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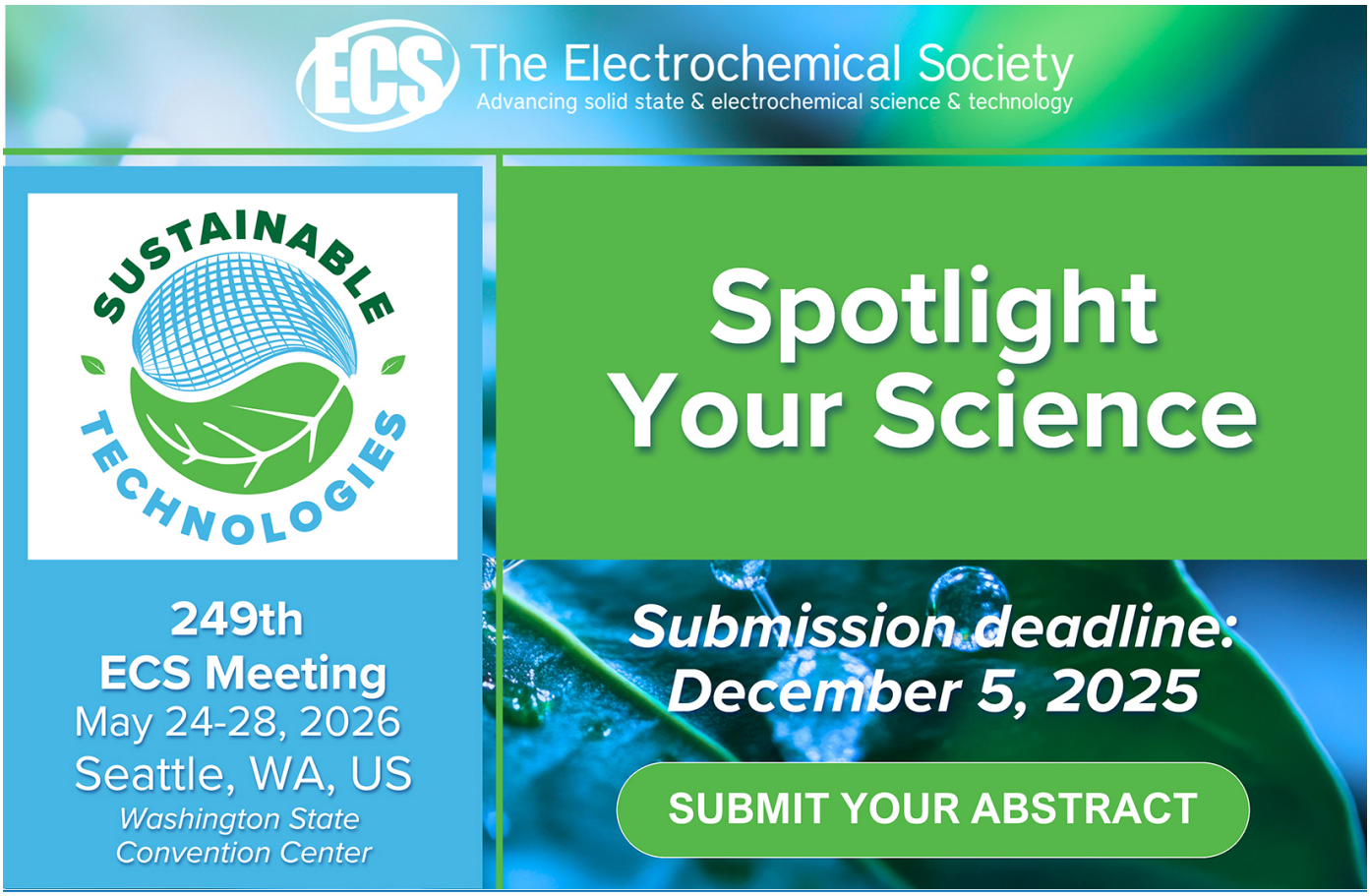
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Flow pattern identification of liquid-liquid (oil and water) in vertical pipelines using machine learning techniques

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Abstract. Given the importance of process control in the petrochemical industry, there is a need to determine the behavior of the fluids inside the pipes. In this work a methodology is developed for the identification of flow patterns in vertical pipes with diameters between 0.01 m and 0.10 m, from the implementation of artificial intelligence techniques, for a liquid combination of two phases composed of oil with viscosity in the range of 792 Kg/m^3 to 1823 Kg/m^3 and water at room temperature. The predictive models generated in the structuring of the methodology were trained with 70% of data based on viscosity parameters, pipe diameter, volume fraction and surface velocities of the working fluids stored in a database. The remaining information, equivalent to 30% of the total, was used to develop the automatic model validation. The flow patterns identified by the intelligent system for oil and water flow, without considering the predominant substance, are churning, dispersed, very fine dispersion, transition flow, intermittent, and annular.

1. Introduction

The oil and gas industry is a pioneer in technological advances that allow optimizing the processes of characterization, measurement, and monitoring in real-time of fields that include fluids [1], specifically multiphase flows [2], typical of field extractions of oil and gas substances [3]. The significant development and immediate application of industry 4.0 in recent years [4], with machine learning [5,6] and deep learning [7] techniques, allows optimized treatment of experimental data. Likewise, these techniques have generated optimizations in the specific processes of extraction, production, and transport of oil [8] and additional substances, given that normally there are combinations of oil together with water, gas, residues, and other solid components typical.

The extraction of these substances generates the formation of flows with more than one phase consecutively which are monitored with intrusive devices or techniques [9-12] that quantify parameters of each of the fluids present [13] such as viscosities, densities, surface velocities [14,15], Reynolds number, holdups [16] and in certain cases, they are associated with geometric variables of the pipes, such as their diameter, length, and inclination [17,18].

The identification of flow patterns in pipelines is a fundamental factor [19], being of vital importance to obtain with precision a tool capable of modelling such behaviors of multiphase flows working together with existing artificial intelligence techniques [20,21] such as artificial neural networks [22], in order to train, validate and test an intelligent model [23] capable of generating flow maps [24] for vertical [25], horizontal [26] pipes in which all the performances generated from the modification of the physical

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parameters mentioned above are organized. In this work an intelligent model is developed based on the application of artificial neural networks capable of identifying two-phase flow patterns of oil and water in vertical pipelines.

2. Methods and materials

This research was developed taking as a starting point the information presented by Mydlarz-Gabryk, *et al.* [27], and Guo, *et al.* [28], works in which flow patterns in vertical pipes were determined from the experimental surface velocities obtained in their laboratories for two-phase flow of oil with viscosities between 792 Kg/m^3 to 1823 Kg/m^3 and water at ambient temperature in vertical pipes with internal diameters between 0.01 m and 0.10 m. The total amount of data analyzed in this study was 722, which were organized in a database that underwent a pre-treatment in which the inputs and outputs of the structured intelligent model were defined.

2.1. Artificial neural network modelling

Based on the methodology used by [29] to develop an artificial neural network (ANN) capable of identifying the holdup of a two-phase flow of oil and water in vertical pipes, an intelligent model was structured by two hidden layers, the first with a variation in the number of neurons and the second called the output layer, consisting of the surface speed of water (j_w), and oil (j_o). Additionally, the neural network is formed by an input layer that includes the Reynolds number (Re), the oil holdup (ε_o), the water holdup (ε_o) and the viscosity of the oil (μ_o).

The methodological development of the artificial neural network was carried out in three phases corresponding to training, validation, and testing, for which the data were distributed with respective percentages for each phase of 70%, 20%, and 10%, equivalent to 506, 144, and 72 data. The training phase was structured based on the function specified in the Levenberg-Marquardt backpropagation algorithm.

To determine the most efficient model, several neural network structures were developed, which had in common the training function, the TanSig activation function and a single hidden layer. On the other hand, all models differed in the number of neurons integrating the hidden layer, because these values were varied following the sequence of [10-14].

2.2. Flow maps

The flow patterns generated in the multiphases can be materialized in schemes called flow maps, which are a tool used to establish relationships between physical variables such as fluid surface speeds, fluid holdups, surface speed of the mixture, among others, from the formation of coordinates in the Cartesian plane, which has in its respective axes with the aforementioned variables, as shown in Figure 1, where the following flow patterns schematized are: stratified (ST), oil in water dispersion (Do/w), annular (A), intermittent (I), stratified with oil in water dispersion (ST & Do/w), and finally annular with oil in water dispersion (ST & Do/w).

2.3. Statistical parameters

In order to optimize the selection of the model with the lowest error, some parameters defined by [16] were applied, which determine the performance of the values generated by the predictive models, these statistical parameters are the ones defined in Equation (1), Equation (2), and Equation (3), corresponding to the mean square error (MSE), the absolute average percentage error (AAPE) and the coefficient of determination (R^2).

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

$$\mathrm{AAPE} = \left[\frac{1}{n}\sum_{m=1}^{n}\left|\frac{Y_{(Exp,m)} - Y_{(Pred,m)}}{Y_{(Exp,m)}}\right|\right] * 100, \tag{2}$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}\left(Y_{(Exp,m)} - Y_{(Pred,m)}\right)^2}{\sum_{m=1}^{n}\left(Y_{(Exp,m)} - \overline{Y}_{(Pred,m)}\right)^2}, \quad (3)$$

where $Y_{(Pred)}$ is the result generated by the intelligent model or output of the model, $\overline{Y}_{(Pred,m)}$ is the average of the $Y_{(Pred)}$ obtained based on the total number of input variables n, developed from the experimental outputs $Y_{(Exp,m)}$.

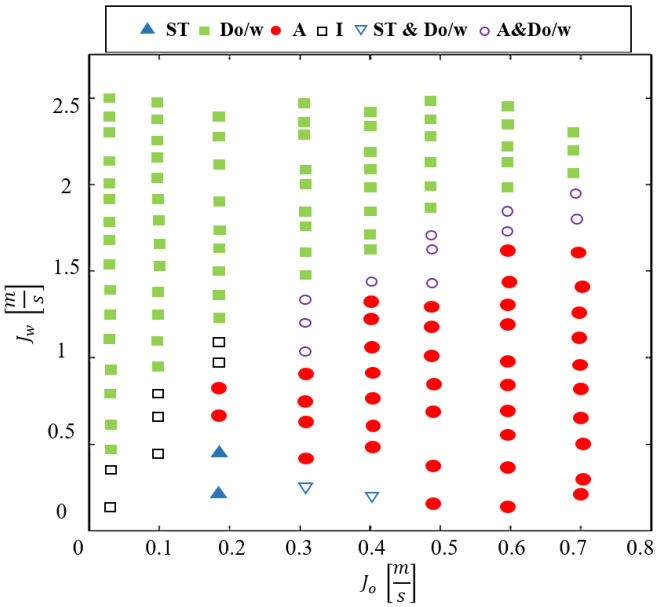


Figure 1. Two-phase flow map, modified from [30].

3. Results

The structuring of the different artificial neural network models that aim to identify the surface velocities of oil and water to identify the flow patterns that are generated from such numerical values, were developed in MATLAB software [31]. Table 1 presents concretely the results obtained in the determination of the oil surface velocity using as input parameters the Reynolds number, the fluid holdups, and the oil viscosity.

Taking into account what was presented in Table 1, the model that presented the best approximation in the calculation of the surface velocity of the oil was selected, being the one structured with 12 neurons in the occulta layer, because it presented an MSE of 0.00368, a R^2 of 0.93617 and an AAPE of 27.19751.

Table 1. Results of the ANN models implemented for oil speed surface.

# Neurons	MSE	R^2	AAPE
10	0.00379	0.93441	36.12858
11	0.00388	0.93219	38.54968
12	0.00368	0.93617	27.19751
13	0.00438	0.91863	77.43548
14	0.00439	0.91893	87.55584

The comparison between the experimental value of the oil surface speed (J_oExp) and the prediction (J_oPred) result for the 722 data implementing this ANN model is shown in Figure 2. Table 2 presents concretely the results obtained in the determination of the water surface speed using the same input parameters.

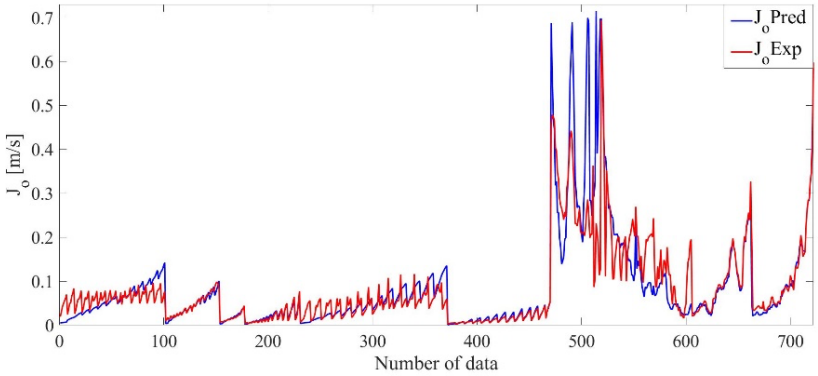


Figure 2. A comparison between J_oExp and J_oPred for the ANN with 12 neurons in the hidden layer.

Table 2. Results of the ANN models implemented for water speed surface.

# Neurons	MSE	R^2	AAPE
10	0.00038	0.99233	32.80226
11	0.00044	0.99110	37.99249
12	0.00038	0.99228	41.14588
13	0.00079	0.98406	75.13605
14	0.00080	0.98398	77.46686

Considering the values contained in Table 2, it is established that the model that represents the best predictive values for the water surface velocity is the one structured with 10 neurons in the occulta layer, presenting values 0.00038, 0.99233 and 32.8% for the MSE, the coefficient of determination and the AAPE, respectively. Figure 3 shows the comparison between experimental value of the water surface speed (J_wExp) and the prediction (J_wPred) for the ANN with 10 neurons in the hidden layer.

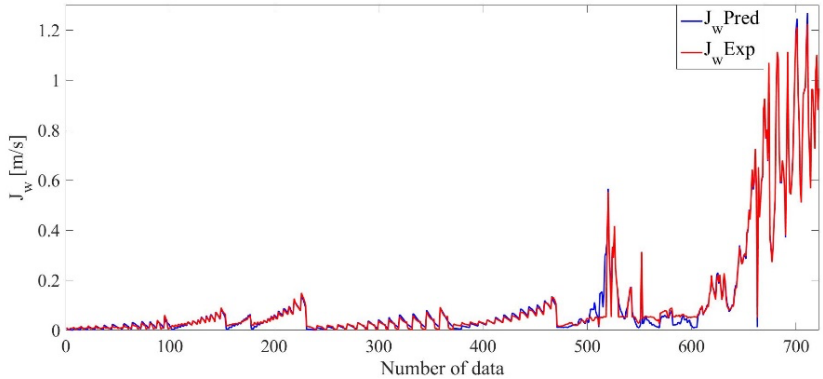


Figure 3. A comparison between J_wExp and J_wPred for the ANN with 10 neurons in the hidden layer.

4. Conclusions

In the present work, a methodology based on artificial intelligence was developed to identify the flow patterns denominated, churning, dispersed, very fine dispersion, transition flow, intermittent, and annular, present in a liquid-liquid two phase flow (oil-water) in vertical pipes, with diameters between 0.01 m and 0.10 m. The predictive models generated in the structuring of the methodology were trained with 70% of data based on viscosity parameters, pipe diameter, holdup and surface speeds of the working fluids stored in a database.

The remaining information, equivalent to 30% of the total, was used to develop the automatic model validation. The best results for the prediction of the petroleum surface speed were achieved with a neural network composed of 12 neurons in its hidden layer presenting values of mean square error , coefficient of determination and absolute average percentage error of 0.00368, 0.93617, and 27.19%, respectively.

On the other hand, the best result for the prediction of the water surface speed was achieved from the structuring of a neural network with 10 neurons in its hidden layer with values of 0.00038, 0.99233 and 32.8% for the mean square error , the coefficient of determination and the absolute average percentage error, respectively. It is proposed as a future work a deep analysis for a database with more data to contribute to industry 4.0 with the amplification of big data by applying the pillars of modern artificial intelligence techniques.

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