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Predicting emulsion viscosity using Artificial Intelligence

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Abstract
Water and oil (W/O) emulsions are present in some of the stages of exploration and operation of oil fields. Therefore, it is important to define the dynamic viscosity behavior of these emulsions, since knowing the rheological behavior of the emulsion is essential for the flow assurance throughout the process. This study applied artificial intelligence (AI) procedures to predict the dynamic viscosity of five (05) oils from Brazilian basins, using oil temperature, shear rate, oil °API and water fraction present in the emulsion as variables for viscosity determination. This study used the computer language Python for data processing and artificial intelligence model structuring. The results obtained in the study were compared statistically using the mean absolute error with the results obtained through other methods already present in the literature, proving to have better results for the majority of the W/O emulsions analyzed.

Keywords
Emulsions; Artificial Intelligence; Viscosity

Introduction
In the oil exploration and extraction process, mainly in mature exploration fields, it is possible to observe an increase in the production of associated water, either in the free form or in the form of water-in-oil (W/O) emulsions that may have volumes of water greater than 60% [1][2]. These emulsions are mainly formed by the presence of natural oil emulsifiers and the multiphase flow of water and oil in the production line, pumps and valves [3]. Thus, it is essential to understand the rheological behavior of these emulsions in order to guarantee the oil flow and adapt to transport, storage and market specifications.
The rheological behavior of these emulsions depends on factors such as: temperature, volumetric fraction of the dispersed phase, shear rate, viscosity of the continuous phase, dispersed phase viscosity, pressure, droplet radius, continuous phase density, dispersed phase density, concentration and nature of emulsifiers and the presence of solids present in the dispersed phase [1][5][6].
Based on rheological data from five (05) Brazilian oils, this study aims to use an artificial intelligence (AI) algorithm (neural network) to predict the viscosity of oils from the correlation with the °API density, shear rate, temperature and amount of water added, something that does not exist in recent literature.

Methodology
The experimental data were obtained from the rheological analysis of 5 Brazilian oils from offshore fields. In these analyzes the effects of temperature, imposed shear rate and emulsified water content on dynamic viscosity were evaluated. All these analyzes were performed with dead oil, that is, not considering the presence of gas in the samples. Table 1 displays the intervals in which the analyzes were made.

Table 1. Properties and intervals analyzed.

Properties	Interval
Oil Density (°API)	17,65 – 18,9
Temperature (°C)	4 – 60
Shear rate (s^{-1})	10 – 250
Water fraction (%)	0 – 60

Classical Correlations
Woelflin (1942) proposed an exponential model that relates the viscosity of water-oil (W/O) emulsions and the fraction of emulsified water [7]. From a series of experiments that measured the kinematic vicosity of an oil with a density of 25.1°API (at 60°F) and saline water with a density equal to 1.023 (at 68°F), Woelflin proposed the division of emulsions in three types: loose (30% emulsion and 70% water), medium (80% emulsion and 20% water) and tight (100% emulsion, no water). The equation generated by this exponential model, that correlates the relative viscosity (ν_r) to the water cut (ϕ) *is* shown in Eq. (1).

$$\nu_r = e^{(a\phi + a\phi^2)} \quad (1)$$

The values for the empirical parameters *a* and *b* of different types of emulsions are shown in Table 2.

Table 2. Woelflin coefficients.

Emulsion Type	*a*	*b*
Loose	2.4740	2.6672
Medium	1.6691	5.1920
Tight	2.1102	5.2456

Rønningsen (1995), from eight oils from the North Sea, proposed that the relative viscosity is influenced by temperature (T), water cut (ϕ) for different values of shear rate. The generated empirical expression is shown in Eq. (2).

$$ln\ v_r = k_1 + k_2 T + k_3 \phi + k_4 \phi T \quad (2)$$

Table 3. Rønningsen coefficients

	Shear rate		
	30 s^{-1}	100 s^{-1}	500s^{-1}
k_1	0.01334	0.04120	-0.06671
k_2	-0.0038010	-0.0026050	-0.0007750
k_3	4.338	3.841	3.484
k_4	0.02698	0.02497	0.00500

Neural Networks

Machine learning is the branch of computing capable of detecting patterns in a set of data and, from them, creating predictions for a new set of data or serving as a basis for decisions [8]. Within the machine learning sphere, there are three most used models: supervised, semi-supervised and reinforcement learning.

Artificial neural networks are machine learning models inspired by the functioning of neural systems of living organisms, since the architecture of neural networks is based on the simplification of the biological architecture of the nervous system. All living organisms are made up of cells and in the nervous system they are called neurons. These cells are typically made up of the cell body, dendrites, and axons. Information in the form of electrochemical impulses enter the cell through the dendrites, pass through the cell body and, depending on the stimulus received (excitatory or inhibitory), propagate a new signal through the axon that will then be received in another cell, which generates a new signal that will be received by another neuron [9]. It is estimated that each brain module has about 100,000 neurons connected to thousands of other neurons, forming a complex architecture [9], which is responsible for the human learning process.

The neural network algorithm relates a series of artificial neurons units in order to interconnect them in order to form a network. Input elements of the neural network receive a stimulus, process this signal distributing new weights and propagating it to the next layers of the network. Layers that are neither part of the input nor the output of the network are called “hidden layers”. This type of algorithm in which information is passed in only one direction is called feedforward. There are also algorithms for feedback networks (recurrent), in which neurons have connections with each other without restrictions. Below, in Figure 1, the topology model of feedforward neural networks is presented.

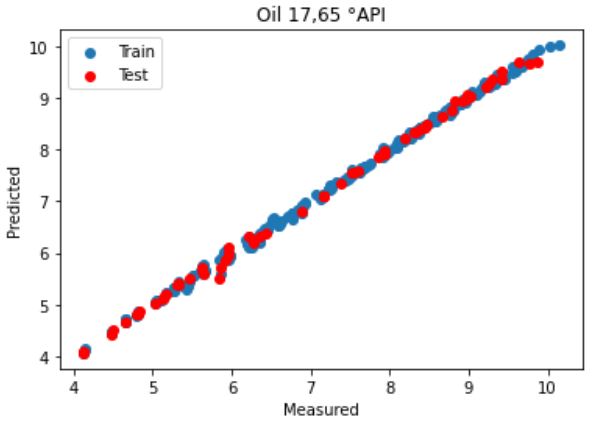
In this work, the multi-layer perceptron model [10], a supervised feedforward neural network algorithm, was used. In it, the algorithm is fed by two subsets of data: training and testing. Training data is added containing the input and output values to create the desired neural network. In this process, the output values of the training subset are used so that the algorithm calculates the weights between the links, causing the generated output values to be close to the values of the subset, causing the network to “learn” as the data input values relate to each other and calculate the test subset output values more accurately.

To estimate the viscosity values of the W/O emulsions, the values of temperature (T), shear rate ($\dot{\gamma}$) and water fraction (ϕ) were used as input variables for the machine learning algorithm. The neural network used in the work had a total of 100 hidden layers, each of them with 100 artificial neurons.

Results and Discussion

The data for each oil was added and pre-processed, as it is necessary for the input data to be normalized before being fed to the neural network algorithm. Then, the dataset of each emulsion was then partitioned into two: the algorithm training set that corresponds to 80% of the total data and the other 20% corresponding to the algorithm test set.

Figure 1 displays the comparison between the measured and predicted values for each oil.



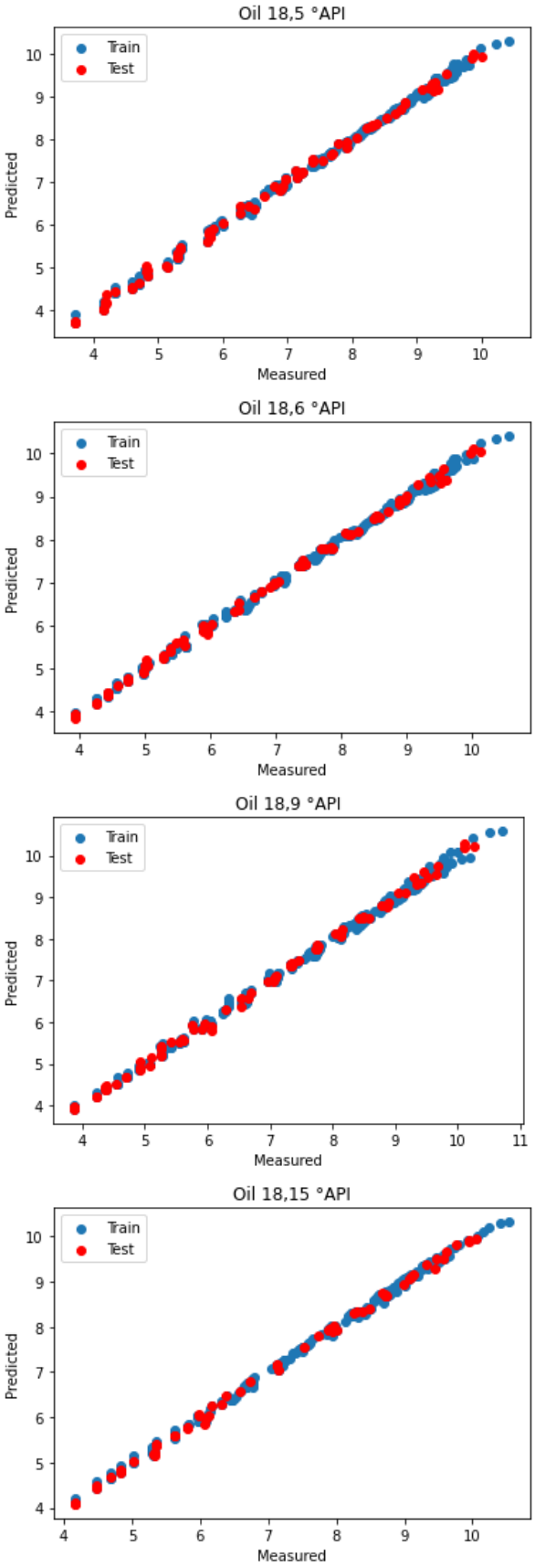


Figure 1. Results for each of the five oils

In all oils, it can be seen that the measured values and the values calculated by the neural network algorithm present a 45° line in each graph, indicating a good approximation of the calculated values.

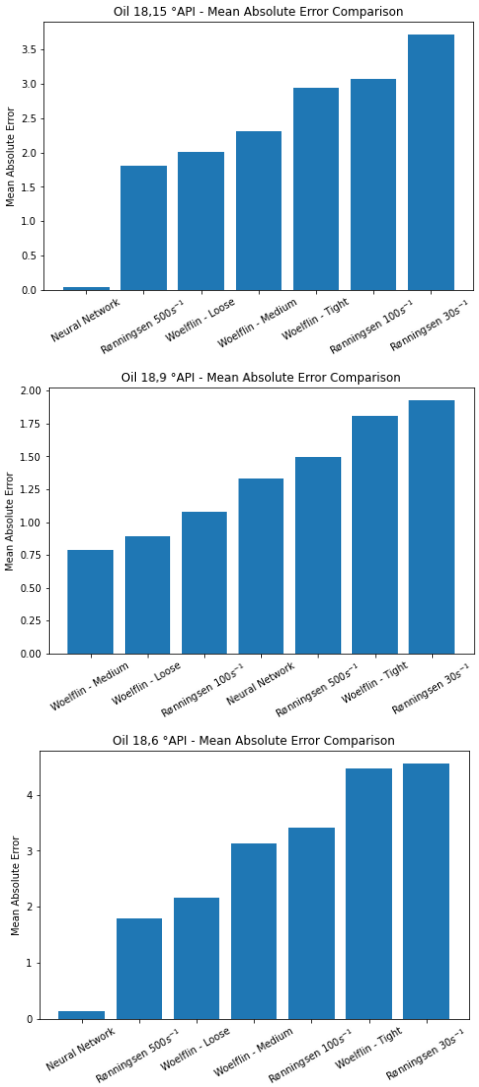
Table 4 shows the Coefficient of Determination (R^2) for each oil.

Table 4. Coefficient of Determination.

Oil (°API)	R^2	
	Train	Test
17,65	0.9985	0.9982
18,6	0.9980	0.9983
18,15	0.9984	0.9984
18,9	0.9974	0.9980
18,5	0.9974	0.9978

Finally, Woelflin and Rønningsen correlations were used to calculate the relative viscosity values in order to compare them to those obtained by the neural network algorithm. These classical correlations (Rønningsen and Woelflin), use the values of water fraction and, in the case of the Rønningsen correlation, also of temperature. Comparing to the classical correlations, the neural network algorithm adds the shear rate as input for the viscosity prediction.

Figure 2 shows the comparison of the mean absolute error between methods for each emulsion, displaying that, besides the 18,9 °API oil, the AI proved to be more efficient predicting the dynamic viscosity of these W/O emulsions.



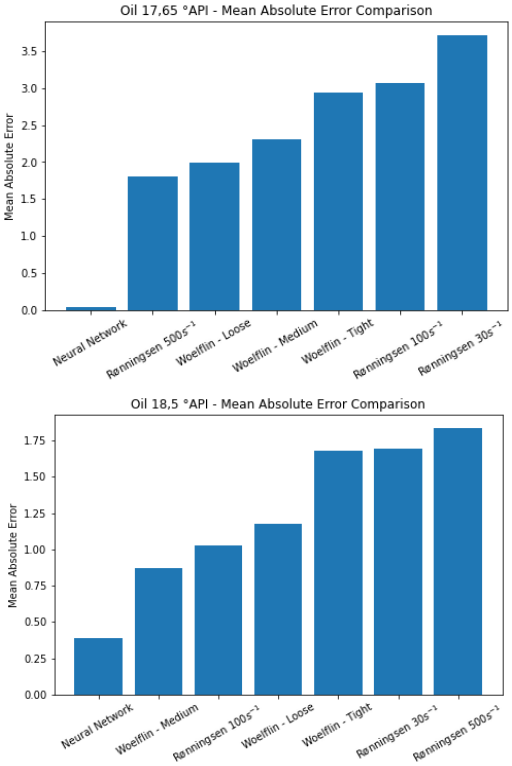


Figure 2. Comparison between methods' error for each Oil

Conclusions

This study demonstrates the applicability of an artificial intelligence algorithm for predicting the dynamic viscosity of oil emulsions. From the large amount of data generated from the analysis of these emulsions, totaling 1782 rheological data from 5 W/O emulsions, it becomes possible for these algorithms to generate results with less error when compared to other correlations present in the literature.

In addition, the prediction of the viscosity of oil emulsions by AI can also be used in conjunction with other tools, such as flow simulators, which makes it possible to study the behavior of emulsions, reducing the number of samples needed and the cost of analysis.

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Responsibility Notice

The authors are the only responsible for the paper content.

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