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PREDICTIVE MODELING OF HOLDUP IN HORIZONTAL WATEROIL FLOW USING A NEURAL NETWORK APPROACH

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Abstract. In this work, the application of an artificial neural network (ANN) is proposed to develop a predicting model for the holdup of a two-phase flow composed of water and mineral oil in a horizontal pipe. For this, the surface velocities of each fluid and the differential pressure in the pipeline are used as input parameters of the multilayer artificial neural network with backpropagation, while the holdup of the fluids is used as the output parameter for the training. A set of 56 experimental data was obtained in the LabPetro-CEPETRO-UNICAMP laboratory. The best performing results for the predictive model show a mean absolute error (AAPE) of 3.01% and a coefficient of determination $R2$ of 0.9964 using 15 neurons in the hidden layer of the network and the TanSig transfer function.

1 INTRODUCTION

The oil industry has focused its interest on the development of technologies that allow obtaining updated systems for the precise measurement of multiphase flow, defining this as a concurrent flow of substances in certain states or phases (solid, liquid, gas) which generate a layer separation with mixture between the phases [1] or characteristic patterns, derived from the initial hydrodynamic parameters of the Flow [2]. Hydrodynamic parameters are identified by applying different methodologies such as electrical impedance [3], pressure variation [4], ultrasonic echoes [5] and optical image analysis [6].

The application of soft computing techniques were studied by [7] for multiphase flow measurement [8] . In [9] they showed the advances developed in multiphase flow meters. In particular, [10] applied a methodology based on the recognition of pulse height distribution patterns of an artificial neural network (ANN), proposing an approach for the independent prediction of the holdup in multiphase flows, as well as [11], which innovated in the recognition of PHD patterns through the neural network. In [12] they introduced a hybrid network in which an optimization algorithm (GWO) is used to train the neural network and obtain mean error values, as well as the determination of fluid velocities [13].

The objective of the present study is to investigate the feasibility of the application of artificial neural networks (ANN) for the prediction of the holdup of a two-phase water-oil flow in a horizontal pipe. For this, various neural network structures are trained and the results obtained are compared and allow to establish the precision of the predictive model generated by applying artificial intelligence in multiphase flows.

2 EXPERIMENTAL METHODOLOGY

The experimental tests were carried out at the facilities of the “Kelsen Valente Serra” petroleum experimental laboratory - LabPetro, located within the Center for Petroleum Studies - CEPETRO, at the State University of Campinas - UNICAMP. which allow to develop research on an industrial scale.

For this investigation a horizontal multiphase flow line was fitted. The fluids used in the experimentation were:

- Luchetti M600 mineral oil with a viscosity of approximately 180 [cP] at room temperature and a specific density of 868 [kg / m³] and water with a viscosity of approximately 1 [cP] at room temperature and a specific density of 1000 [kg / m³].

The experimentation was developed using a horizontal pipe made of carbon steel NBR 5580 with 15 [m] length, 80 [mm] internal diameter and 4.5 [mm] thickness. In addition, the experimental line features a solid acrylic display section 0.5 [m] long and 80 [mm] internal diameter. Once the fluids are directed towards the experimentation pipe, the necessary measurements of pressure gradient, holdup, visualization of flow patterns, etc. are made.

The analysis and treatment of the experimental data was carried out with the MATLAB® software, based on the fluid inlet velocities that were controlled and gradually modified with the LabView ™ software, directly taking advantage of the communication system with the that counts the laboratory.

3 DESIGN OF THE ARTIFICIAL NEURONAL NETWORK

For this study and in order to generate a model capable of predicting the holdup of water and oil, a multilayer perceptron artificial neural network (ANN) was used, since it is based on machine learning from some input parameters. Its flexible structure allows to establish variations in the inputs and outputs, as well as in the hidden layers, which have synaptic weights organized in a matrix and biases organized in a vector, forming a system capable of storing knowledge.

The number of hidden layers can be greater than or equal to one, being a unidirectional network (feedforward) where the neurons of the hidden layer use the sum of the inputs together with the synaptic weights as a propagation rule in order to apply a function of sigmoid transfer, since it limits the generated response. Mathematically, the net input S_i to the neural network is obtained through equation (1) proposed by [14]:

$$S_i = \sum_{j=1}^{m} x_i w_{ij} + b_j \tag{1}$$

Where j is the node of the hidden layer in which S_i, x_i are the inputs to node j (or outputs of the immediately previous layer), w_{ij} are the weights that represent the degree of relationship or connection between the nodes i and j, i is the number of nodes and b_j is the bias that is related to each node j.

The terms described above are processed by a transfer function, which precisely determines the output that is being searched for. For this study, the hyperbolic sigmoid tangent (TanSig) and logarithmic sigmoid (LogSig) activation functions were used [15], these being the most common activation functions in data processing with non-linear equations defined by equations (2) and (3), respectively. These functions generate values that fall within the intervals [0,1] and [-1,1]. Other activation functions are ReLU, Scaled Exponential Linear Unit (SELU) and radial basis function among others.

$$TanSig\ (S_j)\ = f(S_j) = \frac{e^{S_j} - e^{-S_j}}{e^{S_j} + e^{-S_j}} \tag{2}$$

$$LogSig\ (S_j)\ = f(S_j)\ = \frac{1}{1 + e^{-S_j}} \tag{3}$$

Where $f(S_j)$ is the output of node j, as well as it is the input element to the nodes of the next layer. For the neural network to learn the relationship between the data, it is necessary to develop a training in which the weights are modified and the errors between the input values and the values produced by the trained neural network are reduced. To develop this phase of the design of the artificial neural network, an algorithm called backpropagation of errors or *backpropagation*, from a perceptron multilayer network obtained using the toolbox offered by MATLAB 2019 a ®.

3.1 Treatment to minimize errors by selecting the appropriate number of neurons

The complexity of the problem is directly related to the number of neurons that make up both the input and output layers, as they are equal to the number of parameters included in each phase respectively. The parameter that is used as the initial determinant to establish the proximity of the model is generated with the minimization of the mean square error, which follows equation (4).

$$MSE = \frac{1}{n} \sum_{m=1}^{n} \left(Y_{(Exp,m)} - Y_{(Pred,m)}\right)^2 \tag{4}$$

Where n is the total number of input data, $Y_{(Pred)}$ is the output value obtained by the RNA and $Y_{(Exp)}$ is the experimental value of the output.

Two parameters are consecutively included that minimize the error generated in the selection of the appropriate number of neurons that make up the network. The first is called absolute mean percentage error (AAPE) expressed in equation (5), because it is the descriptive value of the performance of the ANNs developed during the study and includes the average value of the output data $\bar{Y}_{(Pred,m)}$. The second parameter is the coefficient of determination R^2, which is calculated by equation (6).

$$AAPE = \left[\frac{1}{n}\sum_{m=1}^{n}\left|\frac{Y_{(Exp,m)} - Y_{(Pred,m)}}{Y_{(Exp,m)}}\right|\right]*100 \tag{5}$$

$$R^2 = 1 - \frac{\sum_{m=1}^{1}\left(Y_{(Exp,m)} - Y_{(Pred,m)}\right)^2}{\sum_{m=1}^{1}\left(Y_{(Exp,m)} - \bar{Y}_{(Pred,m)}\right)^2} \tag{6}$$

4 RESULTS AND DISCUSSION

Table 1 presents the results obtained integrally when training the RNA with the TanSig transfer function, determining as minimum values of the AAPE at 6.6, 5.03 and 3.01 and coefficient of determination of 0.9955, 0.9963 and 0.9964 for 8, 10, and 15 neurons, respectively.

Table 1: : Results of the variation in the number of neurons in the hidden layer using the TanSig transfer function

# NEURONS IN THE HIDDEN LAYER	MEAN SQUARE ERROR	R^2	AAPE %
1	0,00541	0,9746	14,33
2	0,00151	0,9929	8,87
3	0,00337	0,9842	8,81
5	0,00305	0,9857	14,12
8	0,00095	0,9955	6,60
10	0,00079	0,9963	5,03
12	0,00123	0,9942	6,48
15	0,00077	0,9964	3,01
20	0,01085	0,9491	23,14

By analyzing this information, it was possible to determine that the optimal RNA to develop the holdup predictive model for the water and oil fluids is the one that integrates the TanSig transfer function with two layers. The hidden layer is composed of 15 neurons and achieves an AAPE 3.01% calculated with Equation (5), a coefficient of determination R^2 equal to 0.9964 calculated with Equation (6) and a mean square error (MSE) of 0.00077, allowing to conclude that in a comparative way, this predictive model is the best of the 18 that were simulated, presenting the best results in the calculations and in the simulation.

5 CONCLUSIONS

- An RNA model was implemented to predict the holdup of water and oil that form a biphasic flow in a horizontal pipe. The recognition of the surface velocities of the fluids and the differential pressure in the RNA inlets were studied, which had in its best performance an absolute mean percentage error (AAPE) of 3.01% and a coefficient of determination R^2 0.9964 for all experimental data measured in LabPetro.

- The optimal neural network model for the experimental data used is one that has an input layer, a hidden layer made up of 15 neurons with their respective vector of weights and biases, and an output layer composed of the results of the holdup of the prediction.

- Knowing the values of the surface velocities and the differential pressure in the pipe, the holdup of a two-phase flow can be accurately predicted using neural networks.

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