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RESEARCH ARTICLE

DESIGN OF FEED-FORWARD ARTIFICIAL NEURAL NETWORK (FFANN) TO PREDICT W/O EMULSION VISCOSITY

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ABSTRACT

Accurate prediction of the viscosity behavior of crude oil emulsion is essential for the design, selection and routine operation in many petroleum applications. The aim of this work was conducted to predict viscosity using feed forward artificial neural network FFANN. The factors are studied include the effect of mixing time, mixing speed, emulsifying temperature and shear rate. Experimental laboratory data are used to develop the viscosity correlations. The results shown that the predicted model has a good compatibility with experiments obtained in R= 0.99992 and best validation performance 143.3434 and high correlation coefficient RC= 0.98. The results also show that the achieved model is better than the conventional ANN in the prediction of viscosity with improving the overall percentage of 39.

INTRODUCTION

Water in oil emulsions may be formed during drilling, transporting and processing of crude oils and in a hydrocarbon reservoir, well bores, surface facilities, and petroleum refineries (Karimi *et al*,2011, Maneeintr *et al*, 2010). Viscosity of emulsion plays an important role in demulsification process, and knowledge of their rheological characteristics such as resistance to shear, agitation, or flow pattern may be useful in product quality, controlling of energy cost, process equipments design and pipe selection.

The main factors affecting on viscosity of w/o emulsions are emulsification condition such mixing speed and emulsification time, emulsion temperature, also physical properties such as viscosity and density of crude oil and water phase (Mc Donagh *et al*,1995). In general, crude oil emulsion is non Newtonian fluid and its physicochemical and rheological properties are assumed as complex nonlinear system.

ANN techniques has been conducted for modeling of complex processes and highly non-linear and used on a large scale (Farsetti *et al*, 2014, Konate *et al*,2014). ANN provide techniques to solve problems in remote sensing data analysis, detection of errors, and to identify practical, control and used in a variety of chemical engineering applications (Pirdashti *et al*,2013). Several papers have been carried out in the oil industry with analyzing ANN model patterns (Makinde *et al*, 2012).

The aim of this work was carried out to construct FFANN model using MATLAB software to estimate the effect of mixing speed 1000-2000 rpm, mixing time 10-40 min, emulsifying temperature 20-80 ^oC and shear rate 10-100 s^{-1} on the emulsion viscosity.

MATERIALS AND METHODS

Sample Preparation

Experimental work was performed on the crude oil obtained from Daura Refinery. The physical properties are given in (Tab.1). The w/o emulsion was prepared by mixing 30% water to 70% crude oil using IKA LAB mixer. Salts content in water phase was 3% wt NaCl. The experiments was conducted with mixing speed 1000, 1500 and , 2000 rpm and emulsifying time 10,20 and 40 min . A controlled Brookfield DV-II Viscometer was used for measuring of emulsion viscosity. Measurements for all samples were carried out in a shear rate range of 10-100

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s^{-1} and temperature 20-80 °C. Experimental results are shown in (Tab. 2).

Data Normalization

Normalized data of viscosity is a transformation performed on a single data input to distribute a different range of the network. The training data were normalized by (eq.1).

X new=(X-X min)/(X max-X min) ………(1)

Where *X* is an input or output variable, *X min* is the minimum value of variable, and *X max* is the maximum value of variable (Makinde *et al*,2012, Chandrashekhar *et al*,2014).

Table 1 Physical Properties of Daura Refinery Crude Oil

API GRAVITY @15.6 °C	29.5
SP. GRAVITY @15.6 °C	0.8789
Density @ 15 °C	0.8784
Sulfur content %wt	3.31
Kin. Viscosity cst @21.1 °C	22.9
Kin. Viscosity cst @37.8 °C	13.4
Pour point °C	Below -30
R.V. P kg/cm^2	0.49
Water &Sediment %vol	0.1
Salt content %wt	0.0021
Carbon content %wt	6.18
Asphaltenes contents %wt	1.99
Ash content %wt	0.0220
Vanadium ppm	81.86
Nickel ppm	20.88
Water content %vol	0.1

Neural Network Development

ANN model is widely applied in the engineering applications (Dagli *et al.*, 2006). The methodology depends on data analysis statistically. The development model classified into the following steps:

1. Preliminary Analysis of various graphs and scatter plots of the examined data to search patterns that capability occur within the data.
2. Statistical Analysis using MatLAB Software. Multiple regression analysis was performed with a regression equation that would be capable to illustrate the model augmented by means of any linear relationships within the input and output variables.
3. Neural Network model construction. There are a various connections within the network that become acceptable for connection weights using a training data set. In this study, the architecture used consists of three input layer, different hidden layer and the output layer.
4. Optimization using FFANN. Input layer provides a pattern of neural network, which is the way to the external environment. When the pattern is provided to the input layer for one time, the output layer creates the other one. Each neuron should inspect independent input variables with the relation to the output layer. The output layer of the neural network is an actual pattern of the external environment and reversely effect on the input layer.

Table 2 Experimental Data of Emulsion Viscosity

Set No.	Mixing Time min	Mixing Speed rpm	Emulsifying Temperature °C	Shear Rate (1/sec) 10	20	30	50	60	100
				w/o Emulsion Dynamic Viscosity(cp)					
1	10	1000	20	50	52	53.2	53.6	53.9	54
2			40	26	28	29	30	30	33
3			60	23	25	27	27	28	28
4			80	15	13	12	12	11	11
5	20	1000	20	51	49	48	48.5	47.1	48
6			40	28.2	28.2	28	27.2	27	26.9
7			60	24	23.4	21.4	21.4	20.7	20.7
8			80	16.2	15	14.3	14.3	13.9	13.9
9	40	1000	20	53	53	50	50	49	49
10			40	30	38	29	29	28	28
11			60	25	25	24	24	23	23
12			80	20	19	19	17	17	16
13	10	1500	20	50	52.8	52.4	52.2	52	52
14			40	30	29.8	28	27.6	27.4	27
15			60	20	19.8	19.3	19	19	18.8
16			80	15.8	15.5	15.2	15.2	15	15
17	20	1500	20	51.9	51.6	51.2	51.1	51	51
18			40	39.6	36.6	35.8	35.5	34.8	34.4
19			60	24.5	24	23.6	23	22.8	22
20			80	14.8	14.7	14.2	13.8	13.5	13
21	40	1500	20	51.9	51.8	51.5	51	50.8	50.8
22			40	27.6	27.6	27	26.2	26.4	26.4
23			60	22.8	22.5	22.2	21.6	21.5	20.9
24			80	14.6	14.4	14.2	14.2	14	13.6
25	10	2000	20	52	52	51.8	51.6	51.6	51.4
26			40	34.2	34	33	32.5	32	31.9
27			60	22.3	22.5	22.2	21.6	21.5	21.5
28			80	14.6	14.4	14.2	14.2	14	13.6
29	20	2000	20	54	53.7	53.4	53.1	52.7	52.2
30			40	35	34	34	33.8	33.6	33.6
31			60	24	22.7	22.7	22	21.7	21.7
32			80	15	14.7	14.6	14.2	14	14
33	40	2000	20	51.7	51.7	51.5	51.2	50.9	50.7
34			40	27.4	27.3	26.8	26.5	26.2	26.2
35			60	22.5	22.3	22.2	21.6	21.5	20.8
36			80	14.4	14.4	14.2	14.2	14	13.6

The number of output neurons is directly affected by the type of the neural network (Godding *et al*, 2008).

5. Multiple tests run on the selected model. A multilayer FANN structure within input, output and hidden layers was applied in this work. Therefore, one neuron is used in output layer namely is the emulsion viscosity. The ANN model was accomplished in accordance with chosen of an input layer, number of layers and neurons in the hidden layer, and the output layer. The network was created using the MATLAB software.
6. Sensitivity Analysis to find correlation between input and output variables (Godding *et al*, 2008 , Pirdashti *et al*, 2013).

The neural network was developed using the following:

>>net = newff (Input_Data, Output_Data,10);

Where, net is the ANN, Input Data consist of temperature, mixing time, mixing speed and the shear rate. Thirdly, the Output Data refers emulsion viscosity. Lastly, the ten in the command line refers to neurons in the hidden layer. (Fig.2) shows the representation of the neural network.

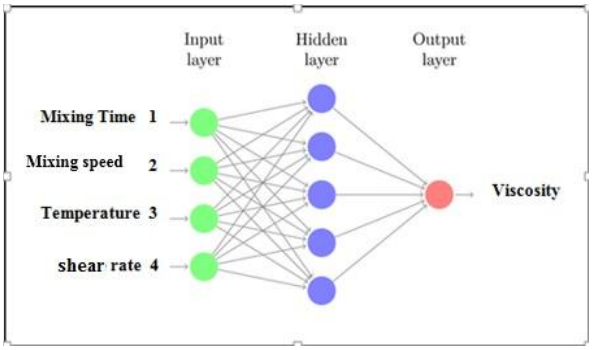

Figure 2 A Schematic of the Achieved ANN Topology

RESULTS AND DISCUSSIONS

Data Analysis and Discussion

The input-output sets were used to train ANN model are reported in table 2 with the following ranges: temperature 20-80 ^{o}C, mixing time 10-40 min, mixing speed 1000-2000 rpm and the shear rate 10-100 sec^{-1}, crude oil viscosity at 11 – 54 cp . Of the 3 table sets for 1000-2000 rpm, 42 were used to train {(10:10:10:10)+(20:20:20:20)+(40:40:40:40) mixing time +(1000:1000:1000:1000) +(1000:1000:1000:1000) + (1000:1000:1000:1000) stirring rpm + (20:40:60:80) +(20:40:60:80) + (20:40:60:80) temperature + (10:20:30:50:60:100) shear rate}= 42 the ANN models, 6 data viscosity sets were used to verify the accuracy of the relationships established during the training process and the remaining 72 data sets ,all the viscosity in one table were used to evaluate their accuracy statistically. The neural network converged after (48 or 16 in one table) iterations with different neurons in the hidden layer.

The (fig 3–8) shows the training data, validation, and testing. The best result shown in the dotted line, where the solid line represents the best fit linear regression between outputs and targets. Furthermore, there is no linear relationship between outputs and targets when R reach to zero, however, when R range to 1 indicate an accurate relationship. For example, there is a data point in the test set which the network is close to 72, while the corresponding target value is around 42.

Comparing ANN models with emulsion viscosity

(Tab.3) shows the results of training, validation, testing, performance and epoch in different mixing time for output viscosity. The obtained FFANN model show that a good agreement with the experimental data at 2000 rpm. Furthermore, the results have also been compared with different neurons. The findings demonstrate that this model is an efficient method and have better accuracy when the epoch reach 1.

Table 3 Results of Training, Validation, Testing, Performance and Epoch at different mixing time for output Viscosity

Mixing speed (rpm)	Training R	Validation R	Test R	All R	Best Validation performance	Epoch
1000	0.97998	0.99408	0.99621	0.98629	9.9305	9
1500	0.99492	0.99508	0.99713	0.97612	3.47	8
2000	1.00000	0.99992	0.99997	0.99998	143.3434	1

(Tab. 4-6) compares the prediction performance of the neural network based crude oil prediction model developed in the previous discussion with two of widely based numerical prediction models. The comparison is based on a single constant mixing time, temperature and shear rate data, and further analysis may be needed at various conditions to give a general conclusion.

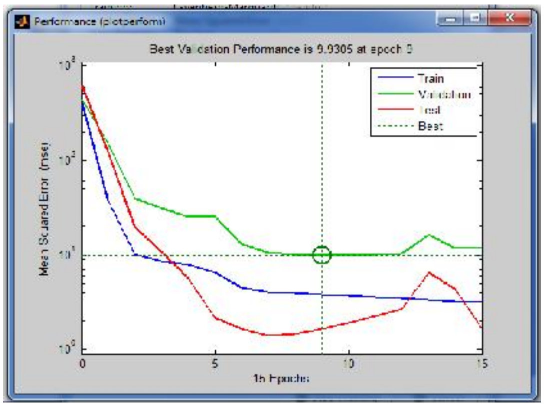

Figure 3 The best validation performance in speed 1000 rpm

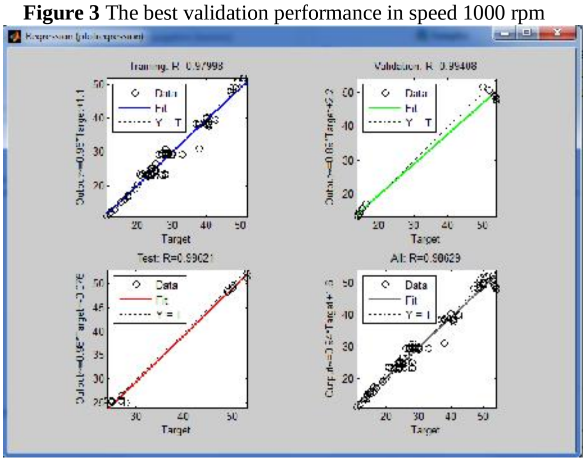

Figure 4 The regression (plot regression) training ,validation and testing R for speed 1000 rpm

Table 4 Comparing the Performance of Models under Mixing Speed 1000 rpm

No. Of Neurons	Training R	Validation R	Test R	All R	Best Validation Performances	Epoch
1.000	0.99577	0.99789	0.99367	0.99561	0.00029839000	38.000
2.000	0.99963	0.99992	0.99956	0.99964	0.00004308600	13.000
3.000	0.99991	0.99991	0.99984	0.99988	0.00000799350	7.000
4.000	1.00000	1.00000	1.00000	1.00000	0.00000043704	116.000
5.000	0.99999	0.99998	0.99953	0.99999	0.00000354470	15.000
6.000	1.00000	1.00000	1.00000	1.00000	0.00000000363	463.000
7.000	1.00000	1.00000	0.99999	1.00000	0.00000000090	1000.000
8.000	1.00000	1.00000	0.99997	0.99999	0.00000064416	163.000
9.000	0.99979	0.99980	0.99973	0.99979	0.00006922700	6.000
10.000	0.99993	0.99961	0.99992	0.99991	0.000013352	31.000
11.000	0.97998	0.99408	0.99621	0.98629	9.9305	9.000
12.000	0.99993	0.99964	0.99336	0.99704	0.00080795000	3.000
13.000	0.99988	0.99967	0.99962	0.99978	0.000054905	4.000
14.000	1.00000	0.99999	0.99979	0.99994	0.0000096013	265.000
15.000	0.99998	0.99945	0.99974	0.99987	0.00012041000	5.000
20.000	1.00000	0.94436	0.99610	0.95839	0.01561800000	27.000

Table 5 Comparing the Performance of Models under Mixing Speed 1500 rpm

No. Of Neurons	Training R	Validation R	Test R	All R	Best Validation Performances	Epoch
1.000	0.99577	0.99789	0.99367	0.99561	0.00029839000	38.000
2.000	0.99963	0.99992	0.99956	0.99964	0.00004308600	13.000
3.000	0.99991	0.99991	0.99984	0.99988	0.00000799350	7.000
4.000	1.00000	1.00000	1.00000	1.00000	0.00000043704	116.000
5.000	0.99999	0.99998	0.99953	0.99999	0.00000354470	15.000
6.000	1.00000	1.00000	1.00000	1.00000	0.00000000363	463.000
7.000	0.99492	0.99508	0.99713	0.97612	3.470000000	8.0000
8.000	1.00000	1.00000	0.99999	1.00000	0.00000000090	1000.000
9.000	1.00000	1.00000	0.99997	0.99999	0.00000064416	163.000
10.000	0.99979	0.99980	0.99973	0.99979	0.00006922700	6.000
11.000	0.99998	0.99978	0.99996	0.99994	0.000027809	9.000
12.000	0.99993	0.99964	0.99336	0.99704	0.00080795000	3.000
13.000	0.99988	0.99967	0.99962	0.99978	0.000054905	4.000
14.000	1.00000	0.99999	0.99979	0.99994	0.0000096013	265.000
15.000	0.99998	0.99945	0.99974	0.99987	0.00012041000	5.000
20.000	1.00000	0.94436	0.99610	0.95839	0.01561800000	27.000

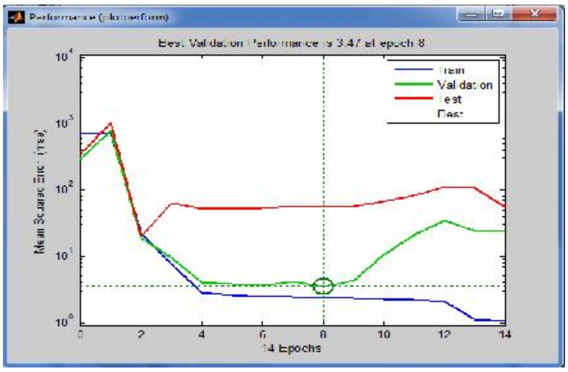

Figure 5 The best validation performance in speed 1500 rpm

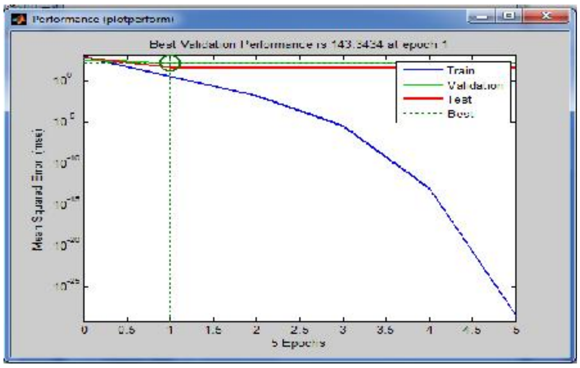

Figure 7 The best validation performance in speed 2000 rpm

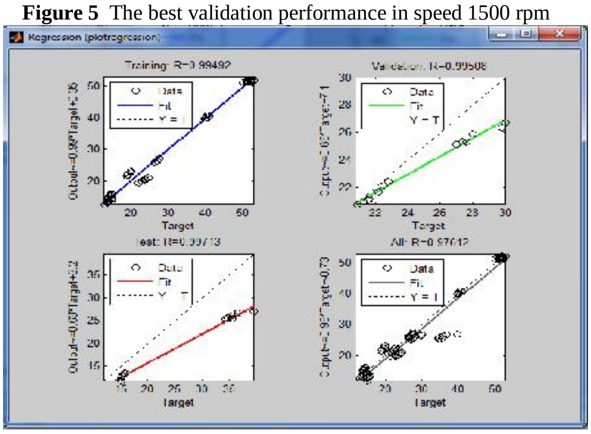

Figure 6 The regression (plot regression) training ,validation and testing R for speed 1500 rpm

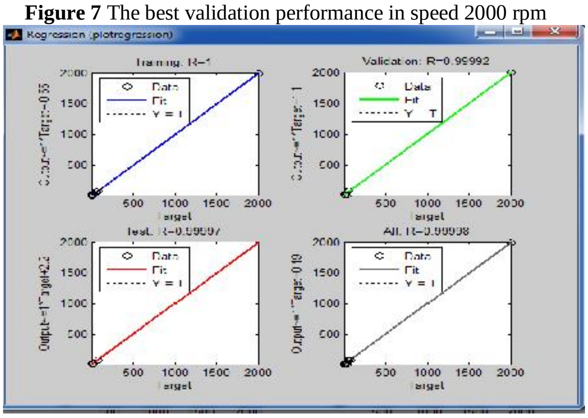

Figure 8 The regression (plot regression) training,validation and testing R for speed 2000 rpm

Table 6 Comparing the Performance of Models under Mixing Speed 2000 rpm

No. Of Neurons	Training R	Validation R	Test R	All R	Best Validation Performance	Epoch
1.000	0.99745	0.99538	0.99922	0.99748	0.0003212900	10.000
2.000	0.99993	0.99987	0.99994	0.99992	0.0000235270	31.000
3.000	0.99997	0.99999	0.99997	0.99997	0.0000086276	134.000
4.000	1.00000	0.99998	0.99996	0.99998	0.0000078410	130.000
5.000	0.99998	0.99996	0.99999	0.99996	0.0000081943	32.000
6.000	1.00000	1.00000	0.99102	0.99900	0.0000008384	29.000
7.000	1.00000	1.00000	1.00000	0.99999	0.0000008563	7.000
8.000	1.00000	1.00000	0.96386	0.99143	0.0000003383	693.000
9.000	1.0000	0.99992	0.99997	0.99998	143.3434	1.0000
10.000	1.00000	1.00000	0.99998	1.00000	0.0000001938	29.000
11.000	0.99989	0.98968	0.80572	0.98147	0.0001229310	6.000
12.000	1.00000	0.99994	0.99994	0.99997	0.0000259160	1000.000
13.000	0.99989	0.99769	0.99956	0.99939	0.0007657500	3.000
14.000	0.99551	0.98641	0.99892	0.99278	0.0029610000	1.000
15.000	0.99985	0.99990	0.99951	0.99981	0.0000356610	3.000
20.000	0.99996	0.99921	0.99865	0.99938	0.0004276800	6.000

CONCLUSION

The correlations to predict w/o emulsion viscosity is essential for the design, selection and routine operation in many applications. In this work, a feed-forward artificial neural network is proposed. Input factors are studied include the effect of mixing time, stirring intensity, emulsifying temperature and shear rate is covered. The results have also been compared with experimental data demonstrate that the ability and accuracy of the new ANN model is an efficient method and have better accuracy.

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