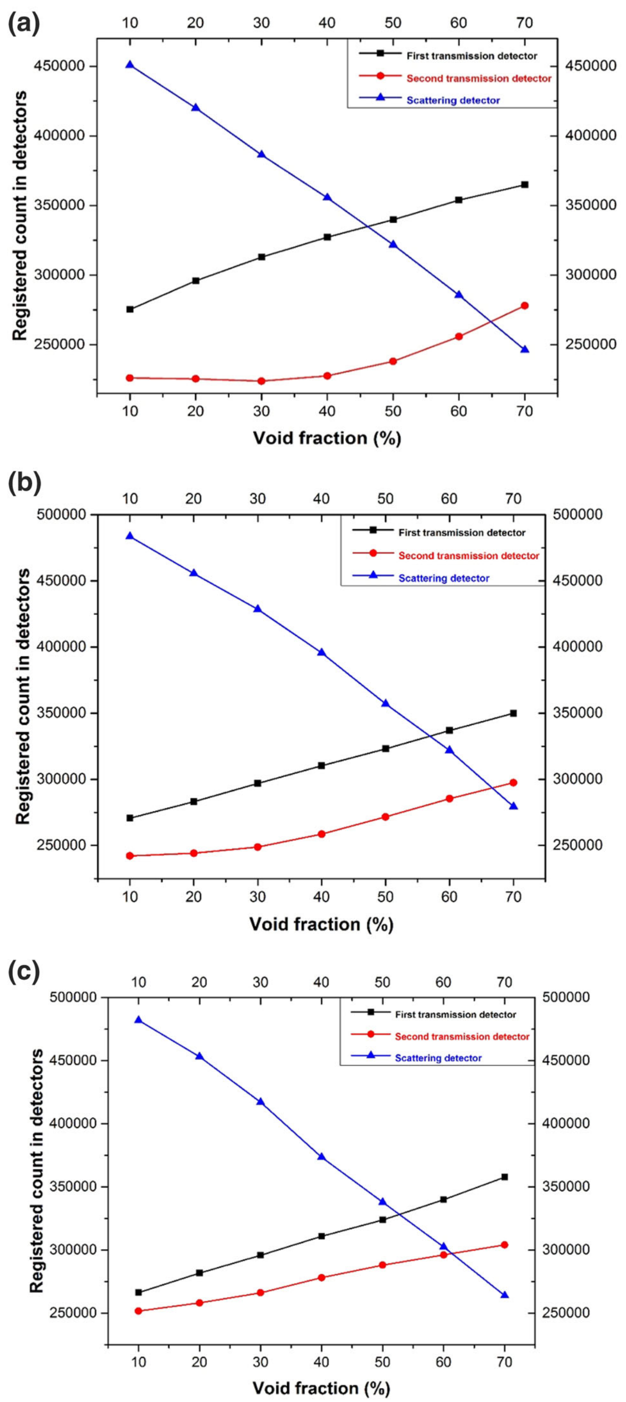

Fig. 7 Registered counts in three detectors for void fractions in the range of 10–70% and liquid phase with density of 0.735 g/cm^3 for flow regimes of: **a** Annular **b** Stratified **c** Bubbly

transmitted detectors and total counts in scattered detector, and the output parameter is the void fraction independent of the flow regime and density changes of liquid phase. The experimental data were implemented for training the ANN model. About 70% (75 data) and 30% (30 data) of experimental data were utilized for training and testing, respectively.

The training process algorithm to obtain the MLP model was shown in Fig. 9. "a" (the maximum acceptable MRE%), "d" (number of repetition in each process), and epochs parameters are set in order to determine the number of epochs and the end of the process conditions. The mean relative error percentage (*MRE%*) is calculated by:

$$MRE\% = 100 \times \frac{1}{N}\sum_{j=1}^{N}\left|\frac{X_j(\text{real}) - X_j(\text{predicted})}{X_j(\text{real})}\right|, \quad (3)$$

where N, "X (real)," and "X (predicted)" are number of data, experimental values, and predicted (using ANN) values, respectively. "u" is set as a counter for the number of neurons in the first hidden layer, and "v" is a frequency counter in each state. Many parameters can be calculated by the network, but the *MRE%*, which is the ending condition of the process, is calculated. As shown in Fig. 9, if $MRE\% \leq a$, then the value of "a" is set to *MRE%*, and the network results are saved. In this case, the number of neurons is increased by one. When the minimum value of *MRE%* is obtained, the condition for the optimized ANN structure of the network is achieved.

3 Results and discussion

The proposed ANN (MLP) model with 3–4–1 structure (i.e., 3, 4, and 1 neurons in the input layer, in the hidden layer, and in the output layer, respectively) has the least MRE%. Table 2 shows the specification of this ANN architecture. Also, in order to evaluate the performance of the ANN model, the predicted results were compared with the experimental results. Figure 10 shows the comparison between obtained results of the proposed ANN model and real data for training and testing sets.

From Fig. 10, it is clear that the predicted void fraction independent of the flow regime and liquid phase density changes by the proposed model are in good agreement with the experimental results, which confirms the application of ANN as a precise and reliable tool for metering two-phase flows. Figure 11a, b, and c shows the obtained void fractions versus liquid density and first considered feature, second considered feature, and third considered feature, respectively. Number of registered counts in the detectors is related to the void fraction, liquid density, and flow regime. If the void fraction increases, the full energy peak of first and second detectors will increase and the total count of scattered detectors will decrease. The liquid density has the similar effect on the registered count. Another important parameter is the flow regime, which can

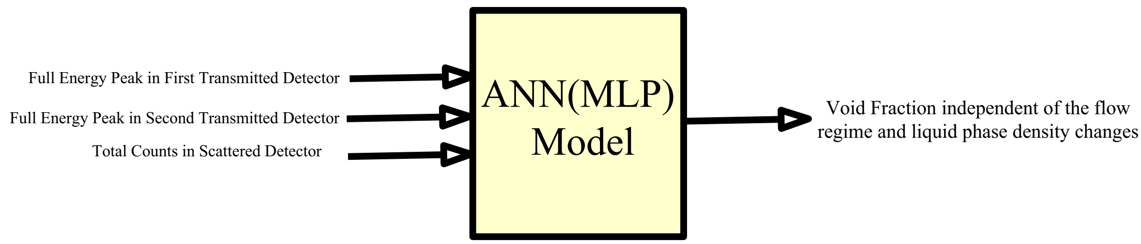

Fig. 8 Proposed computational intelligence model

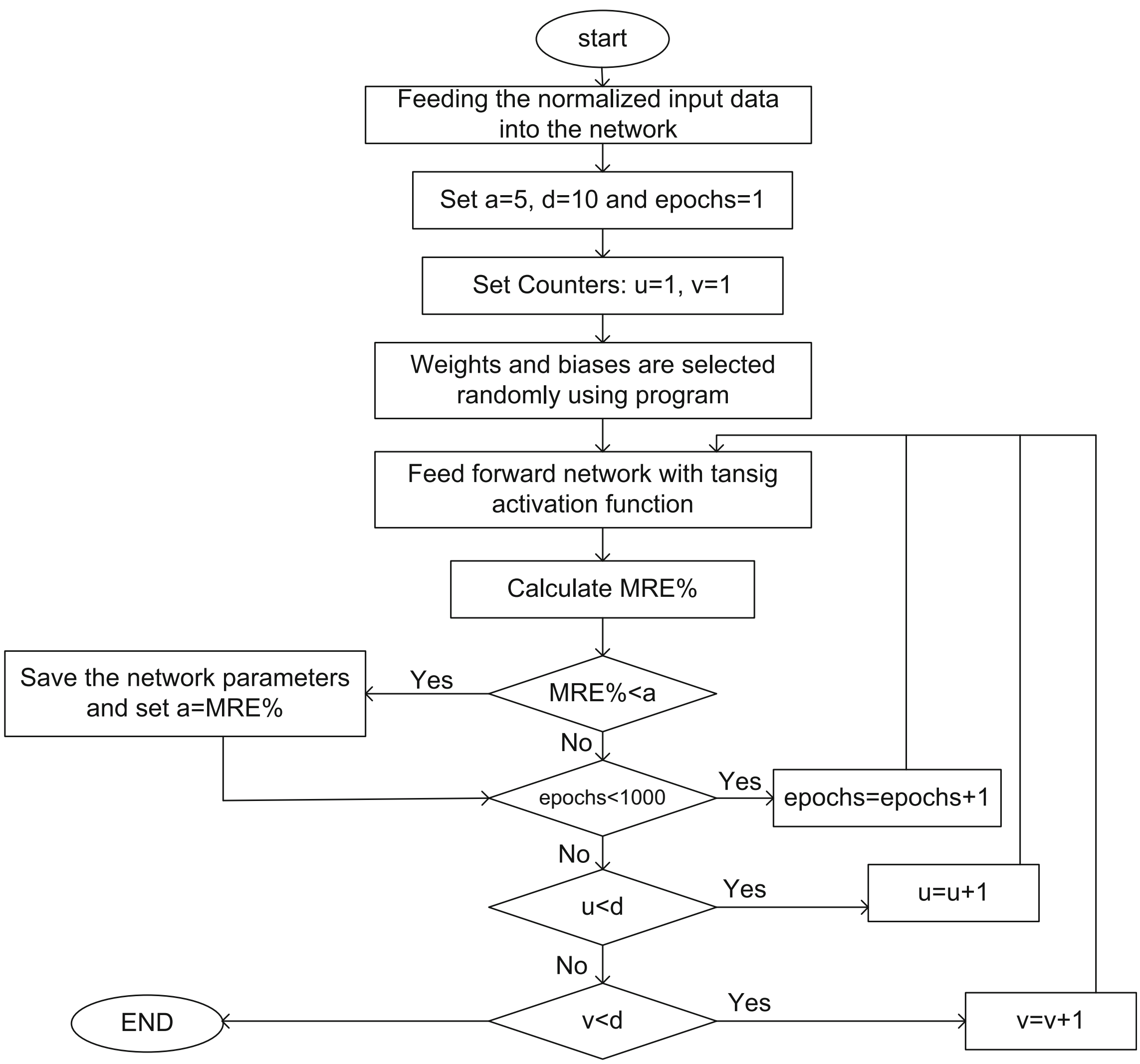

Fig. 9 ANN training process algorithm

affect the measuring system. Therefore, the model is complex, and this fact is the reason of artificial intelligence usage.

The mean absolute error (*MAE*) of the proposed MLP model is calculated by Eq. (4).

$$MAE = \frac{1}{N}\sum_{i=1}^{Z} |X_i(\text{Real}) - X_i(\text{Pred})| \quad (4)$$

In the training set: *MAE* and *MRE%* of void fraction are 2.6197 and 0.2751%, respectively. For the testing set, these errors are 2.1996 and 1.2480%, respectively.

Table 2 Specification of the best proposed ANN model

Neural network	MLP
Number of hidden layer	1
Number of neurons in the input layer	3
Number of neurons in the hidden layer	4
Number of neurons in the output layer	1
Learning rate	0.5
Number of epochs	480
Adaption learning function	Trainlm
Activation function	Tansig

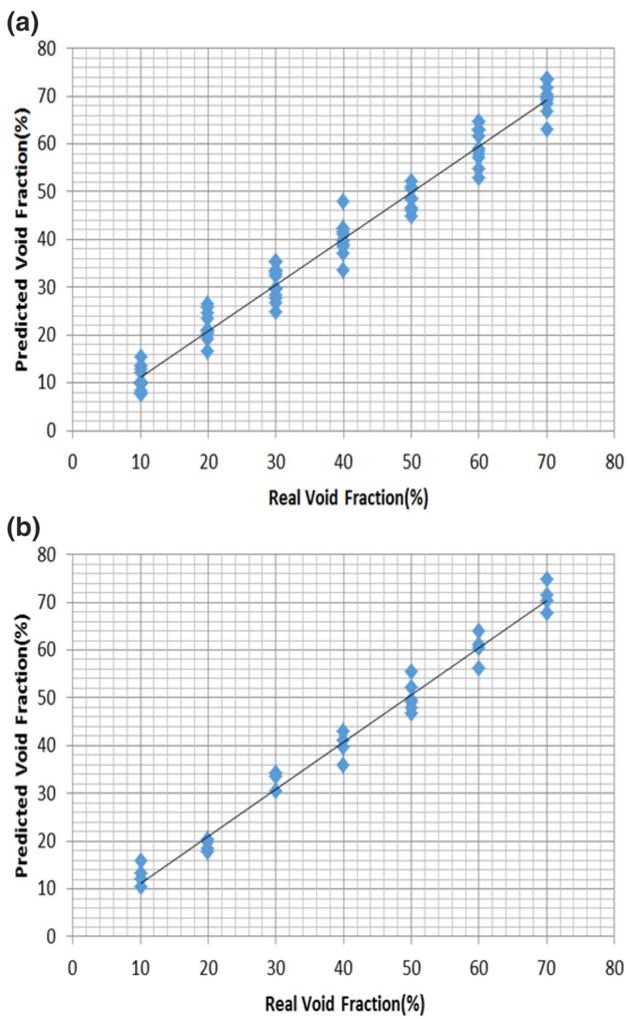

Fig. 10 Comparison of the experimental and predicted results using the proposed ANN model **a** training set **b** testing set

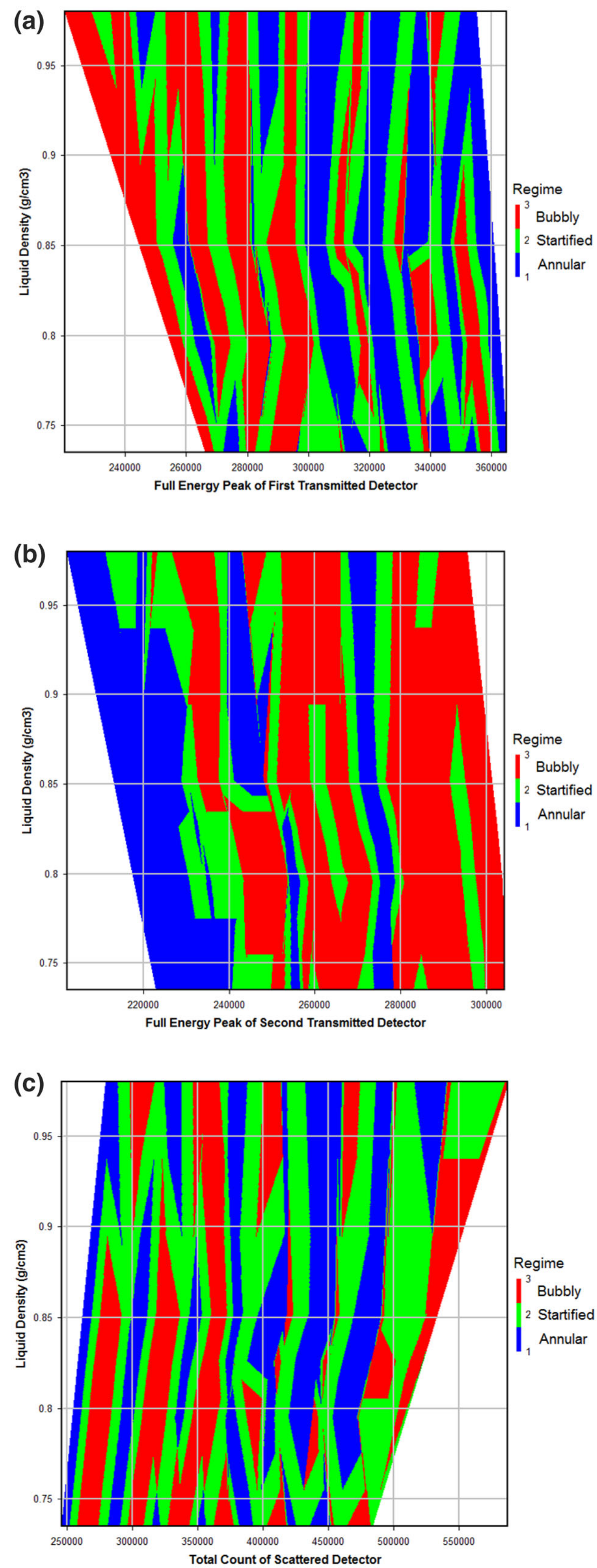

Fig. 11 Flow regime versus liquid density and: **a** first feature **b** second feature **c** third feature

4 Conclusion

In this study, a high-performance metering system using gamma-ray attenuation technique was presented. Three different regimes (annular, stratified, and homogenous) in different liquid densities were considered. The void fraction was measured precisely independent of the flow regime and liquid density changes. The estimated void fraction by the proposed model is in good agreement with the experimental results, which confirms the ability of ANN as a precise and reliable tool for predicting various parameters in two-phase flows. The void fraction was estimated with an *MAE* of less than only 2.6197%.

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