

Prediction of Bubble Point Pressure & Asphaltene Onset Pressure During CO₂ Injection Using ANN & ANFIS Models

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Abstract

Although CO₂ injection is one of the most common methods in enhanced oil recovery, it could alter fluid properties of oil and cause some problems such as asphaltene precipitation. The maximum amount of asphaltene precipitation occurs near the fluid pressure and concentration saturation. According to the description of asphaltene deposition onset, the bubble point pressure has a very special importance in optimization of the miscible CO₂ injection. The purpose of this research is to predict the onset of asphaltene and bubble point pressure of fluid reservoir using artificial intelligence developed models including a software simulator called "Intelligent Proxy Simulator (IPS)" based on structure artificial neural networks and "adaptive neural fuzzy inference system", which is a combination of fuzzy logic and neural networks. To evaluate the predictions by artificial intelligence networks at the onset of deposition, a solid model using Winprop software was employed. Standing correlations were used for comparison of bubble point pressure. The results obtained using artificial intelligence models in prediction of the onset of asphaltene deposition and bubble point pressure during injection of CO₂ were more accurate than those obtained from the thermodynamics Solid model and the Standing correlation respectively.

Key words: Onset Pressure of Asphaltene, Bubble Point Pressure, CO₂ Injection, Back Propagation Algorithm, Swarm Optimizing Algorithm, Adaptive Neural Fuzzy Inference System.

Introduction

Most light and medium oil reservoirs are subjected to miscible CO₂ injection after flooding in EOR practices, which makes the reservoir fluids less viscous and expanded, which enhances the recovery. However, this can also lead to asphaltene in reservoir, which is harmful. Thus, it is necessary to determine the time and amount of asphaltene precipitation [1].

In this phenomenon, many parameters would be effective such as temperature, pressure, oil composition, effect of CO₂ and Gas Oil Ratio (GOR). Each of these effects can be studied in laboratory.

Temperature

The relation between temperature and precipitation of asphaltene is complex and controversial among researchers. Some evidence indicates the reduction of temperature makes asphaltene more concentrated and some observations are contradictory to these.

Peramanu [2] considered the effect of temperature in 60-120 °C range on asphaltene precipitation in 2 types of bitumen where normal heptane was used as a precipitator. They observed that at low temperatures, stability of system increased by increasing the temperature so more precipitator was necessary to form asphaltene. However, at high temperatures, increasing temperature decreased stability so less precipitator was needed. This behavior is explained by domination of solution theory at low temperatures and collide structure of oil at high temperatures.

Hirschberg [2] concluded that raising the temperature would reduce solubility parameter, which results in more asphaltene precipitation. This is because of break resin-asphaltene bound due to the increasing temperature. This conclusion is opposite of past observations because of neglecting the effect of solution theory.

Pressure

Change of pressure as a main thermodynamic parameter

can easily alter the collision stability of oil and has a major role in asphaltene precipitation.

By using a thermodynamic model, Hirschberg [3] showed the effect of pressure in asphaltene precipitation. This observation indicates when pressure is higher than bubble point, the asphaltene solubility increases with increasing pressure because of mole volume and solubility parameter of asphaltene below the bubble point, increasing the pressure causes more gas dissolution in oil, which means reduction of solubility parameter. In other words, in bubble point, there is minimum solubility and maximum asphaltene precipitation.

Oil Composition

One of the major factors of stability parameters in asphaltene precipitation is resin. If the volume proportion of resin is in the range of 1-20, the composition would be stable and if this ratio is lower than 1, the asphaltene would accumulate.

Effect of CO₂ on Pressure of Asphaltene Precipitation

CO₂ can cause asphaltene precipitation by decreasing the pH and making the oil fluid unstable.

Srivastava [4] carried out experiments on three samples of treated oil in PVT lab at reservoir conventional temperature, which indicated the concentration of asphaltene for oil samples is 39-46 mole percent CO₂.

Takahashi [5] considered an oil sample of Middle Eastern carbonate reservoir in PVT chamber with Light Scattering technique that demonstrated the asp raised enormously in 50 mole percent of CO₂.

Gas Oil Ratio (GOR)

Experiments show the asphaltene precipitation would be higher with increasing the GOR. Sunit Kokal [6] observed the asphaltene precipitation occurred in low GOR and would be higher in high GOR oil samples.

Artificial Intelligence Models

Neural network connects the outputs and inputs by using a network of bounded neurons where the weight of each of these bounds is set by historical data. This procedure is called education process and the network can finally discover the relationship between inputs and outputs even though they may be non-linear and complicated [7]. This new approach was presented in the 1940's by McCulloch and Pitts and developed when Hebb invented conditional algorithm of learning process of biological neurons. The first experimental application of ANN took place in the late 1950's when Rosenblat introduced the multilayered perception.

In this research, we used Intelligent Proxy Simulator (IPS) formed of two ANN learning algorithm of BP and PSO to predict the pressure of asphaltene precipitation and bubble point in miscible CO₂ injection operation.

BP Algorithm

BP learning algorithm is based on correcting the er-

ror rule on which the learning is started with random weights. After considering the difference between predicted output and real one, the model would backward and correct the weights. The model is called back propagation because of this going back and forward.

PSO Algorithm

Particle Swarm Optimization (PSO) is a multi-agent global optimization algorithm originally announced in 1995 by Kennedy & Eberhart [8] to find optimum weights of neurons. The main idea is adapted from social behavior of birds and fish. The direction of movement is based on two approaches:

Better directions are memorized by a group and will be experienced by the neighbors as well. The best direction is usually chosen by combination of those two sets of information. Multi grouping is used in PSO for more convergence and avoiding local minimums. Note that even when a particle is trapped in local minimum, the other particles would survive and converge to main minimum. This process is briefly depicted in figures 1-2.

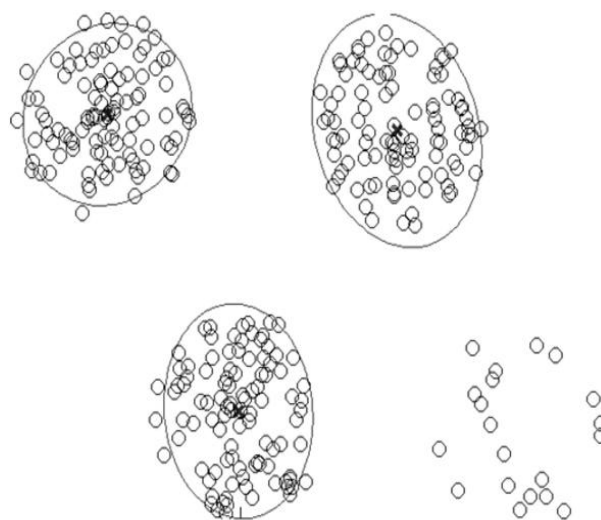


Figure 1. Particle grouping in PSO

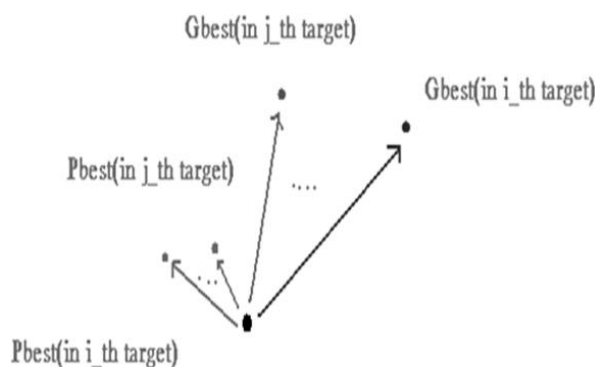


Figure 2. Particle Moving in PSO

Transfer Functions

The product of input of each of the neurons and their weight is a multiple in a function called Transfer Functions. The most common type of these functions is sigmoid, which is very popular because of its derivative.

$$f(s_j) = \frac{1}{1 + e^{-s_j}} \quad (1)$$

Also, input values must be in the same range. If one of them has a large range, it can get more weight than others so the inputs are normalized. If $\min X_i$ and $\max X_i$ are minimum and maximum values of inputs, respectively, we have:

$$X_{\min \text{ new}(i)} = \frac{X_i - \min X_i}{\max X_i - \min X_i} \quad (2)$$

Fortunately, the IPS simulator has an option to assign the appropriate range that is useful to speed up the calculation. also, one can choose the number of hidden layers up to 8 and number of neurons of each layer unlimitedly.

Adaptive Neural Fuzzy Inference Systems (ANFIS)

This system of ANN uses a nonlinear mapping to correlate the inputs and outputs. This fuzzy logic model is still formed of neurons, but it can match the inputs space and outputs space with if-then words called rules. The composition of a method that can make these rules and ANN model with ability of learning can form a strong tool to predict by using digit data inputs. This system is formed of 5 layers with input, output and rules (Figure 3) 1 output. In the first layer, the factors of each input are set by user. the coefficient of this value in neurons is the weight of each rule. in the second and third layers, one relative weight is calculated for each rule.

The fourth layer is rules layer and fifth and the final layer are set to minimize the difference between calculated

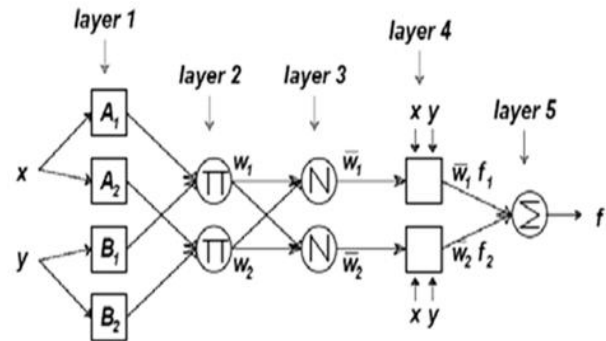


Figure 3. ANFIS structure

output and the real values.

Database Preparation

Database used for learning of ANN model to predict the onset pressure and bubble point pressure are 107 laboratory samples with particular parameters affecting asphaltene precipitation pressure. These are functions of temperature, oil composition and injected gas composition. to sum up, there are 27 parameters (Table 1).

The number of independent parameters is high. this fact may lead to produce errors in time consuming calculations so we need fewer numbers of parameters to minimize error. using critical properties is a reasonable key because of the considering both the composition and type of fluids as long as mixing rules is used here:

$$T_{cm} = \sum_{i=1}^n y_i T_{ci} \quad (3)$$

Table 1. One of database samples

		Sample no. 23	
	Component	Oil Reservoir (%)	Gas Injection (%)
	N ₂	0.13	0.26
	H ₂ S	0.1	0.0
	CO ₂	0.29	79
	C ₁	52.32	7.24
Input	C ₂	5.53	5.2
Data	C ₃	4.25	3.28
	iC ₄	0.85	1.09
	nC ₄	2.91	1.11
	iC ₅	2.28	0.89
	nC ₅	1.93	1.05
	C ₆	5.97	0.88
	C ₇₊	43.78	0.00
	S.G.C ₇₊	0.8985	-
	MW C ₇₊	599	-
	GOR	1396.42	-
	Reservoir Tem. (F°)	270	-
	Reservoir Pressure (Psi)	9300	-
Output	Ponset Asphaltene (Psi)	5300	-
Data	Bubble point pressure (Psi)	4393	-

$$p_{cm} = \frac{Z_{cm} R T_{cm}}{V_{cm}} = \frac{(\sum_{i=1}^n y_i T_{ci}) R (\sum_{i=1}^n y_i Z_{ci})}{(\sum_{i=1}^n y_i V_{ci})} \quad (4)$$

$$\omega_{ci} = \sum_{i=1}^n y_i \omega_{ci} \quad (5)$$

Besides, the b-exponent is also used to minimize independent parameters. after taking care of mixing rules and critical parameters, the 27 inputs is decreased to 9 inputs (Table 2).

Table 2. Final input parameters

	Component	
	T_R	280
	$T_{cm(oil)}$	178.22
	$\omega_{cm(oil)}$	0.723
	$P_{cm(oil)}$	1944.5
Input	Mw_{pluse}	550.52
Data	GOR	1661.56
	$T_{c(co_2)}$	66.50
	$P_{c(co_2)}$	1707.01
	$\omega_{c(co_2)}$	0.19
Output	P_{onset} Asphaltene (Psi)	5300
Data	Bubble point pressure (Psi)	4393

Architecture of ANN Models

Firstly, both parameters of onset and bubble point pressure are predicted at the same time. for this purpose, we set 80% of inputs for train and 20% of them for test randomly after choosing the best architecture with trial and error. at last, the BP model is set by 2 hidden layers of 20 neurons and PSO is set by one hidden layer of 30 neurons (Figures 4 and 5).

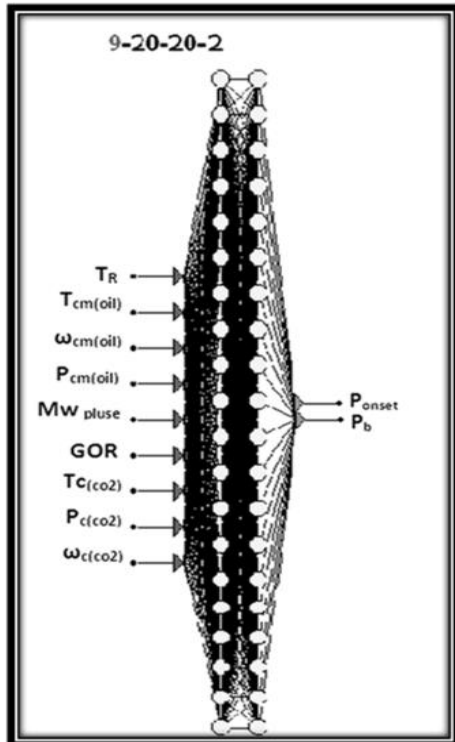


Figure 4. BP structure for prediction P_{onset} & P_b

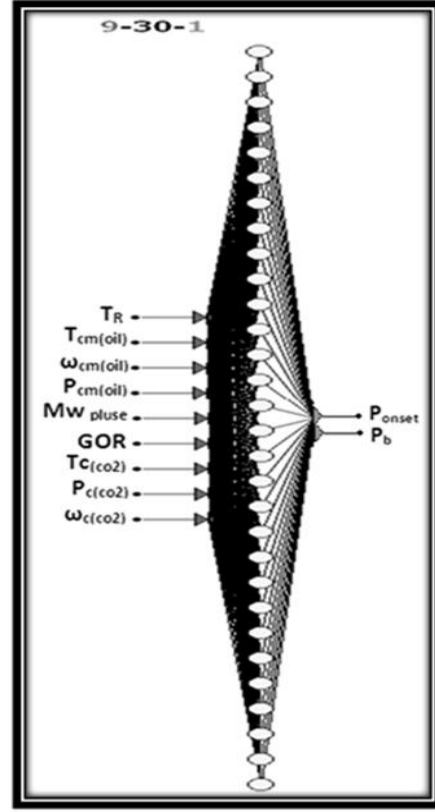


Figure 5. BP structure for prediction P_{onset} & P_b

Architecture of ANFIS Model

In this paper, we used Gaussian and Liner functions in MATLAB software for making fuzzy inputs and non-fuzzy outputs, respectively, and we used hybrid algorithm composed of BP and Minimum Square for optimal learning of model.

Predicting the Pressure of Asphaltene Precipitation

To verify the results of ANN model, we used developed solid models of Winprop (CMG Software). The simplest model of solid asphaltene precipitation is stated by gupta et al, where asphaltene precipitation is considered as a pure solid phase and oil and gas are supposed to be volume shifts. then, solid fugacity is calculated by equation:

$$\ln f_s = \ln f_s^o + \frac{V_s(p - p^o)}{RT} \quad (6)$$

Though the thermodynamic model and ANFIS model predict the pressure of asphaltene precipitation as a unique output for comparison of results, the ANN model predicts the onset pressure as one output.

Prediction of Bubble Point in CO₂ Injection

To verify the results of bubble point estimation of ANN model, we used the standing model, which uses gravity, GOR, temperature and gravity of oil parameters to calculate the bubble point pressure.

$$P_b = 18/2 \left[\left(\frac{R_s}{\gamma_g} \right) \right] (10)^a - 1.4 \quad (7)$$

Where:

$$a = 0.00091 \left[(T_{OR}) - 460 \right] - 0.0125(API).$$

Comparison of ANN Model with Experimental and Thermodynamic Models

A database of effective parameters in bubble point pressure and asphaltene precipitation pressure contain 107 samples with 9 non-dependent parameters and 2 independent parameters. The first two parameters are cal-

culated Simultaneous with identical error with both IPS ANN model simulators, which are shown in Figures 6-9 and errors calculated from them are shown in Table 3 .after that, the IPS ANN model predicts 2 parameters individually and the other model ANFIS calculates 2 with noted structure parameters.

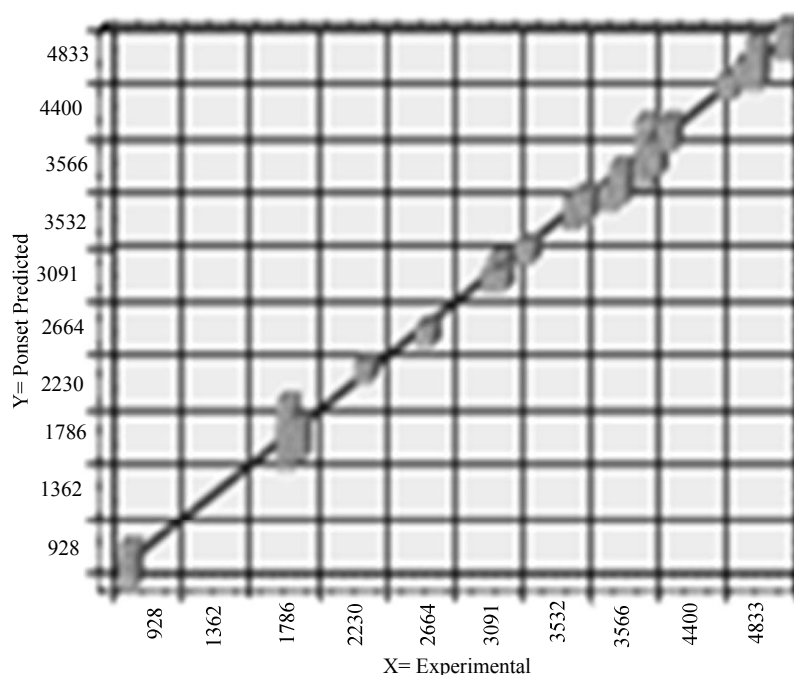


Figure 6. Prediction of Ponset with BP (In prediction same time)

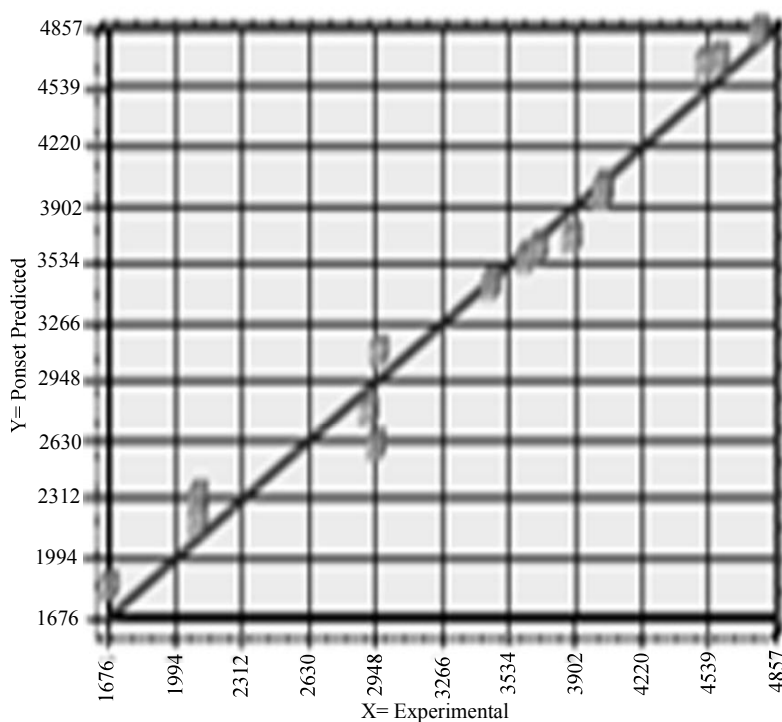


Figure 7. Prediction of Pb with BP (In prediction same time)

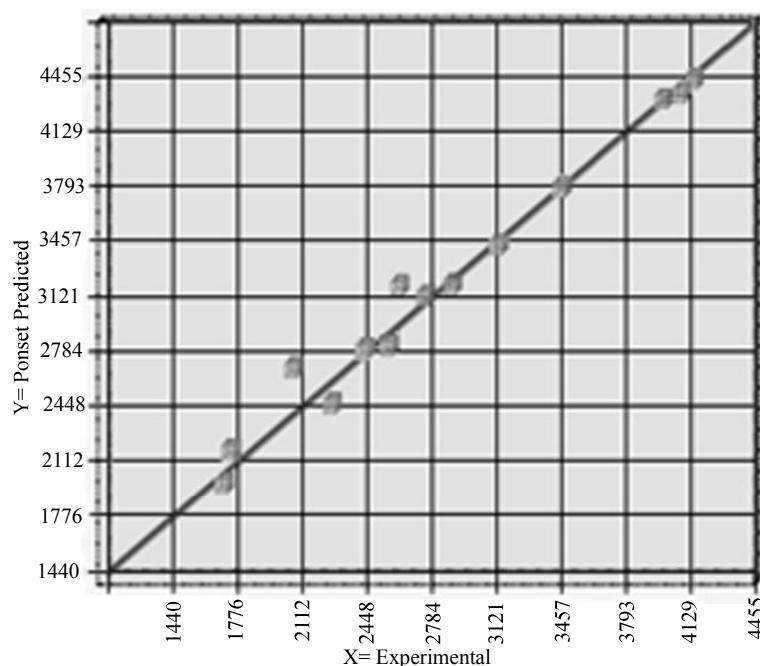


Figure 8. Prediction of Ponset with PSO (In prediction same time)

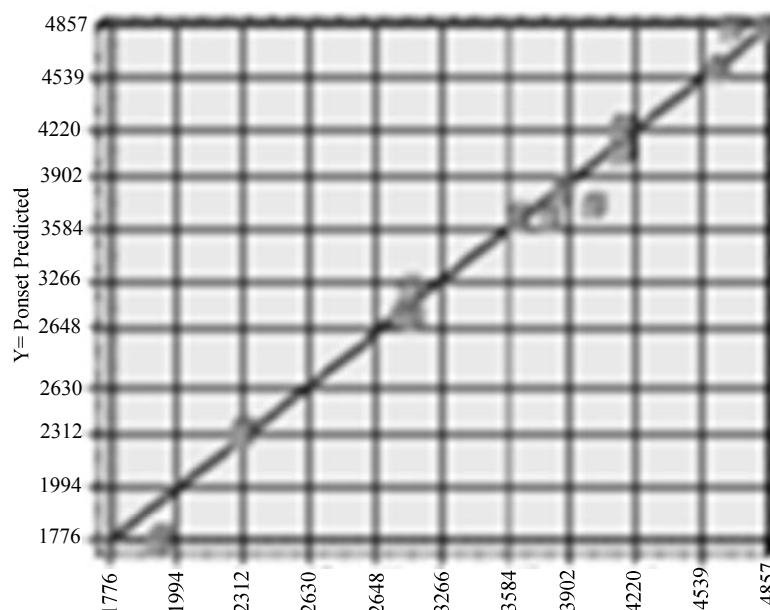


Figure 9. Prediction of Pb with PSO (In prediction same time)

Table 3. Comparison between ANN models

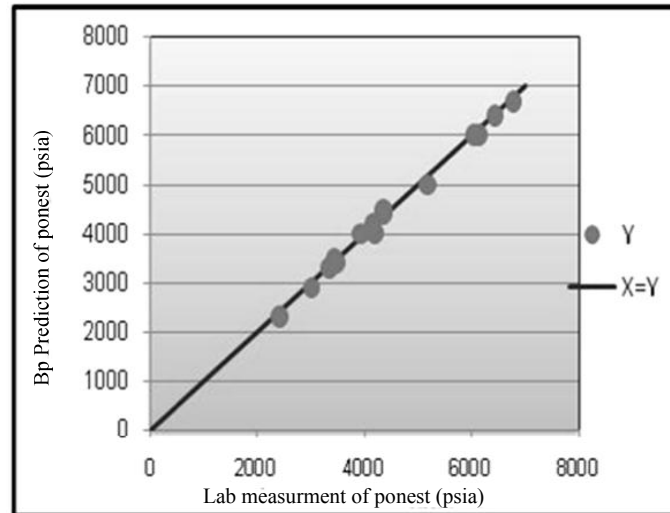
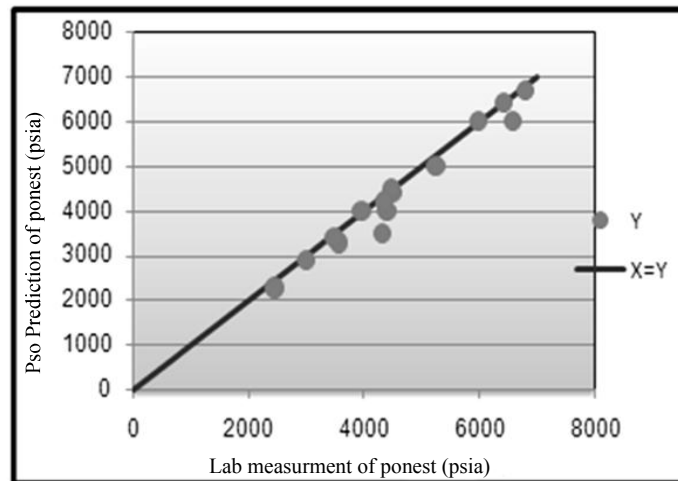
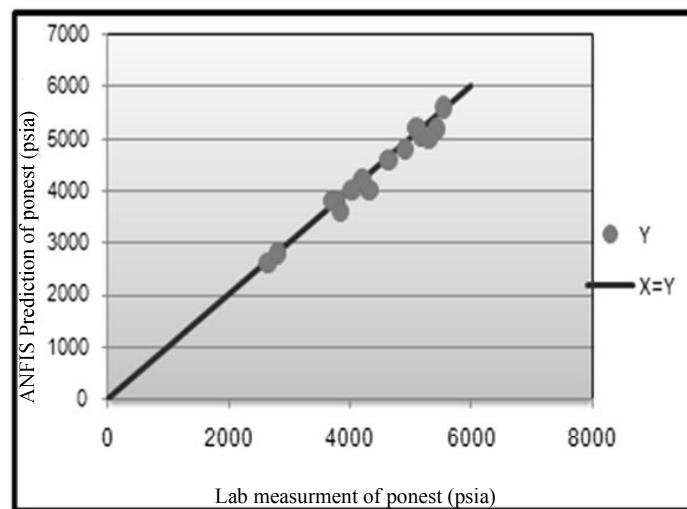
	Train Ponset Pb (BP)	Test Ponset & Pb (BP)	Train Ponset & Pb (PSO)	Test Ponset & Pb (PSO)
Min Square Error (%)	2	2.22	1.94	4.97
Max Square Error (%)	9.53	24.93	18.23	20.08

Finally, to verify the ANN results, estimated Ponset is compared with solid thermodynamic model which are shown in Figures 10-13 and errors them in Table 4. and bubble point is compared with standing model, which are shown in Figures 14-17 and errors them in Table 5.

In figures 10-13, the results of prediction of asphaltene precipitation by ANN model and experimental methods are shown indicating that BP model yields better results. In figures 14-17, bubble point pressure is calculated with

ANN model and standing correlation. it is obvious that ANFIS model has more accuracy.

Considering the above figures, it can be concluded that ANN & ANFIS models have obviously less error than solid models and between ANN models, BP proxy is the most accurate in prediction asphaltene onset pressure (Figure 18), results of some of last conclusions and ANFIS model have way better predictions for bubble point than other models (Figure 19).

**Figure 10.** Prediction of Ponset with BP**Figure 11.** Prediction of Ponset with PSO**Figure 12.** Prediction of Ponset with ANFIS

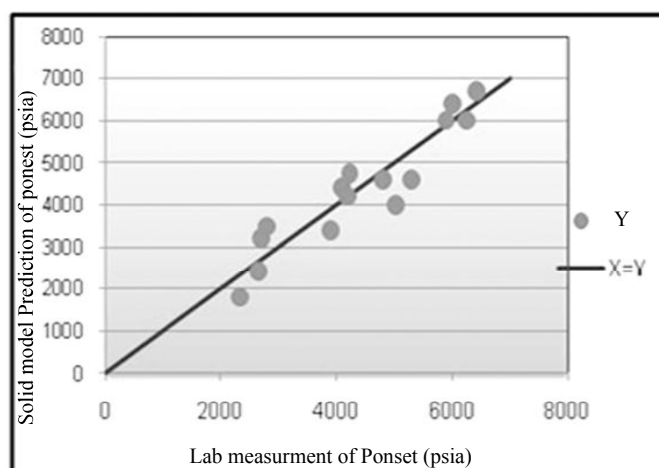


Figure 13. Prediction of Ponset with Solid model

Table 4. Comparison between all models in prediction of asphaltene onset pressure

	BP model	PSO model	ANFIS model	Solid model
Min Square Error (%)	2.8	5.3	5.13	16.16

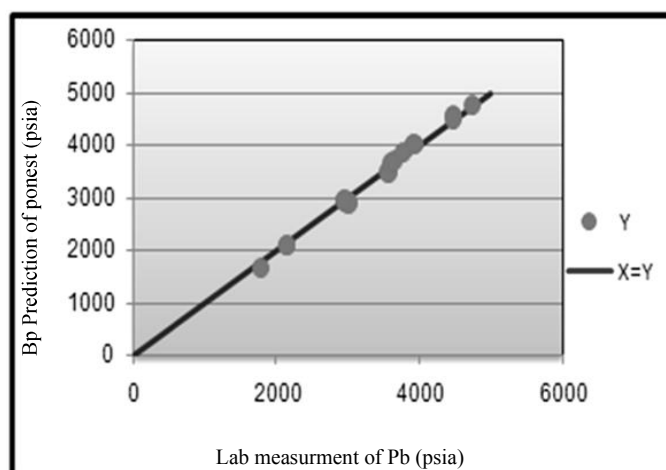


Figure 14. Prediction of Pb with BP

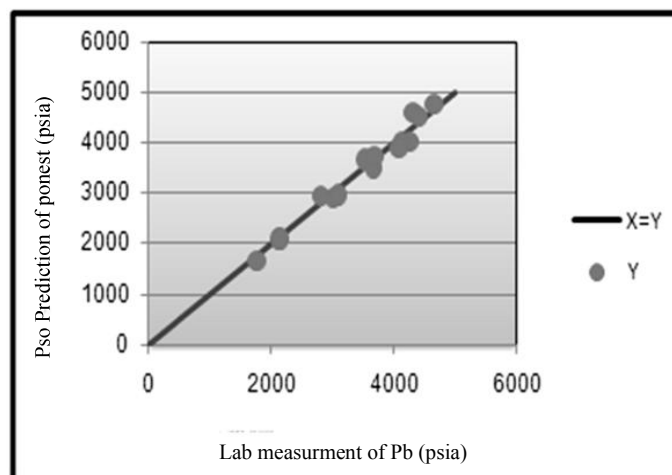


Figure 15. Prediction of Pb with PSO

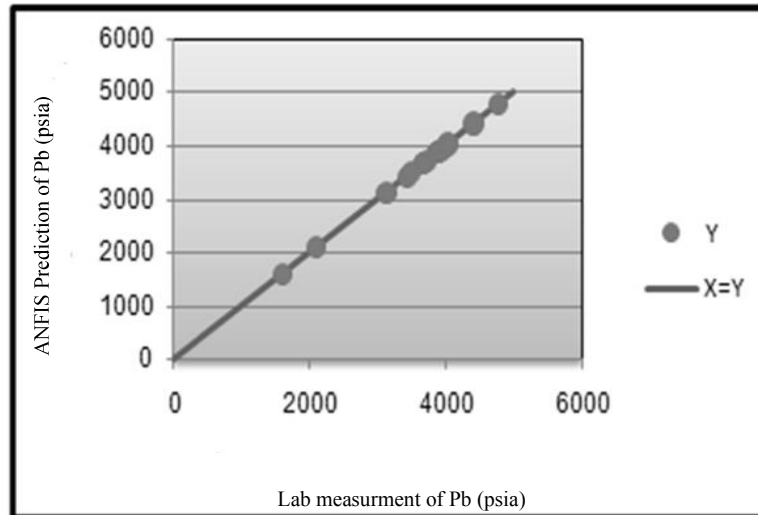


Figure 16. Prediction of Pb with ANFIS

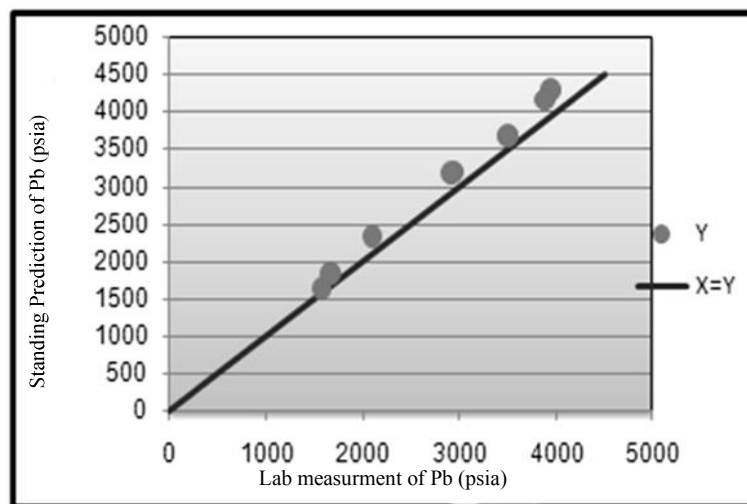


Figure 17. Prediction of Pb with Standing

Table 5. Comparison between all models in prediction of bubble point pressure

	BP model	PSO model	ANFIS model	Standing model
Min Square Error (%)	3.42	5.74	2.86	14.27

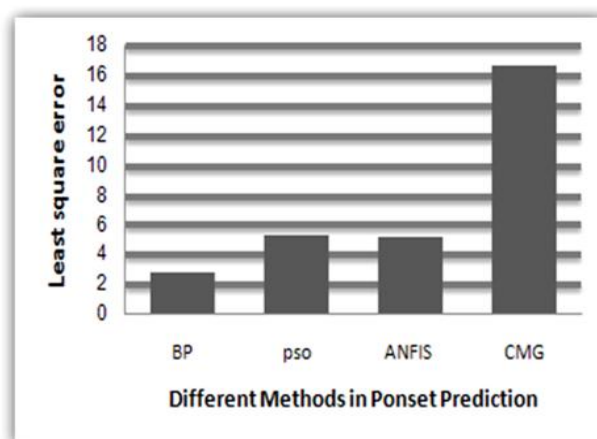


Figure 18. Comparison of different models to prediction of Ponset

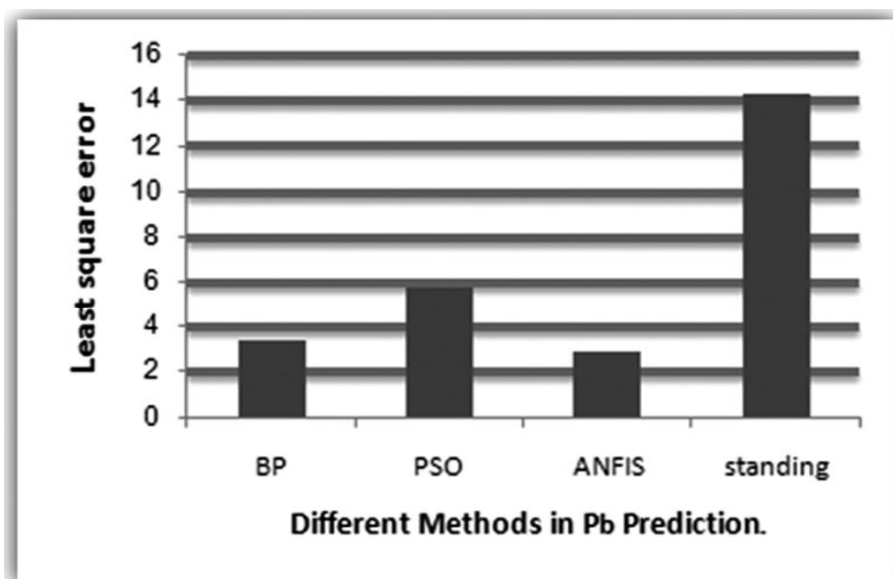


Figure 19. Comparison of different models to prediction of Pb

Controversially, comparison between ANN model performance shows that multi output model gives better results than unique output for both of them which are shown in figures 20-21. This is very important in solving future complex problems in petroleum enquiring.

Conclusion

- Estimation of Ponset and bubble point pressure with ANN and ANFIS models are more accurate than both solid and standing models
- Using the mixing rule and critical properties increase

error due to many inputs which are needed. However, this has effective role in system control

- IPS simulator with ability of extrapolation and large number of hidden layers and optimized algorithm for multi objective models has an excellent performance in this study
- Good prediction of bubble point with non-linear parameters of ANN model compared with linear parameters of standing model presents the non-linear nature of ANN model, which means good ability for approximation of unknown non-linear functions.

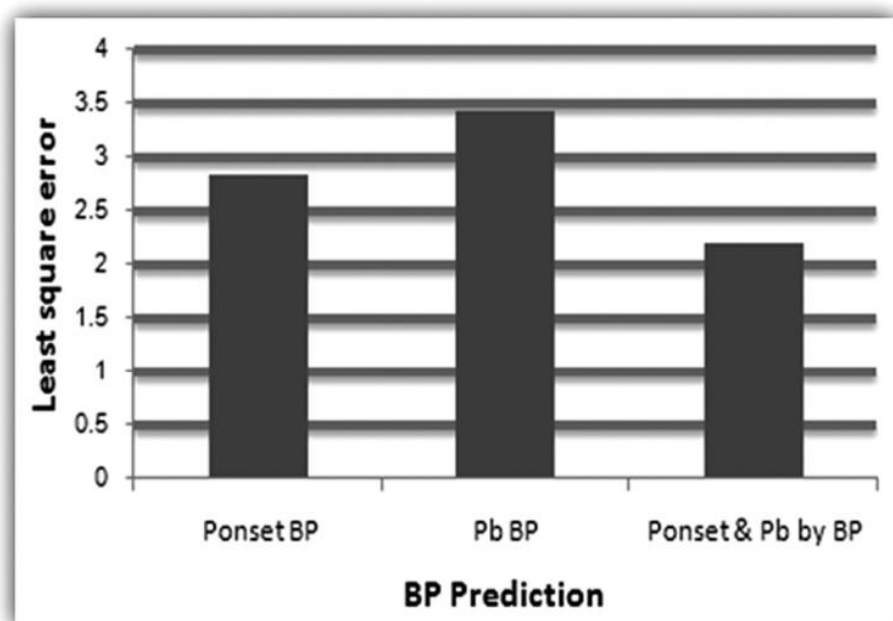


Figure 20. Comparison of results of BP

Nomenclature

f_s : Solid fugacity [Kpa]

f_s^o : Reference solid fugacity [Kpa]

P_o : Reference pressure [Kpa]

R : Gas constant gas constant $\left[8.314 \frac{\text{Kpa} \cdot \text{m}^3}{\text{Km} \cdot \text{ol} \cdot \text{k}}\right]$

V_s : $\left[\frac{\text{m}^3}{\text{kmol}}\right]$ Solid mole volume

MSE: Minimum square error

References

[1] Asghari M., Dong, "Development of a Correlation Between Performance of CO_2 Flooding and the Past Performance of Water flooding in Weyburn Oil Field", SPE pp. 99789, 2006.

[2] Peramanus et al, "Flow loop apparatus to study the effect of solvent temperature and additives on asphaltene precipitation" Journal of Petroleum Science and Engineering, 1999.

[3] Hirschberg A., "Influence of temperature and pres-

sure on asphaltene flocculation" SPE, June 1984.

[4] Srivastava R.S. & Huang S.S., "Asphaltene Deposition during CO_2 Flooding: A Laboratory Assessment", SPE, p. 37468, 1997

[5] Takahashi S., Hayashi Y., Yazawa N. & Sarma, "Characteristics and Impact to asphaltene Precipitation during CO_2 Sandstone and Carbonate Cores: An Investigative Analysis through Laboratory Tests and Compositional Simulation", SPE, pp. 84895, 2003.

[6] kokal S., Al-Ghamdi A. & Krinis D., "Asphaltene Precipitation in High Gas-Oil Ratio Wells", Saudi Aramco Journal of Technology, 2005 .

[7] Menhaj M., *Neural Network*, first copy, tertiary printing, AmirKabir University Publications.

[8] Kennedy J., & Eberhart R., "Particle Swarm Optimization," IEEE International Conference on Networks, Piscataway, NJ, vol. 4, 1995, pp. 1942-1948

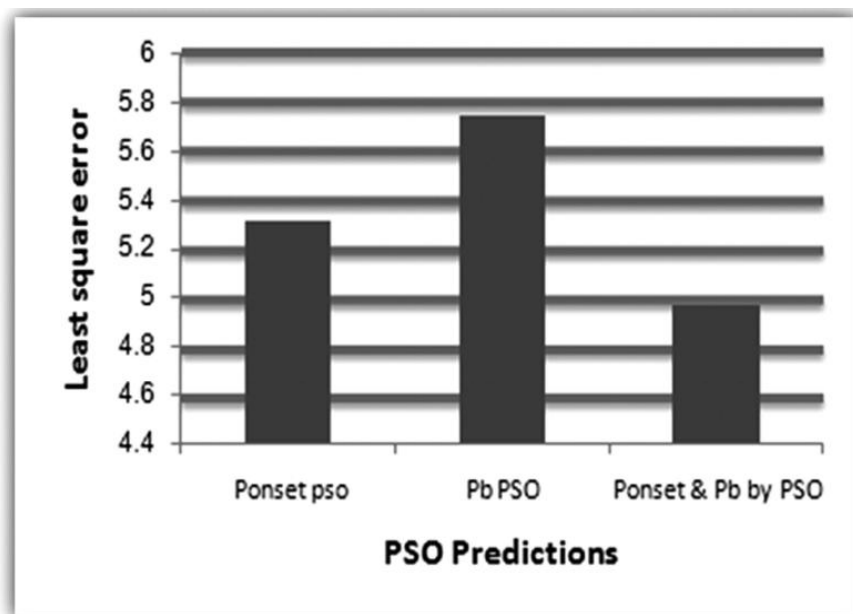


Figure 21. Comparison of results of PSO