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Estimation of Void Fraction for Homogenous Regime of Two-Phase Flows in Unstable Operational Conditions Using Gamma-Ray and Neural Networks

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Abstract

Almost all the multi-phase flow meters (MPFMs) using gamma-ray attenuation, are calibrated for liquid and gas phases with constant density and pressure. When operational conditions such as temperature and pressure change in pipelines, the radiation-based multi-phase flow meters would measure the flow rate with error. Therefore, performance of MPFMs would be improved by eliminating any dependency on the fluid properties such as density. In this work, a method based on dual modality densitometry combined with Artificial Neural Network (ANN) is proposed in order to estimate the void fraction in homogenous regime of gas-liquid two-phase flows in unstable operational conditions (changeable temperature and pressure) in oil industry. An experimental setup was implemented to generate the optimum required input data for training the network. ANNs were trained on the registered counts of the transmission and scattering detectors in various liquid phase densities and void fractions. Void fractions were predicted by ANNs with mean relative error of less than 0.78% in density variations range of 0.735 up to 0.98 g/cm3.

Keywords: Gamma ray; Artificial neural network; Multi layer perceptron; Void fraction.

1. Introduction

During the last three deca des, development, evaluation, and use of multiphase-flow- measurement (MFM) systems have been a major focus for the oil and gas industry worldwide. Within the oil and gas industries, it is recognized that MFMs have several benefits in applications such as layout of production facilities, well testing, reservoir management, production allocation, and production monitoring [1]. Conventional test separators have many disadvantages such their large space for installing hard-wares, more capital and operating expenses, and requiring much time to monitor each well's performance [2-4].

By determination of volume fraction of each phase coupled with flow velocity, the mass flow rate can be achieved; which is one of the key parameters in the oil industry. In order to determine the gas, oil and water volume fractions, there are some methods like nuclear techniques, electrical impedance, and microwave techniques [5]. Utilizing nuclear techniques such as neutrons and gamma ray because of their ability for measuring volume fractions without modifying the operational conditions and being non-invasive, is so useful [6-7]. Aboulwafa and Kendall were the first that proposed a multi-energy gamma attenuation technique to resolve three-phase mixture component ratios [8]. They examined various static mixture of oil-water-gas in a 0.1 m diameter pipe section using cobalt-57 (122KeV) and barium-133 (365 KeV) radioisotopes and a lithium-drifted germanium based detector. Li et al also analyzed static mixtures of stratified regime in a cubic conduit using americium-241 (59.5 KeV) and cesium-137 (662 KeV) radioisotopes and a sodium iodide detector crystal [9].

Also, It has been shown that Artificial Neural Network (ANN) is an useful tool in nuclear engineering [10-17]. In 2014, Roshani et al. used a dual energy source consists of 241Am (59.5 keV) and 137Cs (662 keV) with just one transmission NaI detector to predict volume fraction in oil-water-gas three-phase flows [12]. By using ANN, they predicted the volume fraction of oil, water and gas phases with Mean Absolute error (MAE%) of less than 1%.

Roshani et al. also proposed a method based on dual modality densitometry using ANN to first identify the flow regime and then predict the void fraction in gas-liquid two-phase flows [11].

Operation of a multi-phase flow meter (MPFMs) using gamma-ray attenuation, depends strongly on the fluid properties. By changing the fluid properties such as density, recalibration is required. Removing any dependency on the fluid properties, would improve the performance of MPFMs. In previous studies, little attention has been paid to the changes of the density of the liquid phase. Changes of both temperature and pressure, can influence the liquid density, consequently measuring the void faction deals with significant errors.

In this study, a method is proposed based on dual modality densitometry (using transmitted and scattered photons together) using ANN in order to estimate the void fraction in homogenous regime of gas-liquid two-phase flows in unstable operational conditions (changeable temperature and pressure) in oil industry. As the first step in this study, the optimum position in which the scattering detector is more sensitive relative to density changes, was obtained. As much as the sensitivity of detector relative to density changes is more, the ANN could better predict the void fraction independent of density. After obtaining optimum positions for the detectors, the registered counts in these detectors for different void fractions and densities, were used for training the ANN.

2. Approach

2.1. Experiment

In this work, all the experiments were done in static conditions. A plexy-glass pipe with inner diameter of 9.5 cm and wall thickness of 2.5mm is used as the main pipe. For modeling the homogenous regime in static conditions, an arrangement with 80 cubic plastic straws distributed over the whole pipe cross section was used. This was done systematically, so for each of the two straws covered by the measurement volume between the 1th detector and source, a corresponding number of straws (6) over the total pipe cross section is treated the same way. A schematic cross sectional view of the various void fractions in the range of 10 to 70 percent is shown in Fig. 1. The blue and white cells correspond to gas phase and liquid phase, respectively. This method was used to model homogenous regime, because making the ideal homogenous regime with different void fractions in static conditions is so difficult.

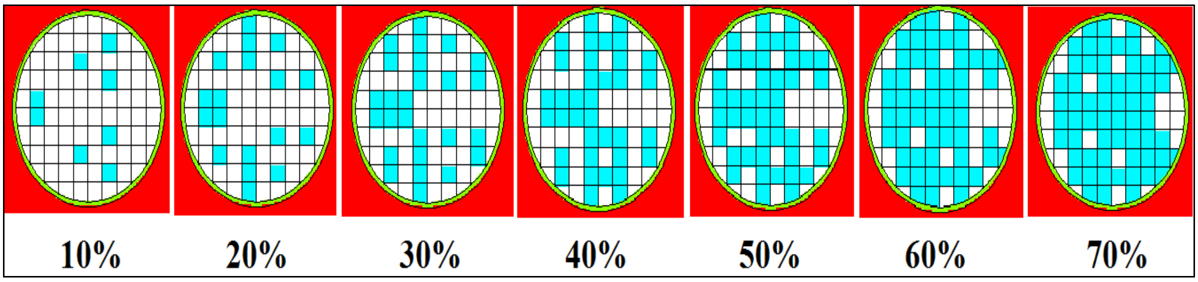


Fig 1: A schematic cross sectional view of the made void fractions for homogenous regime in the range of 10 to 70 percent.

A ^{137}Cs (662 KeV) source with activity of 2 mCi was used as the gamma-ray emitter source. Also a measurement time of 600 s was chosen was chosen for all the experiments. The source was collimated (a cubic collimator with 0.6 cm width, 2 cm height and 10 cm length) in order to make a narrow beam passing through the center of the pipe. Two 1-inch NaI detectors used in this work. The experimental configuration is shown in Fig. 2.

As the first step in this study, best position for the detectors in dual modality densitometry configuration was investigated. As shown in Fig. 3, the position of transmission detector was kept fixed in the angle of 0^{o} and the scattering detector was located in angles of 45^{o}, 90^{o} and 135^{o} respect to center of the pipe.

The void fractions in the range of 10% to 70% for homogenous regime of gas-liquid two-phase flows were tested at each position of the scattering detector. Air with density of 0.001 g/cm^3 was used as the gas phase in the pipe. For making a wide range of density for liquid phase in laboratory (from 0.735 g/cm^3 to 0.980 g/cm^3), gasoline, kerosene, gasoil, lubricant oil, and water with the densities of 0.735, 0.795, 0.826, 0.852, and 0.980 (g/cm^3), respectively, have been used as the liquid phases. Since the predominant interaction mechanism for high energy photons in low atomic number materials is Compton scattering and the photoelectric interaction could be negligible, therefore, the interaction probability depends just on the density of the liquid phase regardless of its composition. Also, because the effective atomic numbers of used liquids are close to each other, it could be assumed that all of the 5 liquid phases regardless of their compositions, are considered as one liquid phase with various densities. In transmission detector, the counts in full energy peak of Cs-137 were registered (2 FWHM from centered channel) and the scattering detector was operated in total count mode.

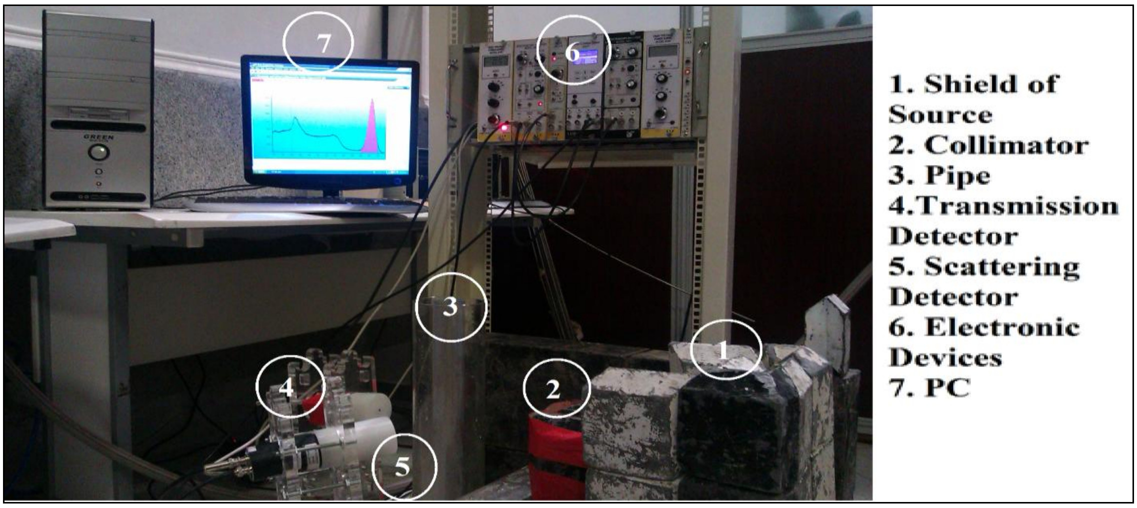


Fig 2: Experimental setup.

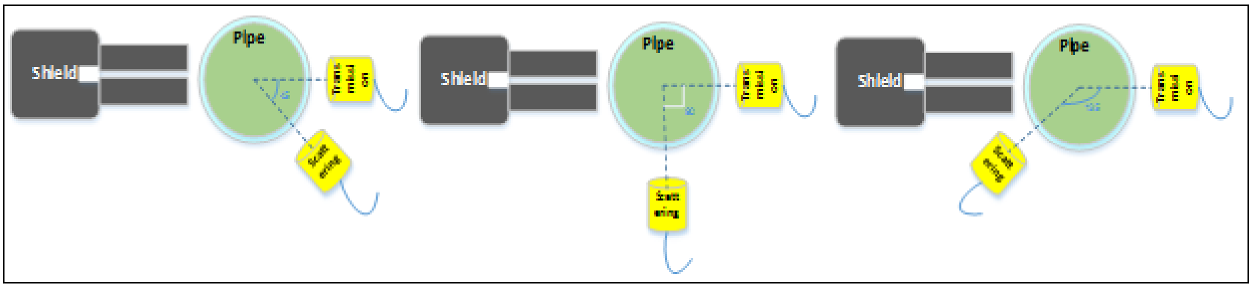


Fig 3: A top view of positioning of the scattering detector in different angles in order to obtain the most sensitive position relative to density changes.

At each position of the scattering detector, sensitivity response of this detector relative to density changes of the liquid phase from the lowest density (0.735 g/cm^3) to the highest density (0.980 g/cm^3) of liquid phase for void fractions in the range of 10% to 70% was calculated according equation 1:

$$Sensitivity = \left(\frac{\text{Registered count for density of 0.98 (g/cm}^3\text{)} - \text{Registered count for density of 0.735 (g/cm}^3\text{)}}{\text{Registered count for density of 0.98 (g/cm}^3\text{)}} \right) \times 100 \quad (1)$$

Sensitivity of the scattering detector relative to the density changes of the liquid phase for different void fractions was shown in Fig. 4.

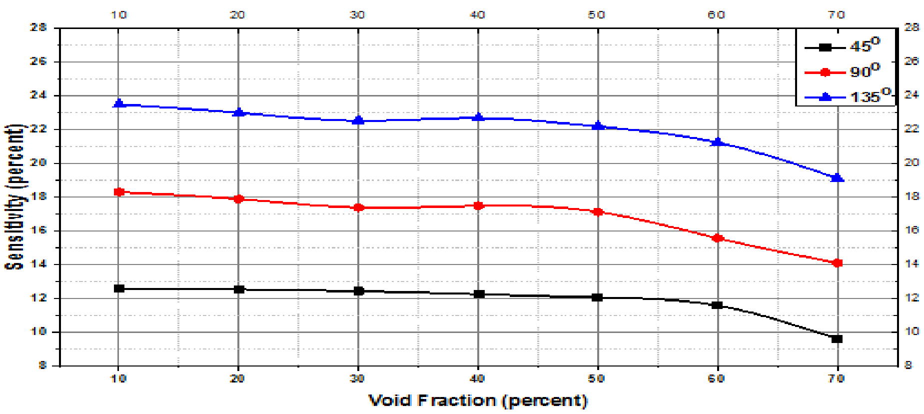


Fig 4: Sensitivity of the scattering detector relative to the density changes of the liquid phase from 0.735 g/cm^3 to 0.980 g/cm^3 versus different void fractions.

2.2. Artificial Neural Network

In the course of the past thirty years, neural networks (NNs) have been a very active field of multidisciplinary research. For applications, an artificial neural network (ANN) uses features of real nervous systems implemented either in hardware or more often in software in general-purpose computing equipment. An ANN consists of a collection of 'neurons' (switching processing elements) communicating with each other via modifiable weighted connections. It has been demonstrated that an ANN can be applied to the recognition and classification of a wide range of situations, patterns and individual features of different systems.

The aim of this study was to apply the technique to predict void fraction independent of the liquid phase density changes in homogenous regime of gas-liquid two-phase flows, using counts registered by detectors. The simplified overview of the proposed MLP model is shown in Fig. 5, where the inputs are registered counts in transmission detector and registered counts in scattering detector and the output is void fraction independent of the liquid phase density.

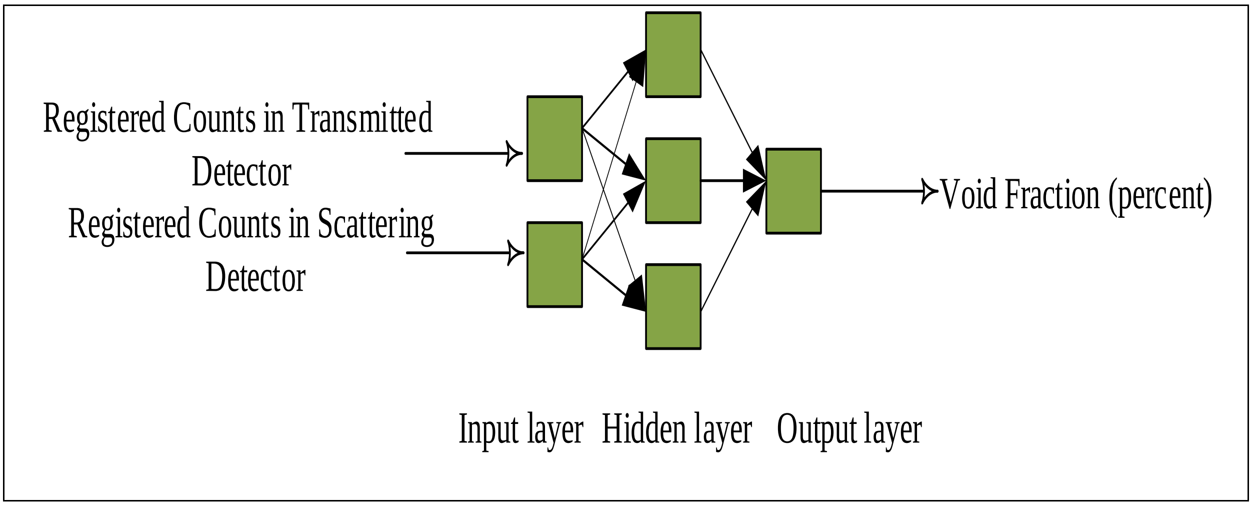


Fig 5: Architecture for the presented MLP neural network.

The input to the node *m* in the first hidden layer is given by [18-19]:

$$\eta_m = \sum_{u=1}^{2}(X_u W_{um}) + b_m \qquad m=1,2,3 \tag{2}$$

The output from *mth* neuron of the hidden layer is given by:

$$U_m = f\left(\sum_{u=1}^{2}(X_u W_{um}) + b_m\right) \qquad m=1,2,3 \tag{3}$$

The output of the neuron in the output layer is given by:

$$O = \sum_{u=1}^{3}(U_u W_u) + b \tag{4}$$

Where X is the inputs, b is the bias term, W is the weighting factor and f is the activation function of the hidden layers.

By using the experimental data which was described in the previous section, the data set required for training the network is obtained. Training of the presented MLP networks is done by Levenberg-Marquardt (LM) algorithm. In this algorithm, first derivative and second derivative (hessian) are used for network weight correction [20].

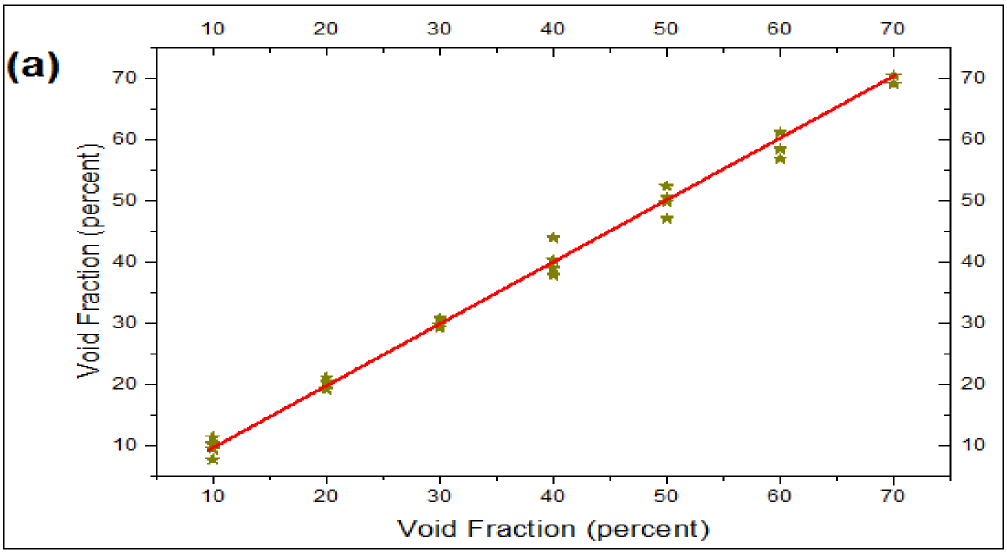
The number of samples for training and testing data are 25(about 72%) and 10 (about 28%), respectively. In this study, various ANN structures were tested and optimized to obtain the best ANN configuration with minimum error. Many different structures with one, two and three hidden layers with different number of neurons in each layer and with different activation function were tested. MATLAB 8.1.0.604 software was used for training the ANN model. Table 1 shows the specification of the proposed MLP neural network being used in this study.

Table 1: Specification of the proposed ANN model

Neural network	MLP
Number of neurons in the input layer	2
Number of neurons in the first hidden layer	3
Number of neurons in the output layer	1
Number of epochs	220
Activation function	tansig

3. Results and Discussion

Fig. 6 shows the comparison between the experimental and predicted void fraction percentage using the proposed MLP neural network for training and testing data. The comparison between experimental and predicted results for training and testing data were tabulated in Table 2 and Table 3, respectively.



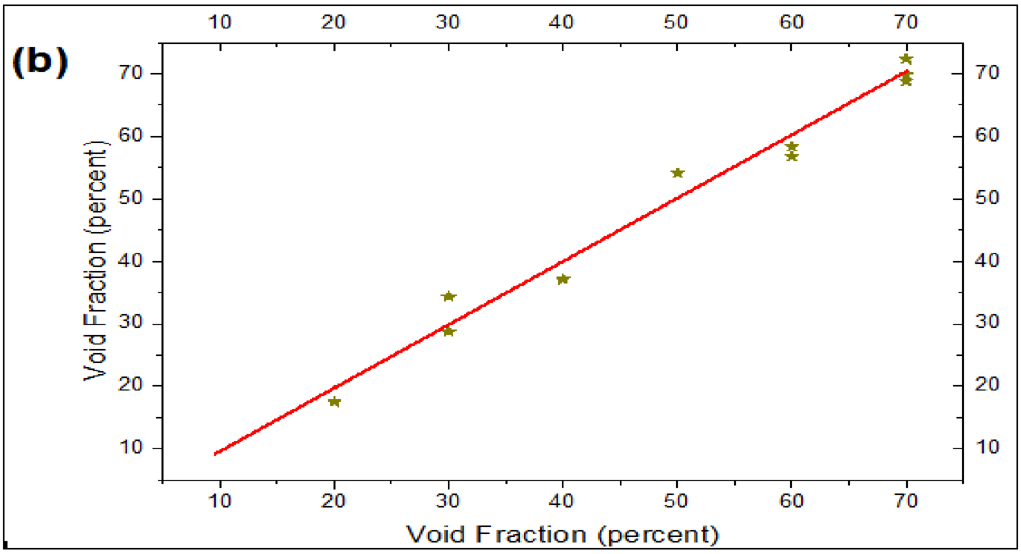


Fig 6: Comparison of experimental and predicted void fraction percentage for (a) training data (b) testing data.

Table 2: The data that were used for training the networks and predicted void fraction (MLP neural network)

Density(g/cm^3)	Registered Counts in transmitted detector	Registered Counts in scattering detector	Void Fraction	Predicted Void Fraction
0.735	213936	149794	10	7.69
0.735	225004	136652	20	20.28
0.735	251423	109239	40	43.94
0.735	282511	80718	60	58.46
0.795	204644	159486	10	11.35
0.795	216903	145525	20	21.15
0.795	244748	116462	40	38.97
0.795	261490	101845	50	50.52
0.795	278096	85466	60	61.18
0.826	199885	164773	10	10.42
0.826	212628	150850	20	20.27
0.826	226097	135078	30	30.72
0.826	240298	120976	40	40.30
0.826	257058	104573	50	52.39
0.826	292372	72435	70	70.41
0.852	196033	169179	10	9.4
0.852	222963	139551	30	29.23
0.852	238073	123684	40	37.78
0.852	254842	107301	50	47.11
0.852	290174	73810	70	69.05
0.980	175409	195613	10	10.18
0.980	189228	176583	20	19.15
0.980	204606	159231	30	29.71
0.980	239329	122759	50	49.77
0.980	258232	102267	60	56.86

From Table 2, Table 3 and Fig. 6, it is obvious that the predicted unknown void fraction percentage by MLP neural network is close to the experimental results. These results show the applicability of ANN as an accurate and reliable model for predicting the void fraction according to the registered counts in transmission and scattering detectors. Table 4 shows the obtained errors for the proposed ANN model, where the mean relative error percentage (MRE %) and the root mean square error (RMSE) of the network are calculated by:

$$MRE\,\% = 100 \times \frac{1}{N}\sum_{j=1}^{N}\left|\frac{X_j(Exp) - X_j(\mathrm{Pred})}{X_j(Exp)}\right| \tag{5}$$

$$RMSE = \left[\frac{\sum_{j=1}^{N}(X_j(Exp) - X_j(Pred))^2}{N}\right]^{0.5} \tag{6}$$

Where N is the number of data and ‘X (Exp)’ and ‘X (Pred)’ stand for experimental and predicted (ANN) values, respectively.

Table 3: The data that were used for testing the networks and predicted void fraction (MLP neural network)

Density(g/cm^3)	Registered Counts in transmitted detector	Registered Counts in scattering detector	Void Fraction	Predicted Void Fraction
0.735	239528	123449	30	34.32
0.735	268138	95479	50	54.10
0.735	298967	66567	70	72.37
0.795	230574	131500	30	28.74
0.795	294570	70234	70	69.85
0.826	273682	88022	60	56.79
0.852	208803	154399	20	17.52
0.852	271475	90214	60	58.35
0.98	220941	140838	40	37.10
0.98	281381	82246	70	68.83

Table 4: Obtained errors for training and testing results of the proposed ANN model

Error	Train	Test
MRE%	0.44	**0.78**
RMSE	1.57	**2.67**

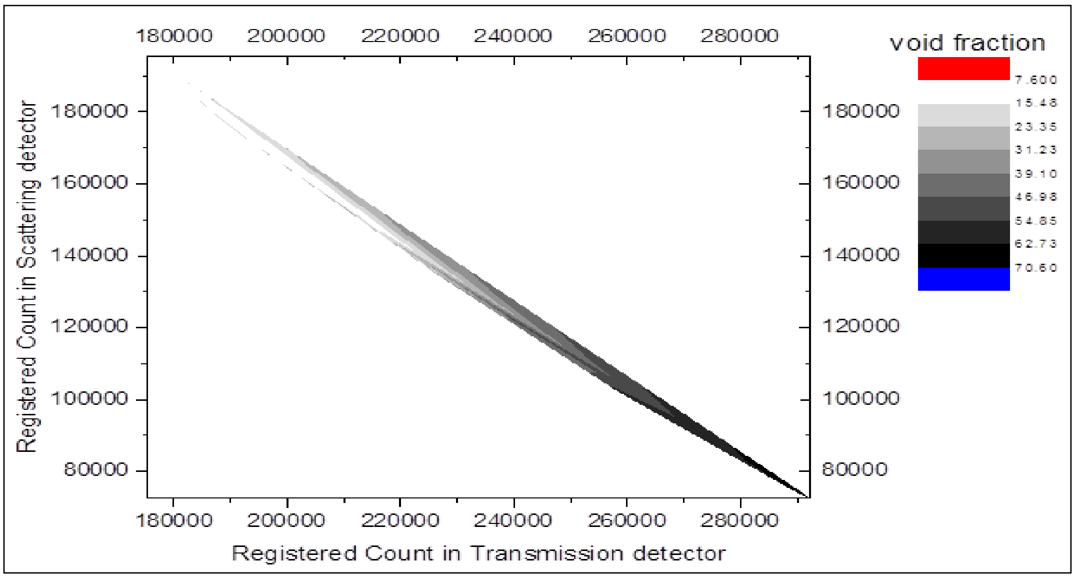


Fig 7: Contour plot for obtained void fraction percentage.

Fig. 7 shows the obtained void fraction percentage using the proposed MLP neural network for whole registered counts in transmission and scattering detectors independent of the liquid phase density.

4. Conclusions

Variations of operational conditions in oil industry's pipelines, would cause large errors in determination of void fraction in radiation-based multi-phase flow meters. A conventional solution for avoiding such significant errors, is continuous recalibration during the measuring of void fraction. In this work, a method is proposed based on dual modality densitometry (using transmitted and scattered photons together) using ANN in order to estimate the void fraction in homogenous regime of gas-liquid two-phase flows in unstable operational conditions (changeable temperature and pressure) without recalibration of system during the measuring. At first, angle of 135^o was obtained as the optimum angle for positioning of the scattering detector. After obtaining optimum position for the detectors, registered counts in these detectors for void fractions from 10% to 70% and density in the range of 0.735 to 0.980 g/cm^3 were used as the inputs of ANN and void fraction was used as the output of the ANN. Trained ANN model, predicted void fraction with mean relative error less than 0.78%. Multi-layer perceptron (MLP) neural network was used for developing the ANN model.

The proposed method could be applied for measuring the void fraction in situations where the operational conditions in pipelines such as temperature and pressure are unstable.

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