Precise Prediction of Interface Distribution of Materials in Multiphase Separation Facilities Using a Low-Cost and Simple Technique: ANN

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ABSTRACT: *The ability to precisely detect the interface of the different phases in a vessel plays an important role in chemical plants, oil, and petroleum industry. The purpose of this research is to apply the gamma-ray attenuation technique (single point source and single detector) together with MultiLayer Perceptron (MLP) neural network to detect the interface present in water-gasoil two-phase flows in pipelines and vessels, for the first time. The experimental setup is comprised of a plastic rod scintillator (BC400) coupled with two PMT tubes at two sides as a position-sensitive detector, a point gamma-ray source (^{137}Cs), and a vessel between the source and detector. The detection system provides the required data for training and testing the network. Using this proposed method, the interface locations were determined in two-phase with mean relative error percentages less than 0.34% and 0.27% for levels of water and gasoil, respectively. The mean absolute error values were measured less than 1.16 and 1. Also, the correlation coefficients were calculated 0.999 and 1. These results presented the accuracy of the proposed method in order to determine the interface position. The used set-up is simpler than other proposed techniques and cost, radiation safety, shielding requirements, and risk production are minimized.*

KEYWORDS: *Interface level position; Plastic rod scintillator; Artificial Neural Network, Single point source - single detector.*

INTRODUCTION

The determination of interface position in vessels and pipelines of petroleum, oil and gas industries plays an important in avoiding a shutdown in a continuous process, good performance of plants, safety, cost, and healthy production. This problem is the key challenge in followed industrials. Therefore, non-destructive instrumentation and techniques have been studied and developed by many researchers in order to determine interface location in water-gasoil two-phase without modifying the operational conditions. In previous studies, radiation techniques, the volumetric, electrical, optical, ultrasonic, electromagnetic were used to measure interface positions in multiple-phase.

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In comparison with the other methods, radiation techniques such as fast neutron scattering, X-ray, and gamma attenuation have many applications and among of these methods, the gamma ray method is more versatile [1-6]. Several types of research have been made to measure interface location using gamma ray attenuation [7-9].

Gholipour Peyvandi et al. determined the liquid's interfaces in multiphase flows using the scanning method. In this study, a vessel containing water and gasoil was used for scanning. Also, a pipe was placed in the center of the vessel to pass the source-detector assembly (^{60}Co source and NaI detector) inside the vessel. The source-detector assembly moves from the vessel bottom with selected position steps in order to scan the vessel. Thus, the liquid's interfaces were determined by using the back scattered gamma ray technique [9]. Also, in many investigations and equipment, some detectors and some sources were used for interface detection in liquid with multiple-phase [7-9].

Pradeep et al. used the electrical capacitance tomography together with Artificial Neural Networks (ANN) in order to estimate the interface levels for water-air and oil-air two-phase flows. According to results, the Root Mean Square Error (RMSE) of validation quantities were 4.73 and 7.56 for 6 and 4 electrodes sensor, respectively.

In all previous literature, the researchers used least two or more detectors or some radioactive sources with different energies for determining the interface level in multiple-phase flows. Also, the source-detector assembly should move through the vessel in single source-single detector designed set up in order to scan the vessel and determine interface liquid level. But in this study, the interface position was estimated precisely in water-gasoil two-phase flows by using a ^{137}Cs source (with the single-energy of 662 keV) and a plastic rod scintillator together with a multi-layer perceptron neural network for the first time.

The used set-up is simpler than those existing in the literature (fewer detectors and sources) and this feature is very advantageous in industrial nuclear gauges, because of reducing cost, and shielding and electronic requirements. A multilayer perceptron neural network was used for developing the artificial neural network model in MATLAB. The MLP neural networks were trained and tested using acquired data from an experimental setup.

EXPERIMENTAL SECTION

Experimental set-up

In order to provide the required training and test data for the ANN to predict the interface location in water-gasoil two-phase, an experimental setup was designed.

An experimental setup comprised of a plastic scintillator detector, a ^{137}Cs source, and a vessel. The rod plastic scintillator (BC400) with a diameter of 5 cm and a length of 150 cm was used as a crystal which two photomultipliers were coupled at the ends of two rod sides of the crystal. Also, a point source ^{137}Cs with 40 mCi activity was placed on side of the vessel with a distance of 3cm. A lead collimator with 10 cm diameter was used to make a fan-beam. Also, a polyethylene vessel with 100 cm in diameter and 200 cm in height containing water and gasoil was placed between the source and detector. In the nuclear-electronic system, as followed, two PMTs (Model CR-169 BEIJING Hamamatsu, China), two high voltage (HV) power supply modules (CC228-01Y BEIJING Hamamatsu, China), two preamplifiers, two amplifiers and two counters (G.G.104 PTB- CO. Iran) were used to record count rates due to the transmitted gamma rays. The experimental setup is shown in Fig. 1.

Water and gasoil with densities 1 g/cm^3 and 0.86 g/cm^3 were chosen as the liquid and liquid phases in two-phase. These mixtures were located in a container with 2 layers as height is X_1+X_2 = 150 cm (Fig. 1). As a result, the acquired data set from 46 samples were used for training the ANNs according to Table 1. The number of 51 samples with different height of water and gasoil were produced as experimental to obtain the recorded count rates from the ^{60}Co source. The number of 46 samples (46 count rates) were used for training, validation, and testing of ANN (about 70% training, 15% validation and 15% testing). The number of 5 samples were used for accuracy assessment of the ANN method. Thus, the recorded and attenuated gamma ray count rates from two counters modules together with a multi-layer perceptron neural network can determine interface position, precisely.

Training data using ANN

ANN models are a good modeling tool in investigations and complex systems for their ability to solve problems stochastically. They used the acquired experimental data for training and applying to predict

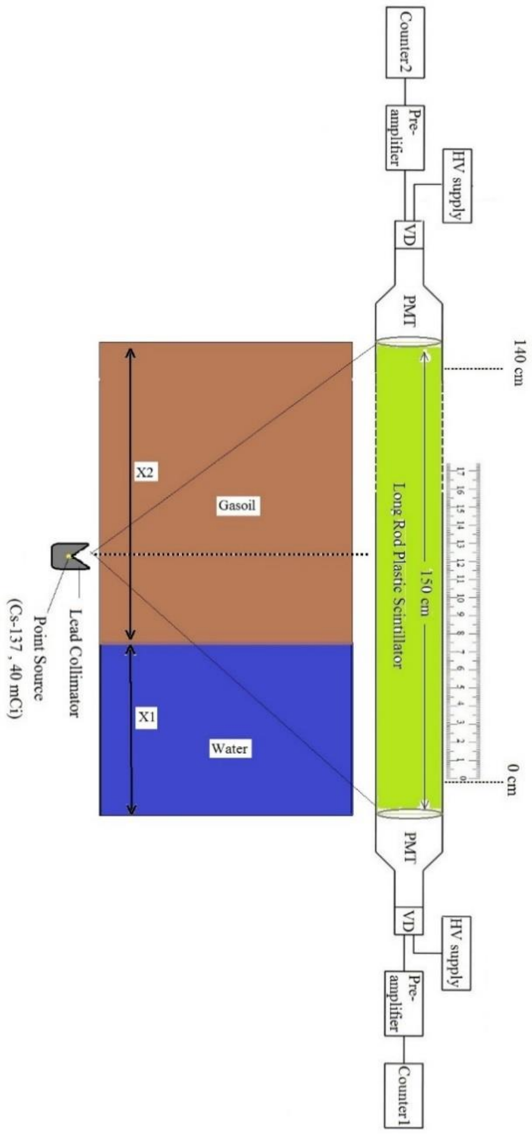

Fig. 1: Arrangement of the vessel, source and nuclear electronic system (experimental set-up).

output responses of systems. The simplest and smallest recognized division of processing elements in ANNs are neurons which have special importance in solving the problems[10-15].

In this study, the interface position in the liquid was predicted using MultiLayer Perceptron (MLP) neural networks which they are the most widely used ANNs. Most of MLPs have a connection structure with connections from all neurons of one layer to all neurons of a successive layer. The MLP is consists of an input layer, one or more hidden layers, and an output layer. These layers were illustrated in Fig. 2. In this research, the number of neurons for the MLP neural network in the input, hidden and output layers are 2, 10 and 2, respectively. The experimental data provided the required data set for training the network. The inputs are registered count rates in the two ends of rod detector and the outputs are the predicted interface positions as the Y (m×n) matrix represents the obtained count rates from the two ends of rod detector, with n sample with different interface and m counters (1 and 2). Thus, the dataset for ANN consisted of a matrix ($Y_{2\times46}$) in which the rows correspond to the two detectors and columns corresponded to recorded count rates with different interface positions.

Table 1: The acquired data set (count rates) from 46 samples for training the ANNs.

ID sample	X2 (cm)	X1 (cm)	Counter1	Counter2
1	150	0	5190	5210
2	147	3	5185	5150
3	144	6	5210	5040
4	141	9	5190	4914
5	138	12	5180	4887
6	135	15	5170	4853
7	129	21	5185	4774
8	126	24	5187	4735
9	123	27	5173	4698
10	120	30	5145	4650
11	117	33	5124	4611
12	114	36	5095	4592
13	111	39	5040	4570
14	105	45	4920	4430
15	102	48	4891	4401
16	99	51	4848	4318
17	96	54	4820	4200
18	93	57	4776	4153
19	90	60	4710	4100
20	87	63	4680	3960
21	84	66	4620	3910
22	78	72	4530	3741
23	75	75	4516	3650
24	72	78	4489	3602
25	69	81	4452	3578
26	66	84	4391	3540
27	63	87	4320	3510
28	60	90	4210	3510
29	57	93	4140	3460
30	51	99	4020	3350
31	48	102	3938	3314
32	45	105	3840	3281
33	42	108	3800	3211
34	39	111	3768	3148
35	36	114	3710	3150
36	33	117	3590	3140
37	30	120	3520	3100
38	24	126	3365	3073
39	21	129	3291	3024
40	18	132	3247	3011
41	15	135	3214	2994
42	12	138	3190	2987
43	9	141	3146	2971
44	6	144	3114	2980
45	3	147	3101	2991
46	0	150	3085	2983

Table 2: Comparison of experimental and ANN predicted data for the interface position in water-gasoil two-phase.

Sample ID		Water-X1 (cm)	Gasoil-X2 (cm)
1	Real	18	132
	ANN	19.2	131
2	Real	42	108
	ANN	40.7	109.2
3	Real	69	81
	ANN	67	83
4	Real	96	54
	ANN	97.3	53.2
5	Real	123	27
	ANN	123	27

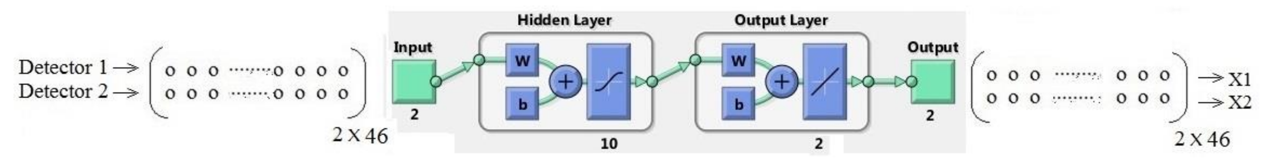

Fig. 2: The multilayer perceptions (MLP)-feed forward network.

The Bayesian regularization algorithm trained the presented ANN networks which training function updates the weight and bias values according to Levenberg-Marquardt optimization [10-15]. The number of 13 iterations in epochs were done for achieving the best results. MATLAB 8.3.0.532 was used for training the ANN model.

In order to evaluate precision the proposed method (ANN), the predicted results were compared with experimental data with three types of errors composed of the mean absolute error (MAE), mean relative error percentage (MRE%) and Correlation Coefficient (R). The errors relations were calculated by:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|X_i - \hat{X}_i\right|$$

$$MRE\% = 100 \times \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_i - \hat{X}_i}{X_i}\right|$$

$$R = \frac{\sum_{i=1}^{n}\left\{\left(X_i - \bar{X}\right)\left(\hat{X}_i - \bar{\hat{X}}\right)\right\}}{\left\{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2 \sum_{i=1}^{n}\left(\hat{X}_i - \bar{\hat{X}}\right)^2\right\}^{1/2}}$$

Which X_i and $\hat{X}_i$ are experimental and predicted (ANN) quantities, respectively. Also, $\bar{X}$ and $\bar{\hat{X}}$ are mean of experimental and predicted (ANN) quantities[16]. N is the number of all data. Also, Regression between the real and predicted data (in plots) was used to describe the predictive ability of the models.

RESULTS AND DISCUSSION

In this experiment, we used a ^{137}Cs source (with the single-energy of 662 keV) and a plastic rod scintillator together with a multi-layer perceptron neural network in order to estimate the interface position in water-gasoil two-phase. Table 2 shows the predicted and real liquid interface positions for different two-phase samples. The MAE, MRE% and Correlation Coefficient (R) errors were used in order to compare the experimental and predicted results. The mean relative error percentages were measured less than 0.34% and 0.27% for liquid levels of water and gasoil, respectively. The mean absolute error values were measured less than 1.16 and 1. The correlation coefficients were calculated 0.999 and 1. The MRE% for interface

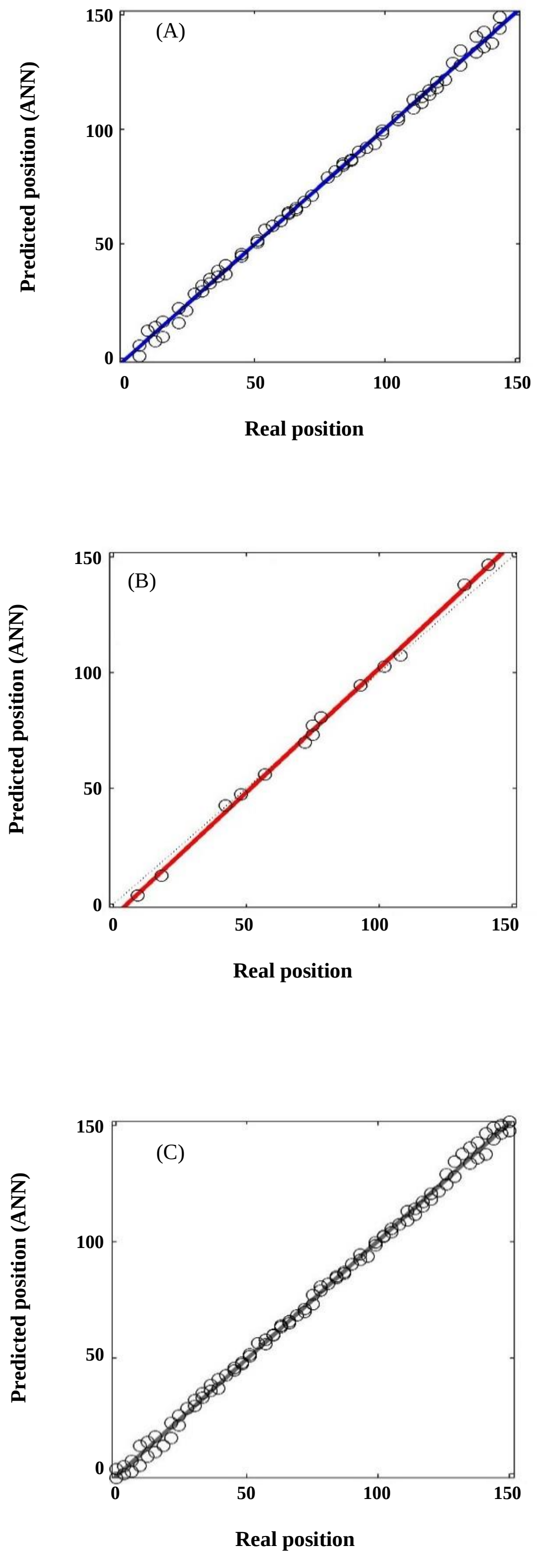

Fig. 3: Comparison of experimental and predicted interface position (the graphic of regression). (A) training data and (B) testing data and (C) for all data.

level was determined 0.3%. Also, the comparison between real and predicted results using the presented ANN model for training and testing data in regression diagrams have been shown in Fig. 3. The acquired insignificant errors are due to the accuracy and precision of the proposed ANN.

Finally, the ability of prediction and accuracy for our proposed technique was compared with the obtained results from different studies (*Gholipour et al.* and *Pradeep et al*) [7, 9].

Gholipour et al. and *Pradeep et al* determined the liquid's interfaces in multiphase flows (water-gasoil) with MRE% of 3.3% by using the scanning method (moving of the source-detector assembly through the vessel).

Also, Pradeep et al. estimated the interface levels for water-air and oil-air two-phase flows by using the electrical capacitance tomography together with Artificial Neural Networks (ANN). According to results, the Root Mean Square Error (RMSE) of validation quantities was calculated 4.73. But this comparison is inaccurate due to some differences in the number of detectors, sources, the number of phases in multiple-phase flows, the recorded spectra including scattered and transmitted spectra for data training.

In all the reported studies, the presented set up is complicated and expensive whereas the proposed design is certainly very simple. So the cost is minimized as low as possible.

CONCLUSIONS

There are different techniques for measuring an interface between two phases. The geometry of vessel, radiation safety, economic aspects and etc are crucial when deciding on which of the arrangements is selected to solve the measurement task. Our design fulfilled all of these requirements. In this design, a plastic rod scintillator (BC400) coupled with two PMTs at two sides (1 and 2 PMTs) as a position sensitive detector and a point source ^{137}Cs (without motion) together with MultiLayer Perceptron (MLP) neural network were used in order to estimate the interface level position. The proposed technique optimized shielding and electronic requirements. Also, cost, radiation safety, and risk production reduced with the present set up.

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