Istraživanja i projektovanja za privredu
ISSN 1451-4117
DOI:10.5937/jaes0-40309
www.engineeringscience.rs

publishing

Journal of Applied Engineering Science
Vol. 21, No. 1, 2023
Original Scientific Paper
Paper number: 21(2023)1, 1072, 285-299

SPECIALIST SYSTEM IN FLOW PATTERN IDENTIFICATION USING ARTIFICIAL NEURAL NETWORKS

July Andrea Gomez Camperos[1], Carlos Mauricio Ruiz Diaz[2], Marlon Mauricio Hernández Cely[3]*

[1] Mechanical Engineering Department, Universidad Francisco de Paula Santander, Seccional Ocaña, Vía Acol-sure, Sede el Algodonal Ocaña, Ocaña 546552, Colombia
[2] Mechanical Engineering Department, Industrial Multiphase Flow Laboratory (LEMI), São Carlos School of Engineering (ESSC), University of São Paulo (USP), Av. Trab. São Carlense, 400 - Parque Arnold Schimidt, São Carlos - SP, 13566-590, Brazil
[3] Control and Automation Engineering, Engineering Center, Federal University of Pelotas, Rua Benjamin Con-stant, n° 989, Porto, Pelotas - RS, 96010-020, Brazil

* jagomezc@ufpso.edu.co

In this work, an application of artificial intelligence in the oils & gas industry is developed to iden-tify flow patterns in horizontal and vertical pipes of two-phase flow of oil and water, normalizing the word information and converting it to numerical values through the development of an artifi-cial neural network, whose input layer is composed of the surface velocities of each fluid, the ve-locity of the mixture, the volumetric fraction of the substances, diameter and the inclination of pipelines and the oil viscosity. The Artificial Neural Networks (ANN) has two hidden layers composed of 45 neurons. The database with which the model was trained, validated, and tested has 6993 rows of information corresponding to the inputs of the intelligent system and particular-ized for annular flow in horizontal pipes and DO/W in vertical pipelines. Notice that the infor-mation was obtained after re-engineering the information presented by 12 and 18 authors for hor-izontal and vertical piping, respectively. Finally, the mean square error obtained by the model was around 1.38%, with a maximum coefficient of determination of 0.79.

Keywords: artificial neural network, flow pattern, two-phase flow, machine learning

1 INTRODUCTION

In the petrochemical, food, chemical, and other industrial processes, two-phase flows are often present as liquid-liquid (oil-water) or gas-liquid (gas-water or gas-oil) mixtures. One of the industry's main goals is to improve the efficiency of the processes. Hence it is necessary to investigate the hydrodynamics of those flows further. This article analyzes the use of artificial intelligence-based on artificial neural networks (ANN). This study is a case where few data obtained in the laboratory are used to train and test the ANN. An artificial neural network can be trained with only some, but reliable data duly validated by other measurement instruments to provide a solution to predict important parameters of processes in which liquid-liquid flow occurs. Operating parameters that require great attention include in situ volumetric fraction related to pressure drop, heat and mass transfer, corrosion, and others.

Techniques based on electrical impedance are one of the options to monitor and control industrial processes[1]. However, the information delivered by the systems quite often requires experience from the operator. For this reason, the automatic system based on artificial intelligence that efficiently retrieves critical information is one of the most useful options.

In the literature, different investigations use artificial intelligence to study two-phase flows of water and air in a vertical duct as those developed by [2] and [3]. These authors used the input signal from the sensor based on electrical impedance to train the neural network to identify the flow pattern. They concluded that it is possible to identify the global and local flow regime using the probability distribution and measured based on electrical conductivity, whose information was used to train the artificial neural network [4]. In order to have better accuracy and identify the flow patterns, this system was analyzed with intelligent algorithms based on Support Vector Machine (SVM) and wavelet transform, efficiently using the electrical characteristics obtained by Electrical Resistance Tomography (ERT) sensor[5]. [6], identified the flow regime through neural networks, having as inputs for the intelligent system the Probability Density Functions (PDF) of the electrical-impedance time signal. Flow patterns have been characterized using the topographic information obtained by a capacitive sensor; the images obtained were used as characteristics for an intelligent system based on fuzzy logic [7]. [8] the pressure-time signal of a flow to train an intelligent system based on the Elastic Maps Algorithm (EMA) technique for identifying the flow pattern. Other authors, as [9], combined the artificial intelligence methods of [8] with Principal Component Analysis (PCA) to obtain the flow rate based on an electrical signal related to the flow pressure signature. Three artificial intelligence algorithms based on Artificial Neural Networks (ANN), genetic programming (GP), and Support Vector Machine (SVM) were compared to obtain the volumetric fraction and flow rate [10]. Recently, an innovative technique, based on a hybrid machine learning system combined techniques such as neural networks and random forest to obtain the liquid-gas flow pattern [11], where phenomenological expressions were used to improve the prediction capabilities of the data-driven approaches.

In a study of water-air two-phase flow in a horizontal pipe to determine the flow pattern using artificial intelligence [12], the band spectrum from hydrophones was used as a neural network input. Artificial intelligence based on neural networks was applied by [11], where the time signal of the flow pressure was used to train the network and determine the flow pattern. Based on Electrical Capacitance Tomography (ECT) signal, [12] trained the back-propagation neural network to determine flow patterns in a horizontal pipe. [13] determined the flow patterns employing six artificial intelligence methods, using the time signal of a gamma-ray sensor as input to train the intelligent models. The above researchers concluded that five methods presented good results, with the exemption of the algorithm based on Single Decision Tree (STD). Using artificial intelligence systems based on fuzzy logic techniques and data of void fraction obtained by a Wire-Mesh Sensor (WMS), [14] identified several flow patterns. [14] used Support Vector Machine (SVM) to identify the oil-air flow patterns. They used the data obtained from an ECT for training. The input parameters for a neural network used by were applied with an ultrasound source, used for training and flow pattern recognition.

Oil-water two-phase flow studies in vertical pipes using computational intelligence were previously reported by [15] and [16]. [15] used the characteristics obtained from an ultrasound source and sensor-based on electrical capacitance as inputs for the training of a neural network to determine the volumetric water fraction. In contrast, [16] used the fluids' superficial velocities to calculate the volumetric water fraction for the network's training. An oil-water flow in a horizontal pipe was studied by [17],[18], who analyzed the different flow patterns through neural networks. The data used in that work were the photographs acquired by an optical probe, the same technique used by[19],[20]. TABLE I summarizes the main studies used in the different studies. This table extracts the main characteristics of the experimental and analytical data of each author, classified according to each artificial intelligence Technique used.

Some works dedicated to recognizing flow-patterns in solid-gas two-phase flow were also found, as [21], who implemented a neural network with back-propagation architecture using time signals of an electrostatic sensor. There are also some investigations developed in water-oil-air three-phase flow using artificial intelligence techniques to identify flow patterns, such as [22], [23], [24], [25]. Works have also been done identifying flow structure and flow regime transitions in two-phase air, and water flows [11] and predicting physical parameters in two-phase oil and water flows [26].

Currently, great technological advances are being presented due to the submergence of industry 4.0 and the industrial internet of things IioT [27], [28], [29]. One of the great pillars of this industrial revolution is machine learning, with its different techniques to solve, analyze and model problems in industrial processes. Motivated by these advances, in this paper he presents a methodology based on artificial intelligence to identify flow patterns, in the oil water process, as a fundamental pillar of industry 4.0. The main objective of this study is to use the data of surface velocities, volumetric fractions, pipe diameters, and inclinations, and viscosities as input parameters for the structuring, training, validation, and testing of a neural network capable of predicting characteristic flow patterns in vertical and horizontal pipes with the two-phase flow of oil and water that currently according to the literature found have been described mathematically without using intelligent models.

For the identification of multiphase flow patterns, we work with conventional or experimental methods based on mathematical modeling, which is sometimes difficult to understand and process, by computer systems or by technical personnel in charge of data analysis. The present work brings the novelty of incorporating artificial intelligence to the study of multiphase flows, contributing to its great identification capacity, when selecting hydrodynamic characteristics of the fluids present in the oil and gas industry.

Table 1. main studies found in the literature applied to multiphase fluids using artificial intelligence

Reference	Pipe	Two phase flow	Artificial Technique	Measured characteristic	Instrument technique	Indicator
[2]	Vertical	Air-water	ANN	Void fraction, void fluctuations	Impedance void meter	Bubbly, Slug, Churn and Annular flow.
[3]	Vertical	Air-water	ANN	Void fluctuations	Impedance void-meter	Bubbly, Slug, Churn and Annular flow.
[4]	Vertical	Air-water	ANN	Voltage void fraction.	Conductivity probes	Bubbly, Slug, Churn- Annular flow.
[5]	Vertical	Air-water	Wavelet transform (SVM)	Voltage signal in time	ERT	Bubbly, Slug and Annular flow
[6]	Vertical	Air-water	ANN, expert systems	Void fraction Impedance sensor	Electrical resistivity probe	Bubbly, Slug Churn, semi annular and Annular flow.

Reference	Pipe	Two phase flow	Artificial Technique	Measured characteristic	Instrument technique	Indicator
[7]	Vertical	Air-water	Fuzzy logic	Tomography imaging using 3D	Electrical capacitance tomography	Bubbly, Bubbly–slug, Slug, Slug–churn, Churn, Churn–annular and Annular flow.
[8]	Vertical	Air-water	Elastic maps algorithm	PDF	Differential pressure	Bubbly, Slug, Churn, and annular flow
[9]	Vertical	Air-water	PCA, ANN	PDF and PSD	Signal in time of differential pressure	Bubbly, Slug, Churn, and annular flow.
[10]	Vertical and horizontal	Air-water	ANN, SVM, GP	Coriolis flowmeter, DP transducer	Signal Coriolis	Liquid mass flow rate, Gas volumetric fraction
[12]	Horizontal	Air-water	ANN	Band Spectra	Hydrophone	Bubbly, Slug, Churn and Annular flow.
[27]	Horizontal	Air-water	ANN	Absolute pressure signals	Differential pressure transducer	Bubbly, slug, and wavy stratified flow.
[30]	Horizontal	Air-water	ANN	Signal electrical capacitance and image tomography	Capacitance tomography sensor	Stratified, Annular, core and bubble flow.
[13]	Horizontal	Air-water	SDT, ANN	Absorption Signal time.	Gamma ray	Slug, plug, bubble, Transitional and plug – bubble flow.
[31]	Horizontal	Air-water	Fuzzy logic c-means	Void fraction PDF.	Wire-mesh sensor	Annular, Bubbly, Stratified, annular, Bubbly flow.
[14]	Horizontal	Oil-air	SVM	Electrical capacitance	ECT	Stratified flow, annular and core flow.
[36]	Vertical	Oil-air	ANN	Acoustic attenuation	Ultrasonic attenuation	Dispersed bubbles, Intermittent, Churn, Annular, gas volumetric fraction (GVF)
[15]	Vertical	Water-oil	ANN	Acoustic measurements impedance	Electrical impedance measurements	Water-cut
[16]	Vertical and inclined	Water-oil	ANN	Literature	Literature	Water holdup
[17]	Horizontal	Water-oil	ANN	Photographic and optical probe techniques	[34], [19], [20]	Stratified smooth, stratified wavy, Plug, Inverted dispersed

2 MATERIALS AND METHODS

This research was developed considering a re-engineering process and the information presented by several authors in the open literature in their works with a two-phase flow of lubricating oil (o) and water (w), obtaining a database with a total of 6993 points, which includes surface velocities (j_o, j_w, j_{o+w}), volumetric fractions ($\varepsilon_o, \varepsilon_w$), pipe diameters ($D$) and inclinations ($\theta$), viscosities ($\mu$), and flow patterns.

The numerical ranges studied in this work are presented in Table 2.

Table 2. Numerical ranges of the parameters used

Parameters	Range	
	Low value	High value
jo [m/s]	0.00035	4.48
Jw [m/s]	0.00035	4.17
Jo + jw [m/s]	0.0069	5.94
εw [-]	0	1
εo [-]	0	1
D [m]	0.0056	0.127
μo [Pa. s]	0.001	5.6
θ [°]	0	90

The literature database for horizontal pipes with the two-phase flow was structured from a re-engineering process of the information presented by 12 authors, reaching around 2129 experimental points, summarized in Table 3, which correspond to rows of information with diameters, viscosities, surface velocities, and volumetric fractions. In this database, eight characteristic flow patterns were identified as follows: ST, ST & MI, D o/w & w, D o/w & D w/o, D o/w, D w/o, I, and A.

Table 3. Horizontal pipeline summary database

Reference	D [m]	μ_o [Pa.s]	No. of data
[35]	0.021	0.799	138
[36]	0.1064	0.00188	49
[37]	0.1	0.002	99
[38]	0.0508	0.0288	106
	0.0508	0.013	30
	0.0508	0.013	88
[39]	0.026	5.6	69
[40]	0.019	0.012	196
	0.0254	0.012	268
[41]	0.025	0.107	536
[42]	0.032	0.0054	57
[43]	0.059	0.022	76
[44]	0.0828	0.00717	43
[45]	0.026	5	64
[46]	0.0056	0.0052	213
	0.007	0.0052	97

Analogously, for the vertical pipe with the biphasic flow of oil and water, a re-engineering process was developed for the information presented by 18 authors. First, a database was structured to store 4864 rows of information with diameters, viscosities, surface velocities, and volumetric oil and water fractions. In the database developed, 10 flow patterns were identified: S o/w, S w/o, TF, VFD o/w, VFD w/o, D o/w, D w/o, churn o/w, churn w/o, and core flow. Table 4 summarizes the information contained in the database obtained from the standpipe literature.

Table 4. Vertical pipeline summary database

Reference	D [m]	μ_o [Pa.s]	No. of data
[47]	0.0284	0.488	392
[36]	0.1064	0.00188	49

Reference	D [m]	µ_o [Pa.s]	No. of data
[48]	0.02	0.011	101
[49]	0.05	0.02	126
[50]	0.04	0.035	92
[51]	0.0263	0.0201	15
[52]	0.02	0.125	175
[53]	0.127	0.001	9
[54]	0.027	0.02	109
[55]	0.0254	0.001	55
[56]	0.0254	0.001	32
[57]	0.01	0.287	1421
[58]	0.026	0.0011	90
[59]	0.03	0.03	252
[60]	0.0284	0.5	92
[61]	0.03	0.044	98
[62]	0.02	0.09732	1699
[63]	0.04	0.0041	57

From the information collected, complementary treatments were carried out on the unified database to structure a predictive model capable of identifying the flow patterns present in horizontal and vertical pipes by applying concepts related to ANN. Additionally, the Reynolds number was calculated to determine the type of flow, obtaining values between 0.12 and 275714.9 (i.e., laminar, and turbulent flows, defined from the surface velocities of the mixture, the diameter of the pipe, together with the viscosity and viscosity of the mixture).

2.1 ANN develops

The artificial intelligence technique used to structure the predictive model was artificial neural networks; this implementation was carried out in MATLAB software. The development of the neural network includes a fractionation of the total database (6993 items), where 70% of it is used in the training of the model (4892 items), another 15% of the information is used in the validation (2098 items), and the remaining 15% is used in the testing of the developed model.

The parameters defined in the input vector of the neural network were the surface velocities of each fluid, the velocity of the mixture, the volumetric fraction of the substances, the diameter and the inclination of pipelines, and the oil viscosity. The variable defined in the output layer was the flow pattern, as shown in Fig. 1.

The hyperparameters set in each structuring developed were the learning rate, the number of iterations (1000), the number of hidden layers (2), the number of neurons in each hidden layer, and the Tangent sigmoid activation function, following the convergence theory defined by [63] for the universal approximation theorem for neural models.

The parameters defined for each layer were the updated synaptic weights at each epoch and the biases. The training function used was identified by Levenberg-Marquardt with the addition of back-propagation to optimize the gradient descent and the loss function. Finally, the performance of each model developed was defined by the mean squared error (MSE). The computer system used to develop the neural network models was a laptop with an 8th generation core i5+ processor, 32 GBytes of RAM and a 1 Tb solid state disk.

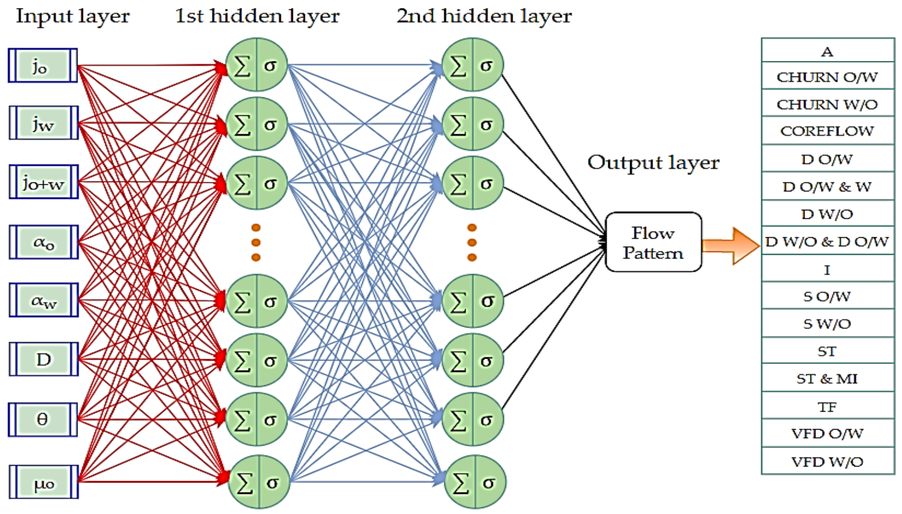


Fig. 1. General structure of the artificial neural network developed.

2.2 Normalization

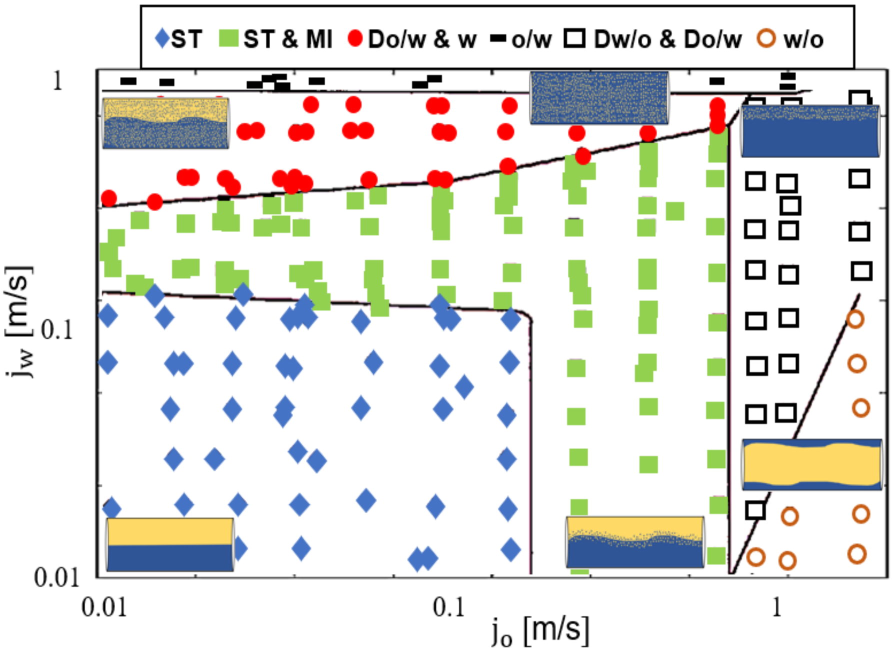
The output vector is composed of the flow patterns for horizontal and vertical pipes, which are symbolically defined from strings, named in different ways in the au-thors nomenclature, and unified by us.

Considering the restriction generated in the structuring of neural networks in MATLAB related to strings, it is necessary to normalize the information in the output vector to convert it to numerical values and fully develop each model with numerical values. This conversion was developed considering a normalization process to the output vector, defining a normalization interval between zero and one ([0-1]), considering a scaling developed alphabetically. Each flow pattern defined corresponds to a single value within that interval shown in Table 5. Notice that the normalization was implemented in Python software.

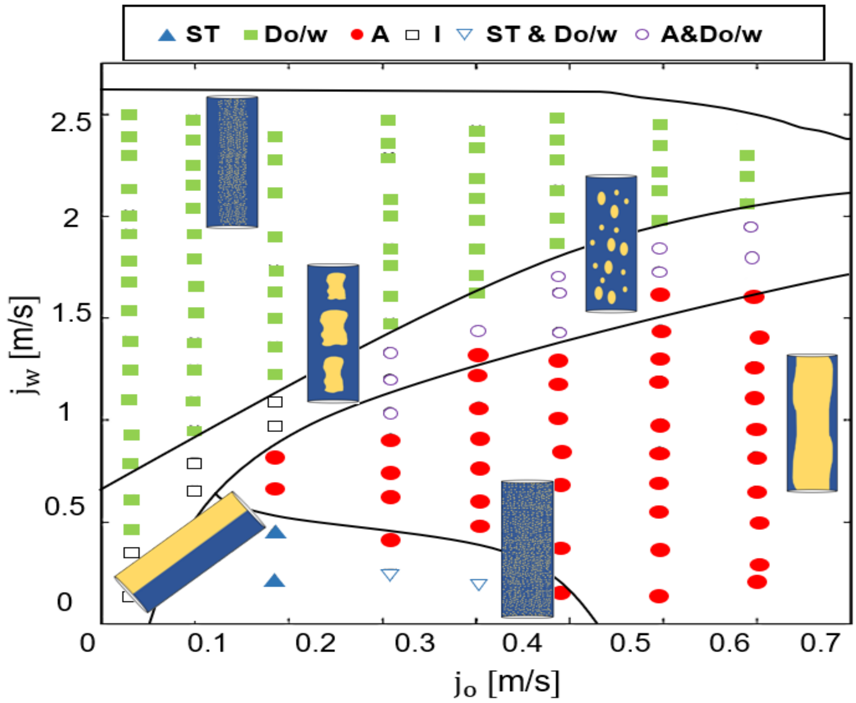
Table 5. normalization of nomenclature used

Normalized values	Flow pattern	Symbol	Number of data
0	Annular	A	247
0.067	Oil-in-water churn	CHURN O/W	21
0.133	Water in oil churn	CHURN W/O	126
0.2	Core flow	COREFLOW	480
0.267	Oil-in-water dispersion	D O/W	1305
0.333	Oil-in-water in water dispersion	D O/W & W	10
0.4	Water-in-oil dispersion	D W/O	1616
0.467	Water-in-oil and Oil-in-water dispersion	D W/O & D O/W	20
0.533	Intermittent	I	304
0.6	Oil-in-water slug	S O/W	459
0.667	Water-in-oil slug	S W/O	656
0.733	Stratified	ST	515
0.8	Stratified with mixing at the interface	ST & MI	351
0.867	Transition flow	TF	314
0.937	Oil-in-water very find dispersion	VFD O/W	365
1	Water-in-oil very find dispersion	VFD W/O	204

Figure 2 shows two flow maps, one for horizontal pipe (a) and one for inclined pipe (b), considering the Cartesian axes, the oil and water velocities. At the same time, representative images of each flow pattern are presented, which visually identifies the specific behavior inside the pipes, and therefore, the identification of the characteristic flow patterns for two-phase flows is generated.



(a)



(b)

Fig. 2. (a) Two-phase flow pattern map for horizontal pipes. Modified of [65]; (b) Two-phase flow pattern map for inclined and vertical pipes with representative images. Modified of [38]

2.3 Inverted results

The normalization inversion process was carried out in Python software, structuring a column vector with the results of each neural network model developed to generate an equivalence between the initial symbolic vector corresponding to the original flow patterns with the flow patterns generated by each system. Furthermore, a database is structured in which the information is stored to be analyzed, considering mathematical parameters that determine the highest level of similarity between the real and the predicted.

2.4 Statistical parameters

The best predictive model structure was selected with artificial neural networks, and two statistical parameters were defined to compare the real values with the experimental ones. These statistical parameters are the mean square error (MSE) and the coefficient of determination R2 because we are working with linear models.

The mathematical assignment for the two statistical parameters is detailed in Equations 1 and 2.

$$MSE = \frac{1}{n}\sum_{m=1}^{n} \left(Y_{(Exp,m)} - Y_{(Pred,m)}\right)^2 \quad (1)$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n} \left(Y_{(Exp,m)} - Y_{(Pred,m)}\right)^2}{\sum_{m=1}^{n} \left(Y_{(Exp,m)} - \underline{Y}_{(Pred,m)}\right)^2} \quad (2)$$

where $Y_{(Exp,m)}$, equivalent to the value of each class obtained from the literature, $Y_{(Pred)}$, corresponding to each value generated by the predictive model and $\underline{Y}_{(Pred,m)}$ as the mean of all the values obtained by the ANN.

3 RESULTS AND DISCUSSION

Sixteen neural network structures were developed with an input vector composed of 8 parameters defined in Table 5, two hidden layers with the same number of neurons in each of them, following a constant increase of 5 neurons in each new structure. The only output layer is composed of the results of the predictive models corresponding to the flow patterns for the horizontal and vertical pipe.

Table 6 presents the results obtained for the statistical parameters defined in the methodology, obtaining results for the mean square error between 1% and 2%. The coefficient of determination of the linear models presents values between 68% and 78%, which allowed the selection of the best artificial neural network model, which was structured with fifteen (15) neurons in each occultic layer, using the sigmoid tangent activation function (TanSig) and the Levenberg - Marquardt training function and the application of back-propagation.

Table 6. Results obtained for each ann structuring developed

Configuration	Activation function	Neurons	R²	MSE	MSE (%)
1	TanSig	15-15	0.68	0.021	2.13
2		20-20	0.74	0.017	1.73
3		25-25	0.75	0.016	1.61
4		30-30	0.72	0.019	1.86
5		35-35	0.74	0.026	2.57
6		40-40	0.75	0.016	1.63
7		45-45	0.79	0.014	1.38
8		50-50	0.74	0.017	1.68
9		55-55	0.74	0.017	1.70
10		60-60	0.71	0.019	1.90
11		65-65	0.71	0.019	1.88
12		70-70	0.76	0.016	1.57

The comparison between the values obtained for the R² of each model allows select the best structuring (7), since an overall maximum of 0.79 was reached, followed by 0.761, 0.76 and 0.754 as shown in Fig. 3.

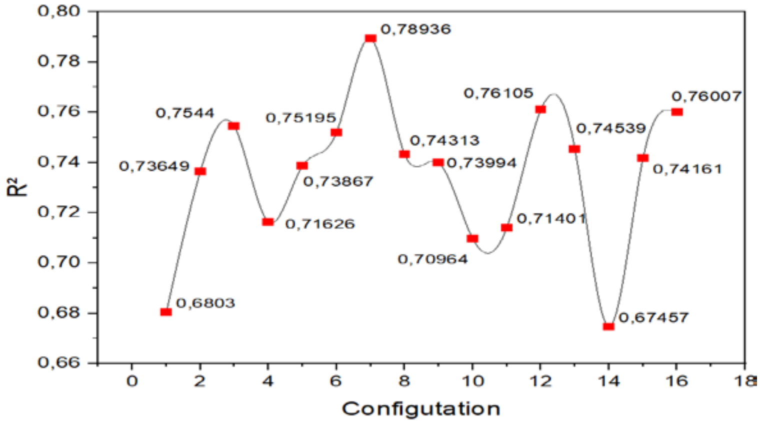


Fig. 3. Coefficient of determination obtained for each structured intelligent model and its respective value

The MSE allowed selecting its best result in structuring with 45 neurons in each hidden layer, reaching the global minimum at 1.38%, followed by the local minimums of 1.57, 1.61, and 1.68, as is shown in Fig. 4.

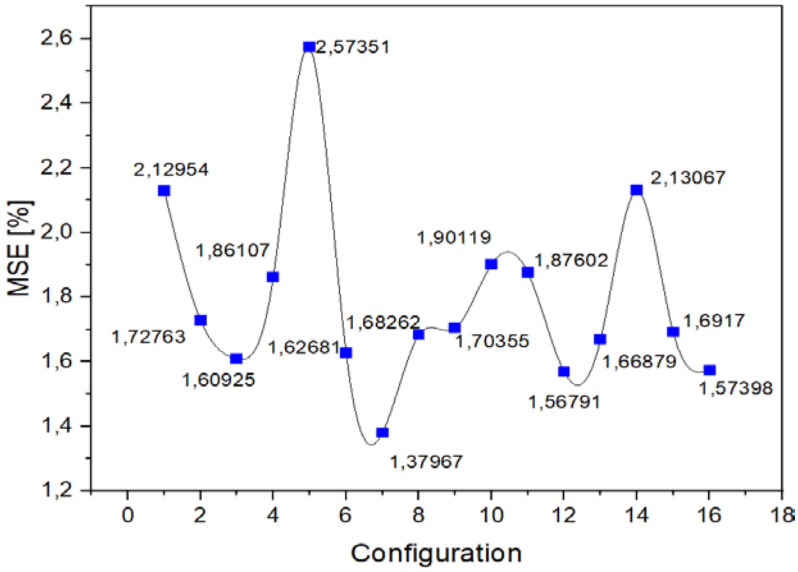


Fig. 4. Mean square error obtained for each structured intelligent model and its respective value

Additionally, the statistical results mentioned in equations (1) and (2) are complemented with an error histogram, presented in Fig. 5, where the values of the error obtained in each one of the intelligent model development stages (training, validation and testing) are shown, featuring a centered normal distribution, indicating the quality of the developed process. A central tendency is identified with error values close to the ideal, which is zero, concentrated in the range of values between -0.1 and 0.1, given that 98.6% of the information, corresponding to 6896 data, are found with an error of less than 0.3, identified by the proximity to the central line that represents the zero error, and representing a low level of error in the 3500 instances included in which the results generated in each phase were numerically close to 0. In the central column, the highest frequency was identified, corresponding to 3607 data, of which 2588 were obtained in the training phase, 514 in the validation phase and 505 in the test phase. Average total error was 3%, with a standard deviation of 0.5 and an evident efficiency in the learning process of the intelligent model, framed by the decrease of the error as the development of the model progressed.

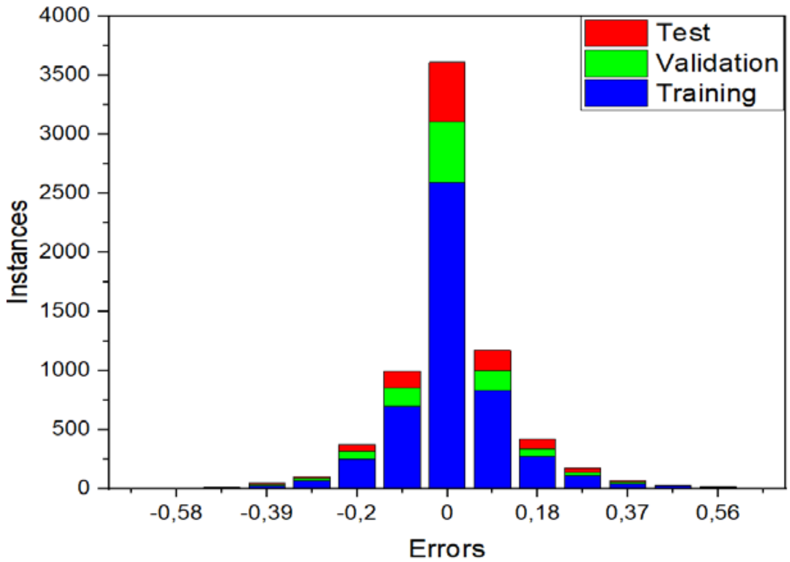
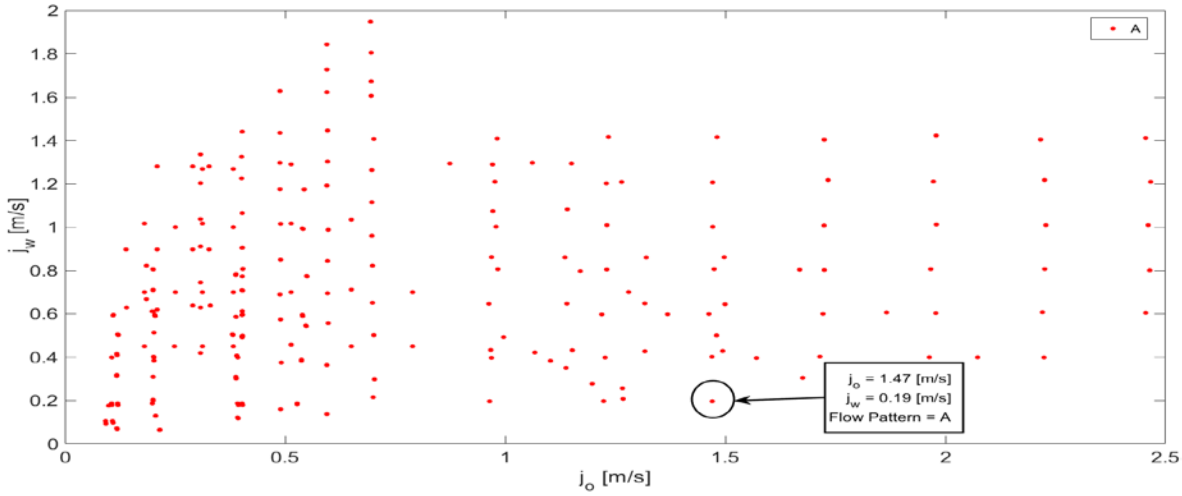


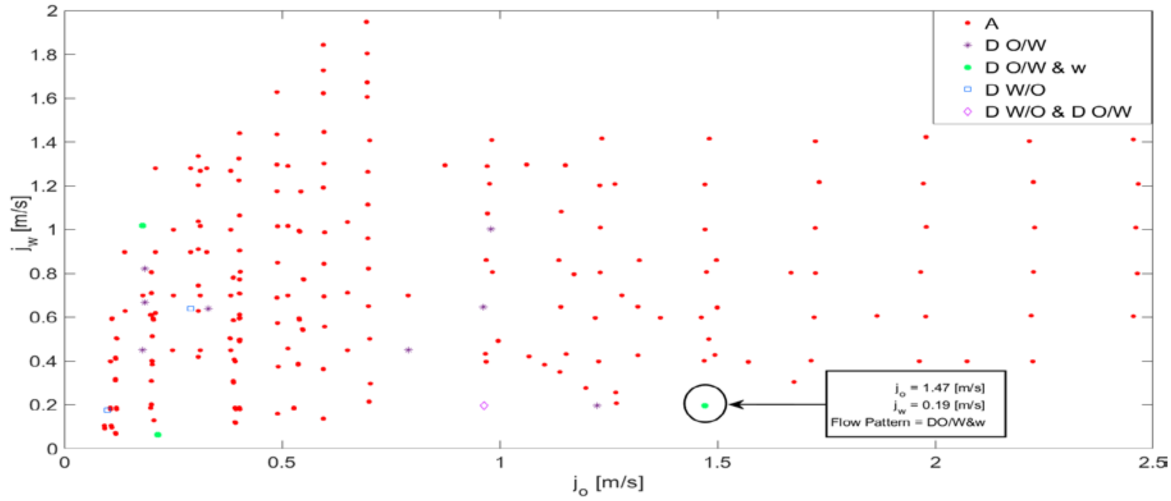
Fig. 5. Error histogram obtained for each structured intelligent model

In the present work, highly accurate comparative schemes were developed for two specific flow patterns since they are the most like other geometric configurations developed inside the pipelines. One of the flow patterns analyzed was the annular (A) in the horizontal pipe due to its physical similarity to flow patterns with the dispersion of oil in water, water in oil, and the combination between them when it begins its formation.

Fig. 6 compares the actual data obtained from the literature for the annular flow pattern in the horizontal pipe (247) (a) and the results obtained by the developed predictive model (b). In the predicted results, four flow patterns different from the annular one are identified due to the minimum level of uncertainty presented considering the model and the similarity in the velocity interval in which the additional flow patterns are developed, with a quantity of 8 data for DO/W, 3 for DO/W & W, 2 for DW/O and 1 for DW/O & DO/W, thus generating 233 annular flow pattern points coincident with the experimental ones, which is shown in the cell in the Fig. 6 with equal velocities values for water and oil in both experimentation and prediction, but showing a different flow pattern.



(a)

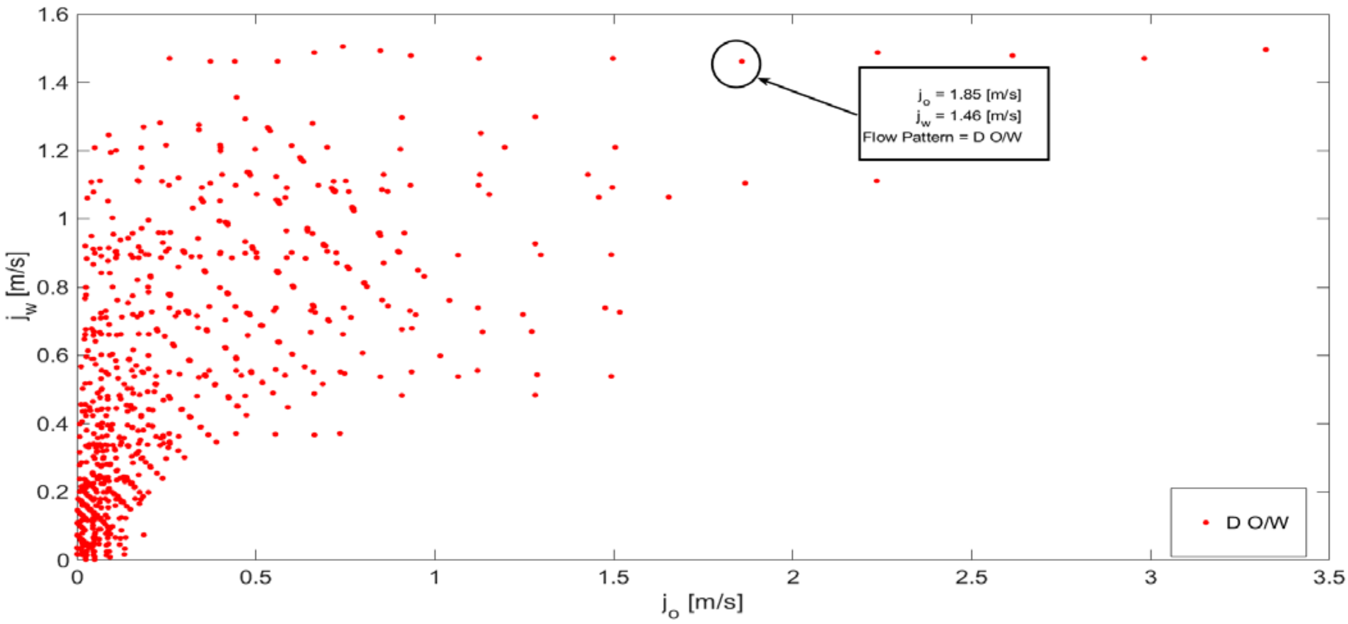


(b)

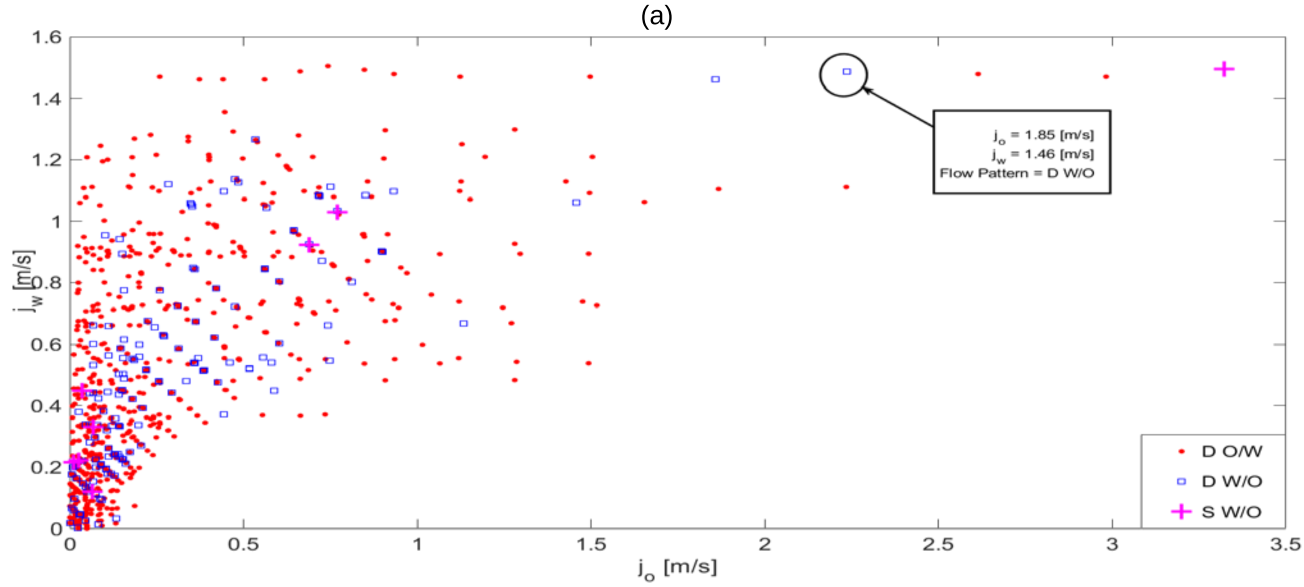
Fig. 6. (a) Annular flow map obtained from literature data; (b) Flow map obtained from the values generated by the predictive model for the annular flow pattern

Velocity range reached by water and oil are [0 to 2.0] and [0 to 2.5], respectively. Asimismo, es percibida una distribución rectangular en la matriz de puntos plasmados en la figure 6 (a) y (b) con una leve tendencia de agrupamiento mayor en las zonas con velocidades del aceite inferiores a 0.7 [m/s].

Figure 6 (b) allows us to conclude that the neural network had a medium level of accuracy in the area where the proximity between the experimental points are numerically similar to those presented by the DO/W, DO/W & W, DW/O and DW/O & DO/W flow patterns, which can be related to the fact that the points are located in the phase inversion zones, characteristic of multiphase flows under certain conditions of each flow.



(a)



(b)

Fig. 7. (a) Oil in water dispersion flow map obtained from literature data; (b) Flow map obtained from the values generated by the predictive model for the oil in water dispersion flow pattern

For vertical pipe, the flow pattern analyzed was DO/W, with a total amount of 947 data Fig 7 (a). The predictive model Fig. 7 (b) has an approximation level of 1.38 %, which is visualized in the graphs generated for this flow pattern since, in this case, 785 points were accurately predicted for DO/W, followed by 154 points for DW/O and 8 points for SW/O. The two flow patterns that appear in the predictive model are directly related to the similarity of the velocity parameters to generate their formation. This comparison is presented in Fig. 7, where it shows for the same water and oil velocities a different flow pattern. The velocity ranges in [m/s] for the collected information are [0 to 3.5] and [0 to 1.6] for oil and water, respectively. Also, Fig. 7 (b) shows the identification of two flow patterns with which the DO/W is similar to DW/O and Slug, since the phase reversal zones are close to the analyzed points.

4 CONCLUSIONS

An artificial neural network model was developed to identify flow patterns in horizontal and vertical pipes taking as input parameters the surface velocities of each fluid, the velocity of the mixture, the volumetric fraction of the substances, diameter, and the inclination of pipelines, and the oil viscosity. The model has eight inputs, two hidden layers, 45 neurons in each hidden layer, the TanSig activation function, the Levenberg-Marquardt training function, and a training set of 6993 data.

The mean square error obtained for the best intelligent model developed was 1.38%, accompanied by a maximum correlation coefficient of 0.79. These values were the maximum overall values of the whole sequence obtained by training the model with 70% of the information, validating it with 15% of the available information, and testing it with around 15%.

One of the disadvantages of the method used is that highly reliable experimental data is needed for training, making it dependent on them. In certain cases, a reasonable or minimum amount of data is needed for correct learning, limiting the intelligent method to the amount of experimental data. One could think in the future of creating hybrid methods that improve their efficiency and reduce their limitations, making them more robust.

The main problems presented in this research were the identification of the ideal combinations in the number of neurons included in each hidden layer of the artificial neural network and the definition of the number of epochs programmed for the training and validation phases. Thus, they were solved by means of the organization and exhaustive execution of simulations with combinations in neuron number within the range between 1 and 100, with a 1 to 1 variation in the number of neurons included in each hidden layer. Also, to define the number of epochs required, was implemented the stabilization criterion generated by the error curve with a variation of less than 1% in 10 consecutive epochs.

5 REFERENCES

[1] H. F. Velasco Peña and O. M. H. Rodriguez, “Applications of wire-mesh sensors in multiphase flows,” *Flow Meas. Instrum.*, vol. 45, pp. 255–273, 2015, doi: 10.1016/j.flowmeasinst.2015.06.024.

[2] Y. Mi, M. Ishii, and L. H. Tsoukalas, “Vertical two-phase flow identification using advanced instrumentation and neural networks,” *Nucl. Eng. Des.*, vol. 184, no. 2–3, pp. 409–420, 1998, doi: 10.1016/S0029-5493(98)00212-X.

[3] Y. Mi, M. Ishii, and L. H. Tsoukalas, “Flow regime identification methodology with neural networks and two-phase flow models,” *Nucl. Eng. Des.*, vol. 204, no. 1–3, pp. 87–100, 2001, doi: 10.1016/S0029-5493(00)00325-3.

[4] J. E. Juliá, Y. Liu, S. Paranjape, and M. Ishii, “Upward vertical two-phase flow local flow regime identification using neural network techniques,” *Nucl. Eng. Des.*, vol. 238, no. 1, pp. 156–169, 2008, doi: 10.1016/j.nucengdes.2007.05.005.

[5] C. Tan, F. Dong, and M. Wu, “Identification of gas/liquid two-phase flow regime through ERT-based measurement and feature extraction,” *Flow Meas. Instrum.*, vol. 18, no. 5–6, pp. 255–261, 2007, doi: 10.1016/j.flowmeasinst.2007.08.003.

[6] E. S. Rosa, R. M. Salgado, T. Ohishi, and N. Mastelari, “Performance comparison of artificial neural networks and expert systems applied to flow pattern identification in vertical ascendant gas-liquid flows,” *Int. J. Multiph. Flow*, vol. 36, no. 9, pp. 738–754, 2010, doi: 10.1016/j.ijmultiphaseflow.2010.05.001.

[7] R. Banasiak *et al.*, “Study on two-phase flow regime visualization and identification using 3D electrical capacitance tomography and fuzzy-logic classification,” *Int. J. Multiph. Flow*, vol. 58, no. January, pp. 1–14, 2014, doi: 10.1016/j.ijmultiphaseflow.2013.07.003.

[8] H. Shaban and S. Tavoularis, “Identification of flow regime in vertical upward air-water pipe flow using differential pressure signals and elastic maps,” *Int. J. Multiph. Flow*, vol. 61, no. May, pp. 62–72, 2014, doi: 10.1016/j.ijmultiphaseflow.2014.01.009.

[9] H. Shaban and S. Tavoularis, “Measurement of gas and liquid flow rates in two-phase pipe flows by the application of machine learning techniques to differential pressure signals,” *Int. J. Multiph. Flow*, vol. 67, no. December, pp. 106–117, 2014, doi: 10.1016/j.ijmultiphaseflow.2014.08.012.

[10] L. Wang, J. Liu, Y. Yan, X. Wang, and T. Wang, “Gas-Liquid Two-Phase Flow Measurement Using Coriolis Flowmeters Incorporating Artificial Neural Network, Support Vector Machine, and Genetic Programming Algorithms,” *IEEE Trans. Instrum. Meas.*, vol. 66, no. 5, pp. 852–868, 2017, doi: 10.1109/TIM.2016.2634630.

[11] A. M. Quintino, D. L. L. N. da Rocha, R. Fonseca Jr., and O. M. H. Rodriguez, “Flow Pattern Transition in Pipes Using Data-Driven and Physics-Informed Machine Learning,” *J. Fluids Eng.*, pp. 1–12, 2020, doi: 10.1115/1.4048876.

[12] A. Van Der Spek and A. Thomas, “Neural-net identification of flow regime with band spectra of flow-generated sound,” *SPE Reserv. Eval. Eng.*, vol. 2, no. 6, pp. 489–498, 1999, doi: 10.2118/59067-PA.

[13] R. Hanus, M. Zych, M. Kusy, M. Jaszczur, and L. Petryka, “Identification of liquid-gas flow regime in a pipeline using gamma-ray absorption technique and computational intelligence methods,” *Flow Meas. Instrum.*, vol. 60, no. April, pp. 17–23, 2018, doi: 10.1016/j.flowmeasinst.2018.02.008.

[14] L. Zhang and H. Wang, “Identification of oil-gas two-phase flow pattern based on SVM and electrical capacitance tomography technique,” *Flow Meas. Instrum.*, vol. 21, no. 1, pp. 20–24, 2010, doi: 10.1016/j.flowmeasinst.2009.08.006.

[15] M. Meribout, N. Al-Rawahi, A. Al-Naamany, A. Al-Bimani, K. Al-Busaidi, and A. Meribout, “Integration of impedance measurements with acoustic measurements for accurate two phase flow metering in case of high water-cut,” *Flow Meas. Instrum.*, vol. 21, no. 1, pp. 8–19, 2010, doi: 10.1016/j.flowmeasinst.2009.09.002.

[16] S. Azizi, M. M. Awad, and E. Ahmadloo, “Prediction of water holdup in vertical and inclined oil-water two-phase flow using artificial neural network,” *Int. J. Multiph. Flow*, vol. 80, no. April, pp. 181–187, 2016, doi: 10.1016/j.ijmultiphaseflow.2015.12.010.

[17] R. Shirley, D. P. Chakrabarti, and G. Das, “LIQUID-LIQUID TWO-PHASE FLOW,” vol. 199, no. 12, pp. 20–22, 2012.

[18] C. M. R. Diaz, “Caracterización hidrodinámica de flujos multifase empleando técnicas de inteligencia artificial,” Universidad Industrial de Santander Facultad, 2021.

[19] D. P. Chakrabarti, G. Das, and S. Ray, “Pressure Drop in Liquid-liquid Two Phase Horizontal Flow: Experiment and Prediction D.,” *Chem. Eng. …*, pp. 20–22, 2005.

[20] D. P. Chakrabarti, G. Das, and P. K. Das, “Identification of stratified liquid-liquid flow through horizontal pipes by a non-intrusive optical probe,” *Chem. Eng. Sci.*, vol. 62, no. 7, pp. 1861–1876, 2007, doi: 10.1016/j.ces.2006.11.056.

[21] H. L. Hu, J. Dong, J. Zhang, Y. J. Cheng, and T. M. Xu, “Identification of gas/solid two-phase flow regimes using electrostatic sensors and neural-network techniques,” *Flow Meas. Instrum.*, vol. 22, no. 5, pp. 482–487, 2011, doi: 10.1016/j.flowmeasinst.2011.07.004.

[22] G. H. Roshani, E. Nazemi, and M. M. Roshani, “Intelligent recognition of gas-oil-water three-phase flow regime and determination of volume fraction using radial basis function,” *Flow Meas. Instrum.*, vol. 54, no. April, pp. 39–45, 2017, doi: 10.1016/j.flowmeasinst.2016.10.001.

[23] A. Karami, G. H. Roshani, E. Nazemi, and S. Roshani, “Enhancing the performance of a dual-energy gamma ray based three-phase flow meter with the help of grey wolf optimization algorithm,” *Flow Meas. Instrum.*, vol. 64, no. December, pp. 164–172, 2018, doi: 10.1016/j.flowmeasinst.2018.10.015.

[24] C. M. Salgado, C. M. N. A. Pereira, R. Schirru, and L. E. B. Brandão, “Flow regime identification and volume fraction prediction in multiphase flows by means of gamma-ray attenuation and artificial neural networks,” *Prog. Nucl. Energy*, vol. 52, no. 6, pp. 555–562, 2010, doi: 10.1016/j.pnucene.2010.02.001.

[25] H. Wu, “International Journal of Multiphase Flow Intelligent identification system of flow regime of oil – gas – water multiphase flow,” vol. 27, no. 3, pp. 1–7, 2001.

[26] C. M. Ruiz-Diaz, M. M. Hernández-Cely, and O. A. González-Estrada, “Modelo predictivo para la identificación de la fracción volumétrica en flujo bifásico,” *Cienc. en Desarro.*, vol. 12, no. 2, pp. 49–55, 2021, doi: 10.19053/01217488.v12.n2.2021.13417.

[27] S. Fu, Z. Li, K. Liu, S. Din, M. Imran, and X. Yang, “Model Compression for IoT Applications in Industry 4.0 via Multiscale Knowledge Transfer,” *IEEE Trans. Ind. Informatics*, vol. 16, no. 9, pp. 6013–6022, 2020, doi: 10.1109/TII.2019.2953106.

[28] J. Dalzochio *et al.*, “Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges,” *Comput. Ind.*, vol. 123, p. 103298, 2020, doi: 10.1016/j.compind.2020.103298.

[29] P. K. Malik *et al.*, “Industrial Internet of Things and its Applications in Industry 4.0: State of The Art,” *Comput. Commun.*, vol. 166, no. November 2020, pp. 125–139, 2021, doi: 10.1016/j.comcom.2020.11.016.

[30] S. Cai, H. Toral, J. Qiu, and J. S. Archer, “Neural network based objective flow regime identification in air-water two phase flow,” *Can. J. Chem. Eng.*, vol. 72, no. 3, pp. 440–445, 1994, doi: 10.1002/cjce.5450720308.

[31] H. Yan, Y. H. Liu, and C. T. Liu, “Identification of flow regimes using back-propagation networks trained on simulated data based on a capacitance tomography sensor,” *Meas. Sci. Technol.*, vol. 15, no. 2, pp. 432–436, 2004, doi: 10.1088/0957-0233/15/2/017.

[32] P. Wiedemann, A. Döß, E. Schleicher, and U. Hampel, “Fuzzy flow pattern identification in horizontal air-water two-phase flow based on wire-mesh sensor data,” *Int. J. Multiph. Flow*, vol. 117, pp. 153–162, 2019, doi: 10.1016/j.ijmultiphaseflow.2019.05.004.

[33] M. M. F. Figueiredo, J. L. Goncalves, A. M. V. Nakashima, A. M. F. Fileti, and R. D. M. Carvalho, “The use of an ultrasonic technique and neural networks for identification of the flow pattern and measurement of the gas volume fraction in multiphase flows,” *Exp. Therm. Fluid Sci.*, vol. 70, pp. 29–50, Jan. 2016, doi: 10.1016/j.expthermflusci.2015.08.010.

[34] T. Sunder Raj, D. P. Chakrabarti, and G. Das, “Liquid-liquid stratified flow through horizontal conduits,” *Chem. Eng. Technol.*, vol. 28, no. 8, pp. 899–907, 2005, doi: 10.1002/ceat.200500067.

[35] B. Grassi, D. Strazza, and P. Poesio, “Experimental validation of theoretical models in two-phase high-viscosity ratio liquid–liquid flows in horizontal and slightly inclined pipes,” *Int. J. Multiph. Flow*, vol. 34, no. 10, pp. 950–965, Oct. 2008, doi: 10.1016/j.ijmultiphaseflow.2008.03.006.

[36] P. Abduvayt, R. Manabe, T. Watanabe, and N. Arihara, “Analisis of oil-water flow tests in horizontal, hilly-terrain, and vertical pipes,” *Proc. - SPE Annu. Tech. Conf. Exhib.*, pp. 1335–1347, 2004, doi: 10.2523/90096-ms.

[37] J. Cai, C. Li, X. Tang, F. Ayello, S. Richter, and S. Nesic, “Experimental study of water wetting in oil-water two phase Flow-Horizontal flow of model oil,” *Chem. Eng. Sci.*, vol. 73, pp. 334–344, 2012, doi: 10.1016/j.ces.2012.01.014.

[38] A. Al-Sarkhi, E. Pereyra, I. Mantilla, and C. Avila, “Dimensionless oil-water stratified to non-stratified flow pattern transition,” *J. Pet. Sci. Eng.*, vol. 151, no. September 2016, pp. 284–291, Mar. 2017, doi: 10.1016/j.petrol.2017.01.016.

[39] J. Shi, L. Lao, and H. Yeung, “Water-lubricated transport of high-viscosity oil in horizontal pipes: The water holdup and pressure gradient,” *Int. J. Multiph. Flow*, vol. 96, pp. 70–85, 2017, doi: 10.1016/j.ijmultiphaseflow.2017.07.005.

[40] T. Al-Wahaibi *et al.*, “Experimental investigation on flow patterns and pressure gradient through two pipe diameters in horizontal oil–water flows,” *J. Pet. Sci. Eng.*, vol. 122, pp. 266–273, Oct. 2014, doi: 10.1016/j.petrol.2014.07.019.

[41] A. Dasari, A. B. Desamala, A. K. Dasmahapatra, and T. K. Mandal, “Experimental studies and probabilistic neural network prediction on flow pattern of viscous oil-water flow through a circular horizontal pipe,” *Ind. Eng. Chem. Res.*, vol. 52, no. 23, pp. 7975–7985, 2013, doi: 10.1021/ie301430m.

[42] R. Ibarra, I. Zadrazil, C. N. Markides, and O. K. Matar, “Towards a Universal Dimensionless Map of Flow Regime,” *11th Int. Conf. Heat Transf. Fluid Mech. Thermodyn.*, no. July, 2015.

[43] M. Nädler and D. Mewes, “Flow induced emulsification in the flow of two immiscible liquids in horizontal pipes,” *Int. J. Multiph. Flow*, vol. 23, no. 1, pp. 55–68, 1997, doi: 10.1016/s0301-9322(96)00055-9.

[44] O. M. H. Rodriguez and R. V. A. Oliemans, “Experimental study on oil–water flow in horizontal and slightly inclined pipes,” *Int. J. Multiph. Flow*, vol. 32, no. 3, pp. 323–343, Mar. 2006, doi: 10.1016/j.ijmultiphaseflow.2005.11.001.

[45] J. Shi and H. Yeung, “Characterization of liquid-liquid flows in horizontal pipes,” *AIChE J.*, vol. 63, no. 3, pp. 1132–1143, 2017, doi: 10.1002/aic.15452.

[46] A. Wegmann and P. Rudolf von Rohr, “Two phase liquid-liquid flows in pipes of small diameters,” *Int. J. Multiph. Flow*, vol. 32, no. 8, pp. 1017–1028, 2006, doi: 10.1016/j.ijmultiphaseflow.2006.04.001.

[47] A. C. Bannwart, O. M. H. Rodriguez, C. H. M. de Carvalho, I. S. Wang, and R. M. O. Vara, “Flow Patterns in Heavy Crude Oil-Water Flow,” *J. Energy Resour. Technol.*, vol. 126, no. 3, pp. 184–189, Sep. 2004, doi: 10.1115/1.1789520.

[48] M. Du, N.-D. Jin, Z.-K. Gao, Z.-Y. Wang, and L.-S. Zhai, “Flow pattern and water holdup measurements of vertical upward oil–water two-phase flow in small diameter pipes,” *Int. J. Multiph. Flow*, vol. 41, pp. 91–105, May 2012, doi: 10.1016/j.ijmultiphaseflow.2012.01.007.

[49] J. Flores, X. Chen, and J. Brill, “Characterization of Oil-Water Flow Patterns in Vertical and Deviated Wells,” in *Proceedings of SPE Annual Technical Conference and Exhibition*, Oct. 1997, vol. 1, pp. 55–64, doi: 10.2523/38810-MS.

[50] T. Ganat, S. Ridha, M. Hairir, J. Arisa, and R. Gholami, “Experimental investigation of high-viscosity oil–water flow in vertical pipes: flow patterns and pressure gradient,” *J. Pet. Explor. Prod. Technol.*, vol. 9, no. 4, pp. 2911–2918, Dec. 2019, doi: 10.1007/s13202-019-0677-y.

[51] G. W. Govier, G. A. Sullivan, and R. K. Wood, “The upward vertical flow of oil-water mixtures,” *Can. J. Chem. Eng.*, vol. 39, no. 2, pp. 67–75, Apr. 1961, doi: 10.1002/cjce.5450390204.

[52] Y. F. Han, N. D. Jin, L. S. Zhai, H. X. Zhang, and Y. Y. Ren, “Flow pattern and holdup phenomena of low velocity oil-water flows in a vertical upward small diameter pipe,” *J. Pet. Sci. Eng.*, vol. 159, no. May, pp. 387–408, Nov. 2017, doi: 10.1016/j.petrol.2017.09.052.

[53] A. R. Hasan and C. S. Kabir, “A New Model for Two-Phase Oil/Water Flow: Production Log Interpretation nd Tubular Calculations,” *SPE Prod. Eng.*, vol. 5, no. 02, pp. 193–199, May 1990, doi: 10.2118/18216-PA.

[54] A. R. Hasan and C. S. Kabir, “A simplified model for oil/water flow in vertical and deviated wellbores,” *SPE Prod. Facil.*, vol. 14, no. 1, pp. 56–62, 1999, doi: 10.2118/54131-PA.

[55] A. K. Jana, G. Das, and P. K. Das, “Flow regime identification of two-phase liquid–liquid upflow through vertical pipe,” *Chem. Eng. Sci.*, vol. 61, no. 5, pp. 1500–1515, Mar. 2006, doi: 10.1016/j.ces.2005.09.001.

[56] A. K. Jana, P. Ghoshal, G. Das, and P. K. Das, “An Analysis of Pressure Drop and Holdup for Liquid-Liquid Upflow through Vertical Pipes,” *Chem. Eng. Technol.*, vol. 30, no. 7, pp. 920–925, Jul. 2007, doi: 10.1002/ceat.200700033.

[57] J. Guo *et al.*, “Heavy oil-water flow patterns in a small diameter vertical pipe under high temperature/pressure conditions,” *J. Pet. Sci. Eng.*, vol. 171, pp. 1350–1365, Dec. 2018, doi: 10.1016/j.petrol.2018.08.021.

[58] R. A. Mazza and F. K. Suguimoto, “Experimental investigations of kerosene-water two-phase flow in vertical pipe,” *J. Pet. Sci. Eng.*, vol. 184, p. 106580, Jan. 2020, doi: 10.1016/j.petrol.2019.106580.

[59] K. Mydlarz-Gabryk, M. Pietrzak, and L. Troniewski, “Study on oil–water two-phase upflow in vertical pipes,” *J. Pet. Sci. Eng.*, vol. 117, pp. 28–36, May 2014, doi: 10.1016/j.petrol.2014.03.007.

[60] O. M. H. Rodriguez and A. C. Bannwart, “Experimental study on interfacial waves in vertical core flow,” _J. Pet. Sci. Eng._, vol. 54, no. 3–4, pp. 140–148, 2006, doi: 10.1016/j.petrol.2006.07.007.

[61] J. Xu, D. Li, J. Guo, and Y. Wu, “Investigations of phase inversion and frictional pressure gradients in upward and downward oil–water flow in vertical pipes,” _Int. J. Multiph. Flow_, vol. 36, no. 11–12, pp. 930–939, Nov. 2010, doi: 10.1016/j.ijmultiphaseflow.2010.08.007.

[62] Y. Yang _et al._, “Oil-Water flow patterns, holdups and frictional pressure gradients in a vertical pipe under high temperature/pressure conditions,” _Exp. Therm. Fluid Sci._, vol. 100, no. September 2018, pp. 271–291, Jan. 2019, doi: 10.1016/j.expthermflusci.2018.09.013.

[63] D. Zhao, L. Guo, X. Hu, X. Zhang, and X. Wang, “Experimental study on local characteristics of oil-water dispersed flow in a vertical pipe,” _Int. J. Multiph. Flow_, vol. 32, no. 10–11, pp. 1254–1268, 2006, doi: 10.1016/j.ijmultiphaseflow.2006.06.004.

[64] G. Jiang, H.-Q. Gao, C.-P. Wu, and G. Cybenko, “Convergence Analysis of Discretization Procedure in Q-Learning,” _IFAC Proc. Vol._, vol. 32, no. 2, pp. 8551–8556, Jul. 1999, doi: 10.1016/S1474-6670(17)57458-3.

[65] J. L. Trallero, C. Sarica, and J. P. Brill, “A Study of Oil-Water Flow Patterns in Horizontal Pipes,” _SPE Prod. Facil._, vol. 12, no. 03, pp. 165–172, Aug. 1997, doi: 10.2118/36609-PA.

Paper submitted: 23.09.2022.
Paper accepted: 23.12.2022.