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A NEURAL MODEL DEVELOPMENT FOR THE DETERMINATION OF ASPHALTENE ONSET PRESSURE IN OIL RESERVOIRS

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ABSTRACT

The upper asphaltene precipitation envelope is obtained from a developed model with artificial neural networks called "Neuross-Asph". This was achieved by training with 58 samples collected from different literature sources and analysing the information before being introduced into the network. The model was constructed in three stages: the first one consisted of grouping the data according to asphaltene onset pressure and saturation pressure ratio (AOP/Pb) using a self-organizing maps (SOM) network. In the second, a subcategorization of information was made; this was based on the chemical composition and SARA analysis using SOM networks. The last stage was designed with a feed-forward network of backpropagation to predict the onset pressures by means of the association with saturation pressure. The main advantage of the proposed model is to predict the asphaltene onset pressure (AOP), requiring little and easily accessible data as input parameters. In reviewing the data output satisfactory results were obtained from the developed tool since it is considered that the model possesses a good design, since it identified the relationships that have more influence on the precipitation of asphaltenes.

Keywords: onset pressure, asphaltene deposition, artificial neural networks, self-organizing maps, feed-forward.

1. INTRODUCTION

Asphaltenes precipitation represents one of the main problems in the oil industry, its adverse effects reflect in almost all areas of the production process. Studies realized to understand this phenomenon and consequences that it generates have led to propose models that allow characterizing and quantifyingthe precipitation of asphaltenes.

So far, the principal models developed for asphaltene precipitation are: colloidal thermodynamic model, polymer solution model, regular solution model, solid model, PC- Salt model, micellization model and numerical model. The latter has the greatest interest and is under constant development since determination of asphaltene onset pressure (AOP), precipitation envelope (ADE) and/or represent the curve weight percent of asphaltene-solid precipitates (% wt) are current tasks that exclude experimental procedures involving time and cost variables that although they are theoretically well supported, on a practical basis generate uncertainties.

Among the latest models proposed for the given case are found: numeric, empirical equations, intelligent systems and artificial neural networks (ANN). As time goes by, the ANNs have demonstrated their potential in the development of outstanding research, not only in the industry of hydrocarbons but in almost all human labours, for this motive this article focuses in the use of this tool.

The first research found in the literature was developed by Mohammadi and Richon (2008) using a mathematical model based on the Feed forward Technique Optimized with the modified Levenberg-Marquardt (LM) algorithm. To model the onset of precipitation of asphaltenes dissolved in a solvent + precipitated solution. Later, Abedini*et al.* (2010) developed an ANN model to predict and simulate the amount of asphaltenes precipitated depending on the dilution ratio, the solvent molecular weight and temperature, using backpropagation (BP) and Levenberg-Marquardt (LM) algorithms.

Ahmadi (2011) developed a hybrid model for the prediction of asphaltene precipitation based on a combination of feed-forward and unified particle swarm optimization (UPSO) networks to decide the initial weight for the network. Later, Ahmadi*et al.* (2011) developed a similar model based on particle swarm optimization (PSO) and BP. Zendehboudia *et al.* (2013) joined the ANN with the imperialist competitive algorithm and PSO to estimate the precipitation and deposition of asphaltenes with and without $C0_2$ injection.

Hemmati-Sarapardeh *et al.* (2013) developed a model for asphaltene precipitation, based on an intelligent system named least squares support vector machine (LSSVM). Kamari *et al.* (2014) also posed a model based on LSSVM to determine the onset pressure from a few parameters: operating conditions, composition and characterization of crude oil.

This field of research delivers a considerable contribution to multiple researches developed on the subject. The presented model, named “Neuross-Asph”, predicts the pressures that form the upper envelope of asphaltene precipitation of oil reservoirs with ANNs; requiring a small amount of easily accessible data for operation, and with predictions of a satisfactory degree of reliability.

2. METHODOLOGY

With the purpose of presenting an efficient model to determine the AOP was necessary to research the variables that have most influence on the mentioned phenomenon. So far, all former studies coincide with pressure changes, temperature and composition have direct influence on the precipitation of asphaltenes. Thus, the search for information took into consideration the following parameters:

- Oil composition in molar percent (%mol).
- SARA analysis in weight percent (%wt).
- Pb in Megapascals (Mpa).
- AOP in Megapascals (Mpa) at different temperatures (T) in degrees Kelvin (K).

The collected data consisted on 58 samples (54 from literature and 4 from Colombian oil).
The oil composition was classified in 10 components: N_2, CO_2, H_2S, C_1, C_2, C_3, C_4, C_5, C_6 y C_{7+}.

From the analysis information, a temperature range was established 294 K - 423 K (69 °F - 302 °F) because the majority of samples did not contain data at low temperatures (<315 K).In the majority of cases, the reservoir temperature worldwide is above 294K.

Since the success of the ANN depends upon the representativeness of information used for training, it was necessary to perform two procedures before building the network to achieve onset and saturation pressure data in all of the temperature range established. For the case of Pb, commercial software was used to generate the envelope for vapour-liquid equilibrium. In the case of the AOP, a fitting data commercial software was used, employing equations that best represent the behavior for AOP vs T($R^2 \cong 1$ and creates the curve according to the physical phenomenon).Figure-1 shows an example of processing described.

The next step was to identify the characteristics, relationships, tendencies and/or correlations between the statics (Composition and SARA analysis) and dynamics (AOP and Pb) variables, throughout the temperature range established.After several attempts, two relationships were found: the derivative average of AOP/Pb respect to T expressed by Equation 1, and the average AOP/Pb ratio expressed by Equation 2

$$(\bar{m}_k)_d = \frac{\sum \frac{\partial\left(\frac{AOP}{Pb}\right)_i}{\partial T}}{n} \quad (1)$$

$$(\bar{m}_k)_q = \frac{\sum \left(\frac{AOP}{Pb}\right)_i}{n} \quad (2)$$

where
i corresponds to i-*th* temperature values of the range established (294 K - 423 K).
n = total number of temperature values evaluated.
k = total number of analysed samples.
$(\bar{m}_k)_d$and $(\bar{m}_k)_q$is the average of the derivative and the quotient, respectively.

The samples with similar $(\bar{m}_k)_d$ and $(\bar{m}_k)_q$ ratios group similar compositions. In this way was possible to demonstrate that Pb is the variable that givemost conditions to the behaviour of asphaltene.

3. DESIGN AND TRAINING FOR NEUROSS-ASPH MODEL

Basically, the way the model could determine AOPs for new wells is through a system that "learns" the particularity of the relationships between the chemical compositions, SARA analysis, Pband AOP of representative sample wells, in this way, to obtain a knowledgebase of the dynamics of the phenomenon.

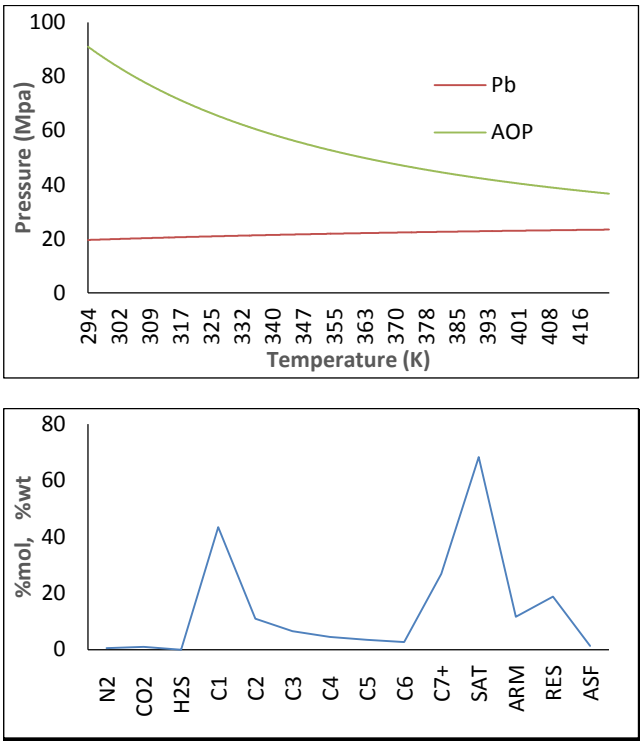

Figure-1. Example of the information entered to the network.

The base of knowledge-learning is implemented with multiple topologies of ANN, in virtue to their characteristics to learn, classify and generalize datasets whose relations correspond to the description or associate properties of dynamic systems, who in this particular case, is the behaviour of asphaltene precipitation and the change in thermodynamic properties. Commercial mathematical software was used to implement the model.Figure-2,illustrates all the training stages for the Neuross-Asph model.

The main processes involved in the design and training of the model are the following.

3.1. Information processing

To properly describe the dynamics of the process and avoiding the generation column vectors of many components, a resolution of 1 K is applied to represent the Pb and AOP in the range of temperature established, obtaining matrices of dimension 129xnm (where mn is the amount of samples).

3.2. First stage: Categorization according to average AOP/Pb

During the information analysis process, it was established that Pb through the AOP/Pbratio is the variable that connects the AOP (variable dynamic because it depends directly to the temperature) with the composition and SARA analysis (static variables); therefore, it was determined that this relationship is the first design criterion of model. For this, a self-organizing map (SOM) network was used. That allows discovering through unsupervised competitive learning, common features, regularities, correlations or categories in the input data, and incorporates them into its internal structure of connections, Marin (2013). The training vector obtained from the AOP/Pb ratio allowed through SOM_r to group samples with similar averages represented by an output vector with a 1xnm dimension which is used to "map" the chemical composition, the SARA analysis, Pb and AOP. For practical purposes, the chemical composition and SARA analysis were referenced as chemical composition.

3.3. Second stage: Subcategorization according to composition

In order to optimize the training, to make it efficient and accurate for grouping samples that share common characteristics, it was decided to design an additional categorization to group similar chemical compositions based on the outputs of the SOM_r according average AOP/Pb. The strategy used involved applying SOMs to each of the categories generated in the first stage (these are the SOM_c shown in Figure-2). Thus 1xCn dimension subcategories are obtained which are used to "map" the groups chemical composition, AOP and Pb depending on the chemical composition.

3.4. Third stage: Association between Pb and AOP

The objective is to "learn" the relationship between the Pb and AOP based on previous subcategorizations, where the Pb and AOP share similar chemical composition and average AOP/Pb. For this a neural network of Feed-forward backpropagation (FFB)

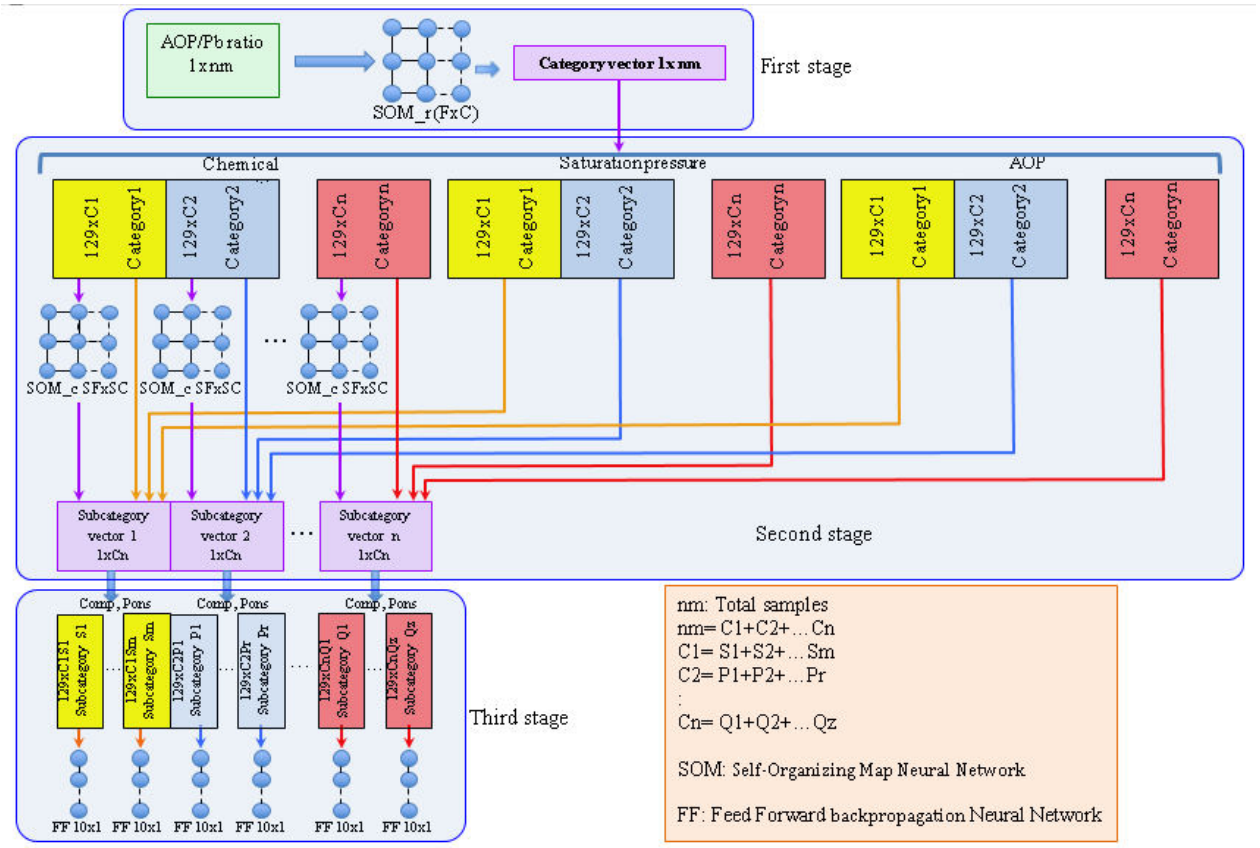

Figure-2. Structural representation of the model.

was used, which is the ANN most studied by the scientific community, receives multivariable information, processes it and generates an answer resulting from the supervised learning in which the weights of the connections are modified to achieve outputs with minimum error, Vasquez (2014). The topology of each ANN has 10 neurons with 129 inputs and 129 outputs due to the matrix dimensions of the subcategory correspondent to Pb (witch act as examples for training) and AOP (that act as objectives or targets).

4. SIMULATION

The simulation consists of verifying the operation of the model built, in which a new sample is introduced

(with all their properties), corresponding to the input space to obtain an answer from the model, that is to say, predicts the upper envelope of asphaltene precipitation. This process is illustrated in Figure-3. The processes at this stage are described below.

4.1 Coupling for the chemical composition

The composition of the sample whose behaviour of asphaltenes is to be predicted is entered. The input vector for the chemical composition is 14x1 according to the vectors used in the training. To locate the category that corresponds the entered composition, the training SOM_cis used.

The entered chemical composition is simulated in all the SOM_c and these compete with each other, ordering the neurons according to their coupling, in the end the SOMs are obtained with their respective winning neuron associated with the input composition.

4.2 Coupling ratio of the AOP/Pb relation

During the training process, the relation AOP/Pb corresponded to the initial category; nevertheless, in the simulation is not possible to make a direct couple in this relation because the AOP is unknown, this will be predicted. In this phase the chemical composition is implied within the SOM_c which is the result of the initial SOM_r (AOP/Pb relation).

4.3 Feed-forward network selection

After the coupling of the new composition with the subcategorization given by the SOM_c associated to the input composition through the subcategory vector, the trained FFB network is selected with the corresponding subcategories directed by the strongest neuron and its neighbours. This is shown in Figure-3, where the subcategory 2 vector selects the FFB whose targets are AOP associated with the chemical composition of input.

4.4 AOP prediction

It is realized in two phases, the first carries out the association between the AOP (which is the answer from the SOM, of chemical composition and said

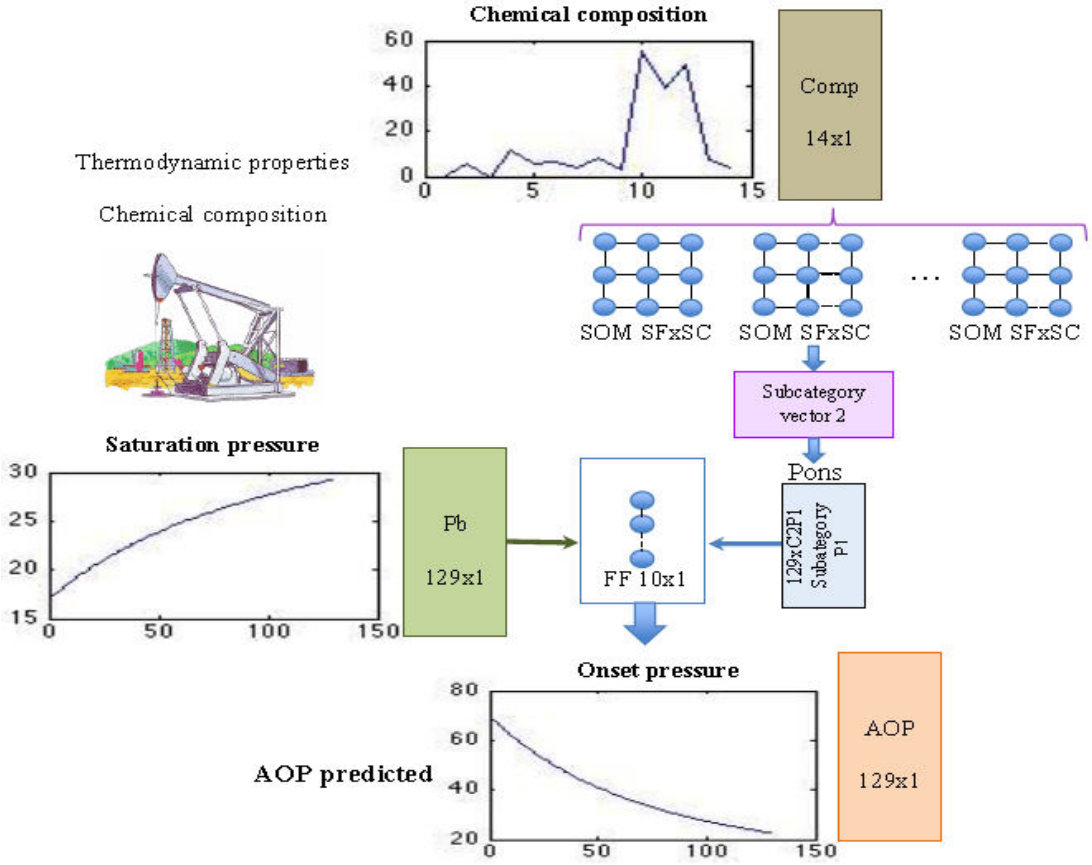

Figure-3. Scheme of the simulation process.

dimension is 129x1), and the Pb of the evaluated samples that is entered in this phase which should be processed previously so that its dimensions to be 129x1, process that was described inhe methodology. The second phase corresponds to the prediction of the AOP, through the input of the training FFB network.

5. RESULTS

To evaluate the results of the proposed model, it was calculated for each case, the average absolute error (AAE) using Equation-1, which consists on the average of the absolute difference calculated between the real value and the value calculated.

$$\boldsymbol{AAE} = \frac{1}{n}\sum_{i=1}^{n}|\Delta x_i| \times 100 \quad (1)$$

To compare punctual results, the error percent was estimated through Ecuación-2

$$\%\boldsymbol{error} = \left[\frac{x_{experimental} - x_{calculated}}{x_{experimental}}\right] \times 100 \quad (2)$$

Where *x* are the values of AOP.

5.1 Validation of the model with the input information

In order to verify the degree of accuracy in the results obtained with the model, it was decided to compare the outputs with experimental AOP of the 58 samples with which was using in the training. Table-1 presents the comparative for 12 of the 58 samples at different temperatures.

Table-1. Comparison of experimental data and predicted with the Neuross-Asph model.

Sample	Temp. (K)	AOP Exp. (Mpa)	AOP Calc. (Mpa)	%Error	AAE
1	300	73.27	73.27	0	0
6	300	57.64	57.64	0	0
10	300	83.76	83.76	0	0
18	334	31.91	31.91	0	0
21	358	18.35	18.35	0	0
27	358	22.00	22.00	0	0
30	358	8.67	8.67	0	0
36	379	34.00	34.00	0	0
40	379	44.50	44.50	0	0
45	397	28.19	28.19	0	0
50	397	3.36	3.36	0	0
51	413	83.11	83.11	0	0

It was observed that the Neuross-Asph model worked perfectly with the information entered for training (chemical composition and Pb).These results allow inferring that the categorization, training and simulation were adequate. The categorization with the two-stage SOM was convenient because it allowed the created neurons to group samples correctly that relate the saturation pressure, the onset pressure, chemical composition and SARA analysis.

5.2 Validation of the model with a new sample

To verify the results of the model during the simulation process, it was decided to train the network with 56 samples and simulate it with the remaining two samples. It's valid to clarify that these two samples were not entered during the training process, the results will correspond to the predictions. Figures-4 and 5 show the output of the network for simulated samples.

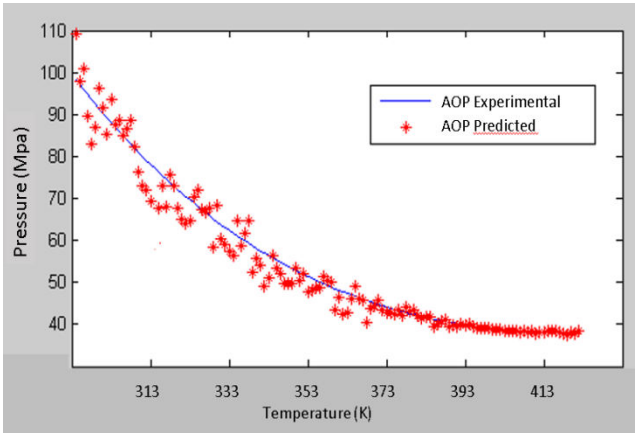

Figure-4. Network Prediction for sample 14.

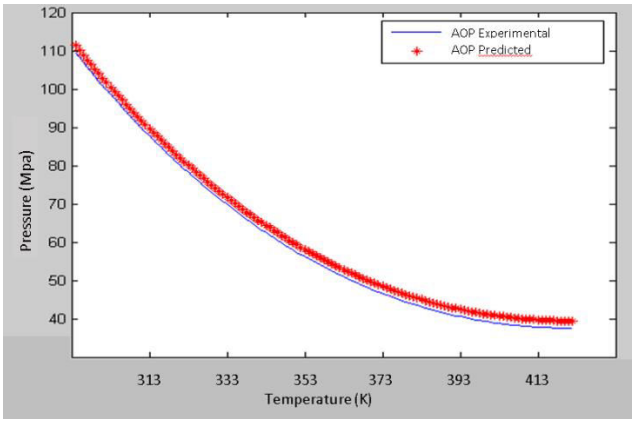

Figure-5. Network Prediction for sample 40.

As shown in Figures-4 and 5, the prediction with Neuross-Asph model is satisfactory since most of the predicted points are closer to the experimental values and the behaviour of the graph corresponds to the physical phenomenon that decreasing temperature, the pressure tends to increase. Table-2 presents the results of some AOP predicted at different temperatures.

Table-2.AOP predicted at different temperatures for 14 and 40 samples.

Sample	Temp. (K)	AOP exp. (Mpa)	AOP Predicted (Mpa)	% Error
14	301.3	90.20	91.53	1.5
	309.3	81.89	82.42	0.6
	319.3	72.85	72.86	0.0
	330.3	64.47	68.45	6.2
	346.3	54.81	52.04	5.1
	365.3	46.64	49.23	5.6
	400.3	38.96	38.73	0.6
40	301.3	100.93	102.82	1.9
	309.3	91.97	93.87	2.1
	319.3	81.90	83.80	2.3
	330.3	72.20	74.09	2.6
	346.3	60.48	62.38	3.1
	365.3	49.96	51.86	3.8
	400.3	39.21	41.11	4.8

The results show that the Neuross-Asph model presents deviations below 6.2%. The AAE for samples 14 and 40 was 2.4 Mpa and 1.9Mpa respectively.

5.3 Comparison with other numerical models

Fahim (2007) developed a model to estimate the envelope of asphaltene precipitation based on empirical equations, with 33 samples of oil mainly from the Middle East.

Del Rio, Ramirez-Jaramillo and Lira (2008) proposed equations to predict the AOP based on a method of least squares regression from 11 samples of oil from Mexico.

By applying previous models to the 58 samples, it shows that the error rates are very high. Table-3 presents the deviation values giving 70% of difference between calculated and experimental values for Fahim Model and more than 100% for Del Rio*et al.*Model, while the Neuross-Asph model error is 0 %.

These results show that the use of few samples to construct the models of discussion considerably limits the range of application thereof. Also trying to characterize asphaltene linearly is a mistake, since it does not represent the physical behaviour of the phenomenon; so it varies, then it is dynamic and depends upon many factors.

5.4 Model restrictions

The limitations of the proposed model are based on the data used in its construction. To ensure greater confidence in the results it is recommended that the input data be in the ranges presented in Table-3.

To achieve better performance from the model, it is necessary that the entered saturation pressures have a dimension of 129x1, which means that the set temperature range must have pressure data every 1 K. In addition, it is

Table-3. Comparison of AOP calculated with Fahim, Del Rio *et al.* and Neuross-Asph models.

Sample	Temperature (K)	AOP experimental (Mpa)	AOP predicted			% Error		
			Fahim Model	Del Rio *et al*. Model	Neuross-Asph Model	Fahim Model	Del Rio *et al*. Model	Neuross-Asph Model
Muestra 2	320	34,98	49,65	-17,09	34,98	41,92	148,87	0
Muestra 4	320	59,15	61,40	-18,25	59,15	3,80	130,86	0
Muestra 6	340	33,01	14,10	11,11	33,01	57,28	66,34	0
Muestra 7	320	40,79	68,09	11,82	40,79	66,90	71,03	0
Muestra 9	340	23,95	7,08	10,59	23,95	70,41	55,76	0
Muestra 10	400	53,54	52,81	28,28	53,54	1,37	47,18	0
Muestra 11	400	52,36	47,55	16,20	52,36	9,19	69,06	0
Muestra 17	380	38,26	20,65	12,60	38,26	46,02	67,06	0
Muestra 32	340	6,38	5,77	17,32	6,38	9,60	171,35	0
Muestra 33	340	33,91	41,96	14,91	33,91	23,72	56,04	0
Muestra 47	360	50,43	64,69	-5,26	50,43	28,29	110,43	0
Muestra 48	380	45,00	43,87	9,57	45,00	2,50	78,72	0
Muestra 49	360	37,03	35,21	10,08	37,03	4,92	72,77	0
Muestra 50	320	31,21	35,69	27,11	31,21	14,35	13,13	0
Muestra 52	380	50,34	50,30	121,40	50,34	0,08	141,16	0
Muestra 56	340	33,31	45,22	7,82	33,31	35,78	76,52	0
Muestra 57	320	62,39	63,57	290,64	62,39	1,90	365,86	0

recommended that saturation pressure data to be entered lies within the area formed by the data used in its construction; this is represented in Figure-3.

Table-4. Variable ranges used for the creation of the Neuross-Asph model.

Component	Range	
	Minimum	Maximum
N2	0.01	5.08
CO2	0.01	32.58
H2S	0	8.26
C1	8.78	57.41
C2	3.75	11.02
C3	2.95	9.59
C4	1.1	6.58
C5	1.92	8.85
C6	1.76	8.04
C7+	16.52	57.77
SAT	26.88	75.56
ARM	11.6	67.99
RES	2.5	18.8
ASF	0.17	16.3

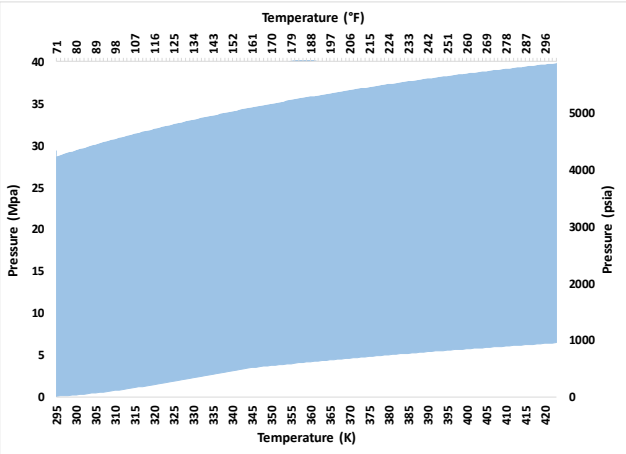

Figure-6. Region formed by the Pb used in the creation of the Neuross-Asph model.

6. CONCLUSIONS

a) The development of the Neuross-Asph model was achieved to calculate with a high degree of reliability the upper envelope of asphaltene precipitation without entering experimental AOP data, which has been a barrier for the use of other proposed models.

b) The model developed is efficient, presents reliable results, ensures a wide application range and high degree of robustness since its base is ANN.

c) One of the main advantages developed in the Neuross-Asph model is that only requires information that corresponding a few and easily access thermodynamic properties (chemical composition, SARA analysis and Pb).

d) The Neuross-Asph model presents an excellent fit for the data that was used for training; the results also generate greater reliability than those obtained through the Fahim and Del Rio*et al.* models.

e) To ensure reliability in the results, three conditions were established: the chemical composition and SARA analysis should be within the range set for the chemical composition and SARA analysis. The Pb must be entered for the set temperature range (294.3 K-423.2K) and also be part of the defined region for Pb.

f) A great success in building the model was to consider the most influential factors in the precipitation of asphaltenes. First, the grouping according to the AOP/Pb ratio, this allowed that the saturation pressure to be established as the dominant property in predicting the onset envelope pressures. The second factor is the composition as their degree of impact is indirect and complementary to the previous grouping.

g) The categorization using the two SOM stageswas convenient because it allowed the neurons created to group samples correctly relating the Pb, the AOP, chemical composition and SARA analysis.

h) Although advances in this area of study have been important, these have been limited because the required information is not easily accessible; quantification of some input variables has a high degree of uncertainty, a small number of existing experimental data, among others.

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