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GAS VOID FRACTION PREDICTION FOR AIR-WATER AND AIR-OIL TWO-PHASE FLOWS VIA ARTIFICIAL NEURAL NETWORK

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Abstract. *This work purpose was to assess the ability of the artificial neural network to predict the gas void fraction for air-water and air-oil vertical upward two-phase flows. The fluid properties and operating conditions were used as input parameters. To obtain the training and testing dataset, two-phase flow experiments were carried out in a 10.4 m long pipe of 0.053 m inner diameter, built in the Experimental Laboratory of Petroleum (LabPetro) at the Center for Petroleum Studies (Cepetro), located at the University of Campinas (Unicamp). A quick closing valve system was installed in the two-phase pipeline to measure the gas void fraction. The measurements carried out by this system presented 8.2% as the highest standard deviation. The artificial neural network (ANN) that best predicted the gas void fraction had six input parameters and one hidden layer with six neurons. The backpropagation was used as the training algorithm. The results showed a fine agreement between the ANN predictions and actual measured values.*

Keywords: *Artificial Neural Network****;*** *Two-phase flow; Gas void fraction*

1. INTRODUCTION

The gas-liquid two-phase flow often occurs in the artificial lifting of petroleum from wells. In this process, the gas amount tends to increase as the pressure in the flowline decreases. Such changes in the gas void fraction (GVF), as well as in the flow pattern, depends on the fluid properties and the operating conditions. In practice, this parameter is estimated as a cross-sectional average or a volumetric average.

The knowledge of the gas void fraction is essential from the processing point of view. Predicting the gas void fraction enables design production facilities, such as separators and compressors. Besides, estimating this parameter upstream the production facilities, in real time, leads to a better performance of their control system, avoiding unexpected shutdowns in the production facilities due to instabilities in the composition of the arriving gas-liquid two-phase flow (Guo *et al.*, 2005). Therefore, methods to predict the gas void fraction have been developed over the years (Fabre and Liné, 1992; Godbole *et al.*, 2011; Ghajar and Tang , 2012; Bhagwat *et al.*, 2014)

An alternative tool to predict the gas void fraction that has been used and presented satisfactory results is the artificial neural networks (ANN). Figueiredo *et al.* (2016) developed an artificial neural network to predict the gas void fraction for multiphase vertical upward flow, using as input parameters acoustic data measured by the ultrasonic technique. Abro *et al.* (1999) and Salgado *et al.* (2010) used artificial neural network to predict the gas void fraction from multiphase flows using as input parameters gamma-ray data. The results presented by these authors showed a good agreement between the prediction and actual data target. However, it is noticeable that the input parameters used by Figueiredo *et al.* (2016), Abro *et al.* (1999), Salgado *et al.* (2010) are more complex to obtain when compared to the fluid properties of the two-phase flow. Thus, this work aims to develop an artificial neural network to predict the gas void fraction for air-water and air-oil two-phase flows using fluid properties and operating conditions as input parameters.

2. METHODOLOGY

The following subsections describe: the main components of the experimental setup used to measure gas void fraction from a two-phase gas-liquid flow; the experimental procedure and test matrix; and the training method and topology of artificial neural network used to predict the GVF.

2.1. Experimental setup

Figure 1 illustrates the experimental setup used in the air-water and air-oil vertical upward two-phase flow experiments, built in the Experimental Laboratory of Petroleum (LabPetro) at the Center for Petroleum Studies (Cepetro), located at the University of Campinas (Unicamp). The liquid phase was stored in a 1.5 m^3 tank. A progressive cavity pump moved the incompressible phase from the tank to the gas-liquid mixture point. Downstream of the mixture point (~8.1m), the quick closing valve system was installed in the pipe to measure the gas void fraction, for each operational condition investigated. It was employed a 10.4 m long pipe of 0.053 m inner diameter, resulting in a length-diameter-ratio of approximately 154 to develop the two-phase flow.

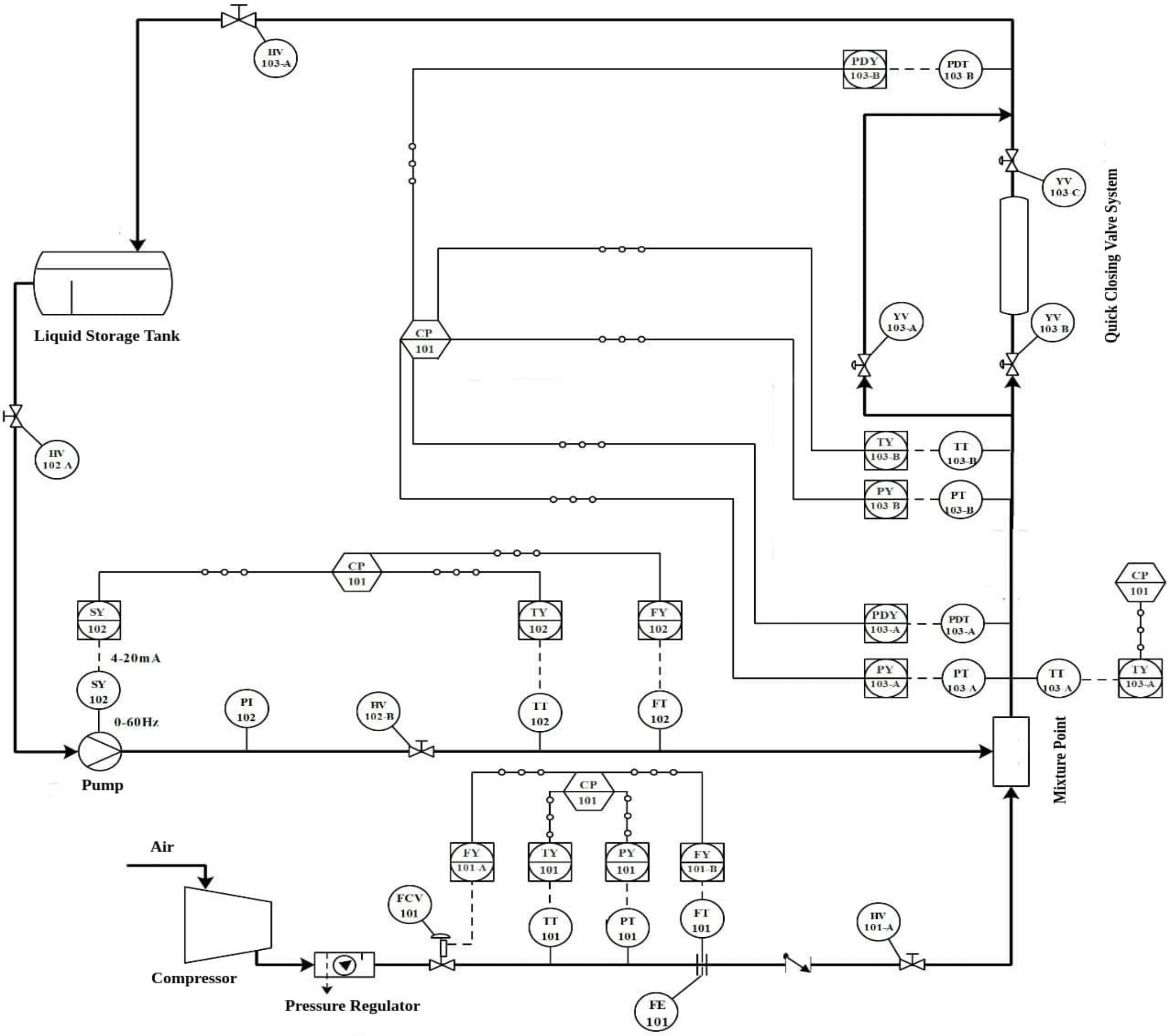

Figure 1. Experimental setup (LabPetro/Unicamp).

The quick closing valve system had three quick closing valves. Two of them delimited the flowline enclosure section, which had 2.3 m, and the last one activated the bypass flowline. In the enclosure section, a pressure relief valve was installed, and pressure and temperature sensors were used to estimate the densities and viscosities for both phases for each studied operational condition. The gas void fraction measurement performed by this system was based on the enclosure of the two-phase gas-liquid flow sample and its subsequent phase separation, due to the density difference. After the phase segregation, the gas phase was released by a relief valve. The liquid level was then estimated by a pressure sensor (BEGA, 2006). Finally, the *GVF* was estimated by Eq. (1), in which L_l and L_s are the liquid level and maximum level of enclosure section.

$$GVF(\%) = \frac{L_s - L_l}{L_s} \cdot 100 \tag{1}$$

2.2. Experimental procedure and test matrix

Figure 2 summarizes the experimental procedure. For each investigated operational condition, this procedure was performed four times, resulting in 102 experimental data for air-water and 102 for air-oil two-phase flow.

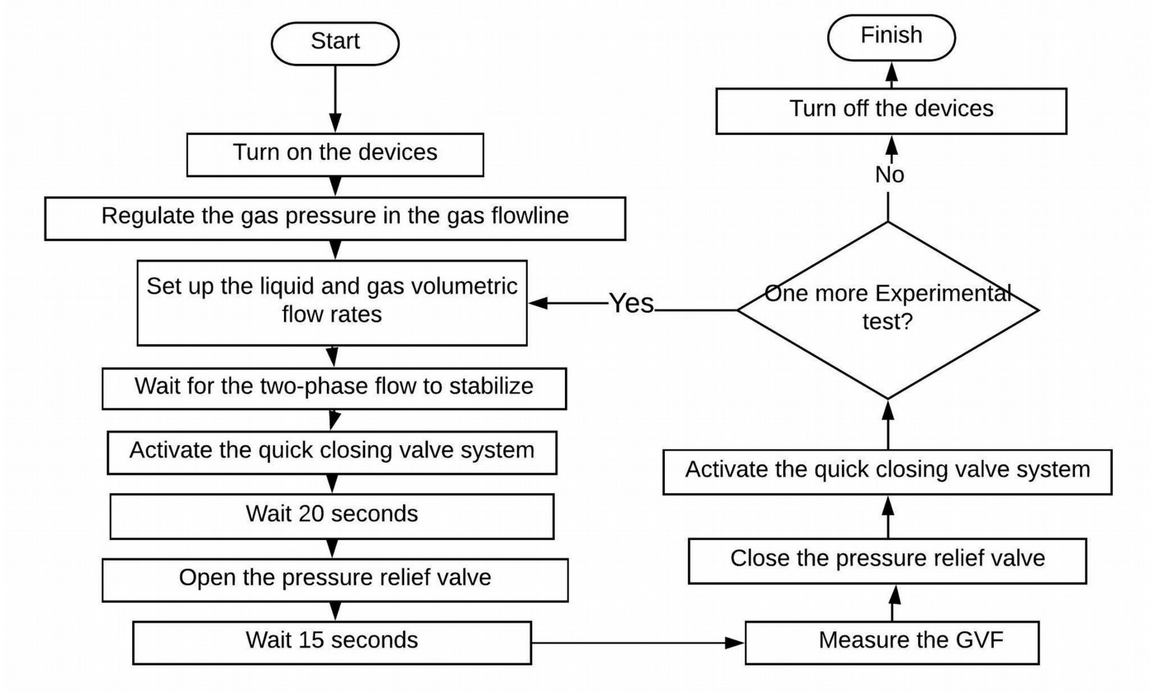

Figure 2. Gas void fraction measurement flowchart.

Table 1 shows the air, water and oil superficial velocities range used in two-phase flow experimental tests. The superficial velocity definition is given in Eq. (2), where Q and A_P are the volumetric flow rate ($m^3\ s^{-1}$) and the cross-sectional area of the pipe (m^2), respectively.

Table 1. Operating conditions range used in the gas void fraction measurement

Two-phase	Gas superficial velocity ($m\ s^{-1}$)	Liquid superficial velocity ($m\ s^{-1}$)
Air-water	0.113 – 3.735	0.532 – 3.941
Air-oil	0.092 – 3.634	0.532 – 3.806

$$v_s = \frac{Q}{A_P} \tag{2}$$

2.3. Training method and topology of artificial neural network

The artificial neural network used to predict the air-water, and air-oil gas void fraction was developed in Python[RM.] The Multilayer Perceptron Feedforward topology was chosen due to its ability to map non-linear relations between inputs and outputs. The training algorithm used in this procedure was the backpropagation. The activation functions used in hidden and output layers were the hyperbolic tangent and linear, respectively. The artificial neural networks inputs were: gas density (ρ_g); liquid density (ρ_L); gas viscosity (μ_g); liquid viscosity (μ_L); gas superficial velocity (v_{sg}); and liquid superficial velocity (v_{sl}). These inputs were normalized, and its values were between -1 and 1. The target dataset was randomly divided into two groups: one group was used as the training set and the other used as the testing set. The artificial neural network performance was evaluated using the Determination Coefficient (R^2), and the linear and angular coefficients of the straight line that fits predicted versus actual values of gas void fraction from the test set.

3. RESULTS

Table 2 shows the gas void fraction range measured by the quick closing valve system, and the properties of the fluids estimated for each experimental conditions studied. The measurements carried out by the quick closing valve system presented 0.2% and 8.2% as the lowest and the highest standard deviation, respectively, which makes the technique used in this work suitable to quantify the GVF.

Table 2. Range of gas void fraction and fluid properties obtained from gas-liquid two-phase flow experimental tests

Gas-liquid two-phase flow	GVF (%)	ρ_g (kg m^{-3})	ρ_L (kg m^{-3})	μ_g (10^{-5} Pa s)	μ_L (10^{-3} Pa s)
Air-water	3.6 – 72.2	1.44 – 1.78	996.07 – 997.88	1.82 – 1.86	8.21 – 9.63
Air-oil	1.5 – 71.5	1.35 – 1.73	840.36 – 848.45	1.85 – 1.91	11.78 – 19.23

The measurements depicted in Table 1 and Table 2 were used to develop an artificial neural network able to predict the GVF for air-water and air-oil two-phase flow. The artificial neural network which presented the best results had an architecture with six neurons in the hidden layer, and its performance for the test set is illustrated in Figure 3. The lower GVF estimated by the artificial neural network presented significant predictions errors, as can be seen in Figure 3. However, this undesirable behavior did not influence the general ability of the artificial neural network in estimating the target values. Its satisfactory performance can be proved statistically: the determination coefficient obtained was 0.9916, and the angular and linear coefficients of the straight line that fits predicted versus actual values of gas void fraction from the test set were 0.9884 and -0.1511, respectively. Those last coefficients would be 1 and 0 for a perfect fitting.

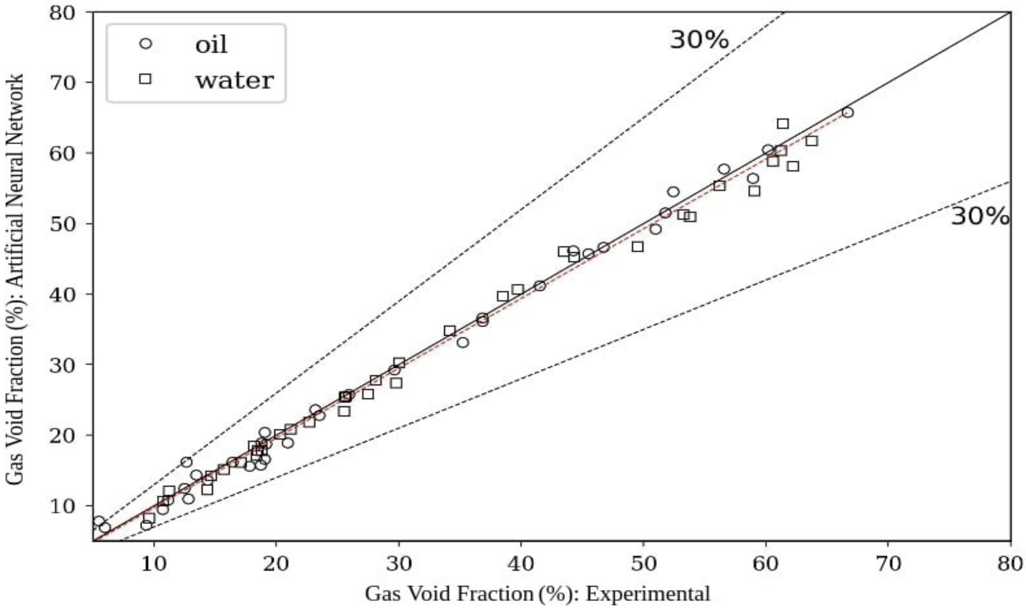

Figure 3. Comparison between the experimental gas void fraction and the prediction performed by the best artificial neural network developed in this work.

We can suggest that the proposed approach is feasible to predict the GVF for air-water and air-oil vertical upward two-phase flow, once that the artificial neural network input parameters used in this work can be estimated by correlations available in the literature, using pressure and temperature data, from actual industrial applications.

4. CONCLUSION

This work assessed the artificial neural network ability to predict the gas void fraction for air-water and air-oil vertical upward two-phase flow, using as input parameters fluid properties and operating conditions (ρ_g , ρ_L, μ_g, μ_L, v_{sg}, v_{sl}). The experimental GVF were measured by a quick closing valve system, and the measurements carried out by this apparatus presented a low standard deviation. The results showed a good agreement between the predicted and actual target values, which lead us to conclude that the proposed technique is suitable to estimate the gas void fraction. In order to increase the applicability of this approach, the artificial neural network training data set could be improved inserting in it points using other liquids as continuous phase, and more experimental data.

5. ACKNOWLEDGMENTS

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7. RESPONSIBILITY NOTICE

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