NEURAL NETWORK TO MEASURE VOLUMETRIC FRACTION OF A BUBBLY COLUMN USING ULTRASONIC WAVE

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Abstract. *The development of advanced nuclear reactor conceptions depends largely on the amount of available data to the designer. Non invasive ultrasonic techniques can contribute to the evaluation of gas-liquid two-phase regimes in the nuclear thermo-hydraulic circuits. A key-point for success of those techniques is the interpretation of the ultrasonic signal. In this work, a methodology based in artificial neural networks (ANN) is proposed to predict volumetric fractions in a bubbly flow. To accomplish that, an air feed system control was used to obtain specific bubbly flows in an experimental system utilizing a Plexiglas vertical bubbly column. Five different volumetric fractions were generated. The bubbles were photographed and measured. To evaluate the different volumetric fractions it was used the ultrasonic reflected echo on the opposite wall of the column. Then, an ANN has been developed for predicting volumetric fractions by using the frequency spectra of the ultrasonic signal as input. A trained artificial neural network using ultrasonic signal in the frequency domain can evaluate with a good precision the volumetric fraction of this system.*

Keywords: *neural network, two-phase flow, volumetric fraction, ultrasonic frequency domain.*

1. INTRODUCTION

The detection and characterization of bubbles in thermo-hydraulic systems is essential for the safety and development of the primary cooling system of advanced nuclear reactors. The experimental measurements of two-phase flow parameters are important to confirm theoretical predictions and to validate computational codes. In nuclear reactors cooling systems great care is necessary in the control of the flow parameters due to the risk of occurrence of loss of coolant and its consequences like the onset of nucleate boiling and formation of different two-phase flow regimes.

There are many techniques for the measurement of two-phase flow parameters. The techniques using electrical conductance like hot wire anemometers and electrical capacitance are invasive and therefore are flow interfering and need a connection between the probe and pipe to each measurement point. This difficult the calibration and the pipe is subject to leakage (Divora, B. et al (1980) e Andreussi P. et al (1988)). The pressure differential techniques are considered as semi-invasive technique. Matsui (1984) studied the vertical two-phase flow identification related to the pressure variation with statistical analysis. Although these techniques are relatively easy to implement, they require measurement points which incur leakage risks.

The main noninvasive techniques used to measure parameters of two-phase flow are optical, radiation techniques (X-ray, γ-ray or neutron absorption radiography and X-ray and γ-ray tomography) and ultrasonic. All of them have advantages and disadvantages and each one contribute to increase the confidence in the final evaluation.

The main optical techniques are laser Doppler anemometry (LDA) and particle image velocimetry (PIV). The LDA technique yields good measurements of flow velocity at specific points. Vial et al (2001) applied this technique in a bubble column to measure the average axial and tangential velocities in a maximum void fraction of 20%. PIV can measure velocities using the laser sheet. Lindken and Merzkirch (2002) used this technique to measure the velocity of a bubbly flow. These two techniques, LDA and PIV, need a transparent pipe and are not applicable in opaque fluids. The radiation attenuation techniques have high power of penetration and do not have the limitation of optical techniques but require a heavy safety structure, while the tomography techniques are expensive.

The ultrasonic techniques have many advantages: they are non-invasive and do not cause any leakage risks and changes in the flow regime because it is not necessary to hole the pipe, they do not need safety care to operators, they are not expensive, they can be used in high pressure and temperature flows, and they can be used in opaque fluids and non transparent pipes.

There are three main ultrasonic techniques to measure two-phase flow parameters: Doppler, transmission and pulse-echo. According to Masala et al (2005) the ultrasonic Doppler technique has relative advantage when applied in low void fraction liquid velocity measurement and gas bubble velocity measurement.

Chang et al (1983) used the ultrasonic transmission technique in a vertical bubbly flow. Emitting and receiving ultrasonic transducers are separated by the two-phase flow. Numerical modeling of the experiment was conducted by using Monte Carlo simulations and equivalent bubble method which consider bubbles with a perfect spherical shape and distributed uniformly along the column. The methods had good agreement for void fraction up to 20%. Faccini *et al* (2004) presented a hybrid ultrasonic technique formed by a contra-propagating transmission ultrasonic flow-meter, pulse-echo transmission ultrasonic voidmeter and a FieldBus data acquisition system. This technique was used to determine the stratified and plug flow pattern in a horizontal air-water two-phase flow. Chang *et al* (1990) used the ultrasonic pulse-echo technique in bubble air-water column and transmission technique in horizontal air-water flow. The void fraction was measured by means of ultrasonic attenuation using the ultrasonic transmission technique and Monte Carlo simulation. Using a polynomial regression method, it was possible to determine the stratified and intermittent flow patterns. Crivelaro-Seleghim (2002) used an invasive ultrasonic technique which provided input data from ultrasonic signals to artificial neural network (ANN) to diagnose two-phase flow regimes in a horizontal pipe obtaining good agreement.

The use of neural network applied to the volumetric fraction measurement with ultrasonic waves in spite of seeming to be promising is still incipient. In the present work the pulse-echo ultrasonic technique was applied to a vertical air-water Plexiglas bubbly column and it was studied the average volumetric fraction. Then, the frequency spectrum of the ultrasonic signal was used as input to an ANN for air flow prediction. For the characterization of bubbles a photographic technique was used.

2. EXPERIMENTAL SETUP AND METHODOLOGY

The experimental development was carried out in the ultrasound laboratory of Centro Federal de Educação Tecnológica of Rio de Janeiro. The device consists of a vertical transparent Plexiglas column with 700 mm long and a rectangular cross section (50 x 80 mm), as shown in figure 1. The bubble feed system was constituted by a set of four stainless steel calibrated orifices, fixed at the intermediate base seat. The orifice set consists of 0.45 mm inner diameters. In the present work, these calibrated orifices sets will be referred as orifice 045.

Figure 1. Bubbly column and ultrasonic system.

The ultrasonic system was constituted of a Physical Acoustic Corporation model DS345 – 30 MHz pulser and receiver board, a Hewlett Packard model 54616B digital oscilloscope (500 MHz) and a NDT Systems Inc piezoelectric transducer (6.35 mm (¼") diameter, 5 MHz).

The liquid surface level in the column is a function of air volume within it. Thus the volumetric fraction was obtained by the relation between the increment of the volume in the column, to each air flow rate, and the new total volume. Table 1 presents the measured volumetric fraction for the five air flow rates.

Table 1 – Volumetric fraction to each correspondent air flow.

Orifice	Volumetric fraction (%)				
	Air flow (l/min)				
	0.4	0.5	0.6	0.7	0.8
045	0.645	0.759	0.891	1.038	1.218

The number of bubbles, their mean diameter and other parameters, in each volumetric fraction were obtained by using a photographic technique (digital camera and the Image-pro Plus software). Fig. 2 shows typical images obtained by the photographic technique. Five volumetric fractions were studied.

The neural network uses the signals corresponding to the reflected ultrasonic wave from the opposite wall of the column and this one was treated in the frequency domain. These reflected ultrasonic signals are influenced by the distribution, diameter and density of the ascending bubbles in the flow.

Using the photographic technique, it was observed that the bubbles did not present spherical shape but an elliptical profile which turns accentuated in proportion as the air flow increases. By means of measurement of the main axes of the bubbles, calculations were made to obtain geometric parameters as they are described in Table 2 and presented in Table 3.

Table 2. Summary of data disposition presented on table 3

Number of bubbles	Relation $d/d_1 = r$
Average spherical diameter (mm) – d_{esf}	

Where:

- The number of bubbles represents the total quantity of bubbles obtained in the 10 photos.
- The relation d/d_1 represents the relation (r) between the arithmetic average of the smallest axes and the arithmetic average of the biggest axes of the bubbles
- The average spherical diameter (d_{esf}) was calculated from the average of the smallest axes (d) and from the average of the biggest axes (d_1) of the bubbles, through the equality of the formula of the area of the transversal section of a circular profile sphere with another of an elliptical profile, Eq. (1).

$$\pi.\frac{(d_{esf})^2}{4} = 2.\sqrt[4]{{d_1}^2 - d^2}.\sqrt{d_1} \tag{1}$$

TABLE 3 – Parameters of air bubble dispersed in the vertical column for volumetric fractions

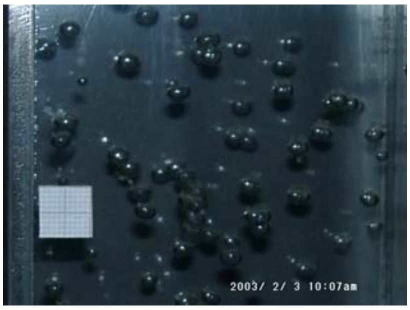
Orifice	Volumetric fraction (%)				
	0.645	0.759	0.891	1.038	1.218
045	421 r = 0.741 d_{esf} = 2.673	449 r = 0.718 d_{esf} = 2.797	472 r = 0.719 d_{esf} = 2.776	708 r = 0.743 d_{esf} = 2.647	919 r = 0.762 d_{esf} = 2.571

Analyzing the bubbles in different volumetric fractions, it was verified that the bubbles show small size, they are distributed, most of the path, uniformly, presenting high density along the longitudinal section of the column. Upon analyzing table 3, it can be verified, too, that between the minimum and the maximum volumetric fraction (0.645 to 01.218 %) happened great variation of the number of the bubbles (184%) and in bubble density (117%). Figure 2 shows the photos of the bubbles within the column at different volumetric fractions.

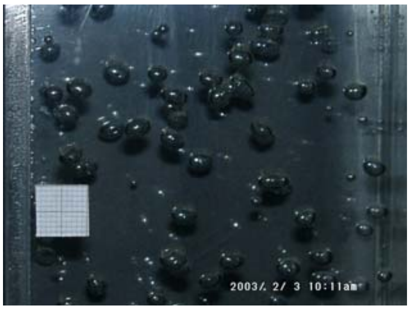
3. VOLUMETRIC FRACTION PREDICTION BY NEURAL NETWORK

This session describes the ANN developed in this work. The ANN takes discrete frequency spectra of ultrasonic signals as inputs and outputs volumetric fraction values.

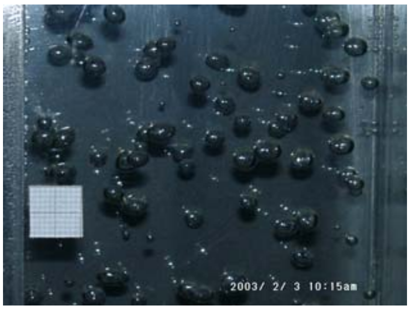
Figure 3(a) shows 10 frequency spectra obtained for a volumetric fraction of 0.645%. Note that such spectra present well-defined shape, which clearly characterizes the volumetric fraction. Figure 3(b) shows that increasing volumetric fraction the values of the maximum amplitude of the frequency spectra declines lineally.



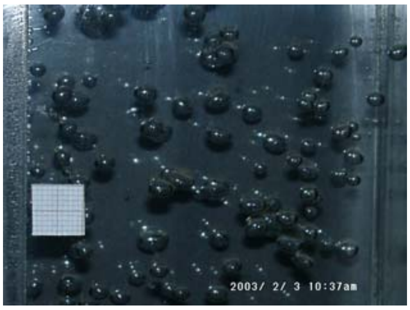
(a)_



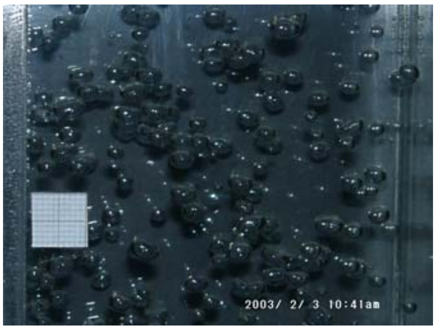
(b)



(c)

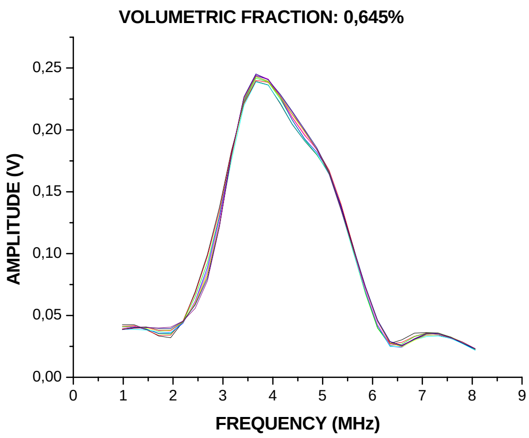


(d)

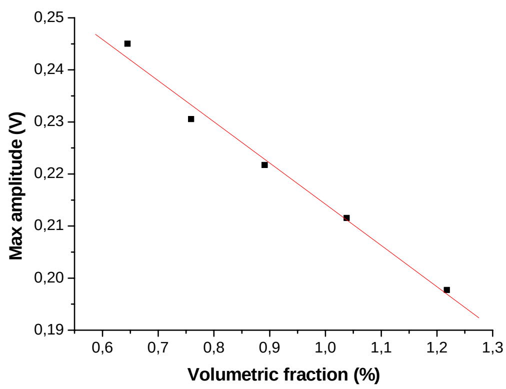


(e)

Figure 2. Image of the bubbles within bubbly column according to the volumetric fraction:
(a) 0.645%; (b) 0.759%; (c) 0.891%; (d) 1.038% and (e) 1.218%



a)



b)

Figure 3 – (a) frequency spectra for volumetric fraction of 0.645%, (b) variation of the maximum amplitude of frequency spectrum as function of the volumetric fraction

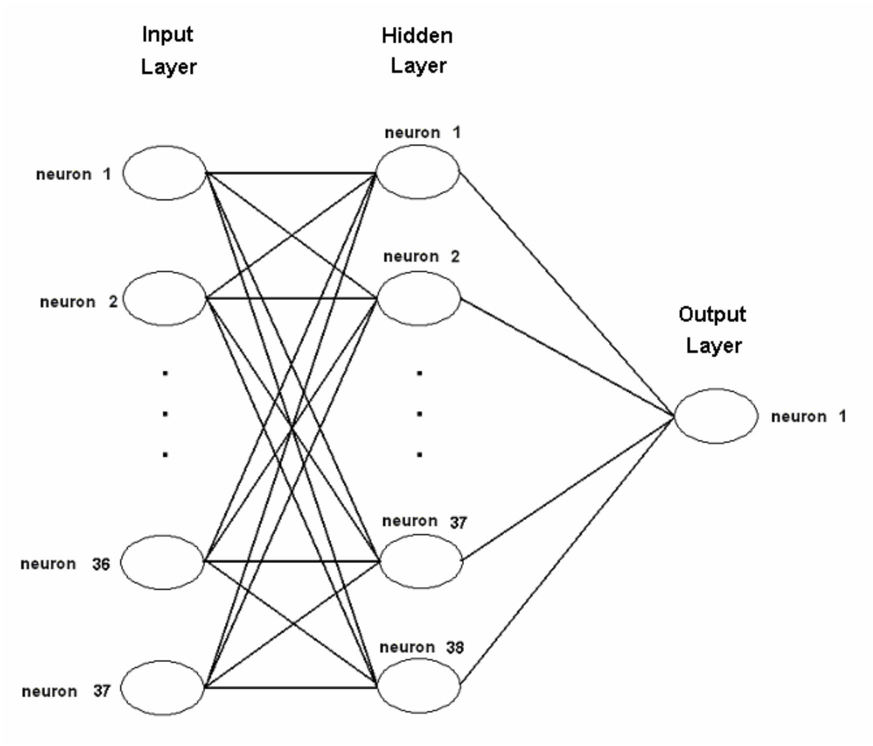


Figure 4 – ANN topology

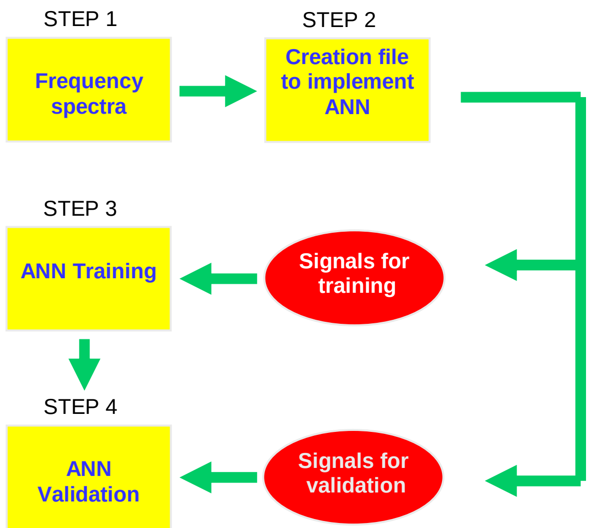


Figure 5 – ANN design and training methodology

Artificial Neural Networks (ANNs) are mathematical models inspired in the human brain and its biological neural networks. The main feature of an ANN is the ability of learning from examples. Prediction, pattern classification and clustering are important capabilities of an ANN.

Basically, an ANN works in two phases: i) training and ii) operation. In the training phase, the ANN is supposed to learn from examples, called training patterns. Generally a database of training patterns is previously defined. In the operation phase, the trained ANN executes the task it has been trained for.

There are many types of ANN, which combine different topologies and learning algorithms. In this work, a typical MLP (Multi Layer Perceptron) with backpropagation learning algorithm has been used. The ANN developed in this work presents 37 neurons in the input layer, which receives the spectra discretized into 37 points, 38 in the hidden layer and 1 neuron in the output layer, which outputs the volume fraction. Figure 4 shows the ANN topology.

A database of 10 spectra (discretized into 37 points) for each one of the 5 different volume fractions has been generated. From a total of 50 patterns, 25 have been used for training, 15 for testing generalization and stop criteria (during the training phase) and 10 for validation of the trained ANN (simulating the operating phase). The methodology used for designing and training the ANN is illustrated in Figure 5.

5. RESULTS

Using examples of all different volumetric fractions in the training set, the ANN was able to predict the volumetric fraction values with maximum relative error of 1.51%. Table 4 shows the errors obtained.

Table 4: Errors obtained using all different volumetric fractions from training set.

Volumetric fraction	Average error	Relative average error (%)
0,645	0,002	0,33
0,759	0,011	1,51
0,891	0,009	0,96
1,038	0,013	0,95
1,218	0,007	0,59

Aiming to verify the generalization ability of the proposed ANN, all patterns related to 0,645 volumetric fractions have been excluded from the training set and used only for validation of the trained ANN. Results of this test are shown in tables 5 and 6.

Table 5: Errors obtained excluding 0,891% volume fraction from training set.

Volumetric fraction	Average error	Relative average error (%)
0,645	0,007	1,12
0,759	0,020	2,65
0,891	0,053	5,93
1,038	0,024	1,70
1,218	0,013	1,04

Table5: Errors obtained for 10 individual characterizations for the 0,891 % volume fraction.

Reference value	*ANN prediction*	*Error*	*Relative Error(%)*
0,891	0,841	0,050	5,61
0,891	0,810	0,081	9,09
0,891	0,852	0,039	4,38
0,891	0,844	0,047	5,27
0,891	0,807	0,084	9,43
0,891	0,865	0,026	2,92
0,891	0,838	0,053	5,95
0,891	0,831	0,060	6,73
0,891	0,837	0,054	6,06
0,891	0,859	0,032	3,59

As expected, average errors have increased due to the exclusion of information from training set. It was observed that errors related to 0.891 volume fractions predictions were responsible for this fact. However, considering that such patterns unknown by the ANN, errors above 10% means a good generalization capability.

6. CONCLUSIONS

In this work a new methodology based on the use of artificial neural networks has been proposed to predict volumetric fraction in a vertical bubbly column. The shape and quantity of the bubbles varied to each different volumetric fraction. The artificial neural network technique shows to be sensitive to the variation of the volumetric fraction. A MLP ANN has been designed and trained in order to correlate the frequency spectrum of ultrasonic signals (ANN inputs) to the respective volume fractions (ANN outputs). Using a training set of 25 patterns (+ 15 test set patterns), the ANN achieved maximum error above 6% and maximum error above 10% in volume fractions prediction, demonstrating to be a promising tool for two-phase flows characterization. The results show the possibility of using just one transducer applying the signals of the ultrasonic pulse-echo technique to evaluate with good precision the volumetric fraction studied in this work.

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5. RESPONSIBILITY NOTICE: