ASPHALTENE DEPOSITION IN PETROLEUM RESERVOIRS: DYNAMIC TEST & CONNECTIONIST MODELING

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ABSTRACT

Asphaltene Deposition is a complex process that can lead to a decline in oil production rates due to permeability and wettability alteration. Asphaltene instability occurs due to variations in thermodynamics properties such as pressure, temperature, and mixture composition. In this study, dynamic experiments were conducted using oil samples to measure important phase behaviour properties such as bubble point pressure (BPP) and the amount deposited as asphaltene. A thermodynamic model was also developed to determine equilibrium composition of the oil samples considering asphaltenes. We investigated the potential application of using feed-forward Artificial Neural Network (ANN) optimized by Imperialist Competitive Algorithm (ICA) and Particle Swarm Optimization (PSO) to estimate the boiling point pressure and asphaltene deposition. Comparison between the smart technique predictions and the experimental data shows an acceptable match. It is found that pressure drop and temperature are the most important factors contributing to asphaltene precipitation. Employing laboratory PVT data and connectionist modeling can result in the construction of an asphaltene phase envelope through an effective and accurate manner. The outcomes of this study, in terms of thermodynamic framework and predictive tools, appear to be useful in the design stage of more efficient EOR processes.

INTRODUCTION

Asphaltene precipitation/deposition during oil production is considered unfavourable as it can cause considerable decline in the effective permeability, leading to the reduction in the oil flow rate [1,2]. Being able to estimate the amount of asphaltene deposition in the reservoir in terms of fluid and formation characteristics would be useful knowledge.

Oil recovery methods including natural depletion, gas-lift operations, acid stimulation, and miscible gas injection may cause asphaltene deposition. Asphaltene phase behaviour is strongly dependent on the fluids and pressure and temperature.

A number of researchers proposed the models to predict the PVT and fluid flow behaviour of hydrocarbon mixtures during the onset of asphaltene precipitation [1-6]. A solubility model was introduced by Hirschberg et al. (1984) to estimate the heat of solution. The heat was taken into account as a function of solubility of asphaltene and the remaining part of the mixture into the reservoir fluid. This technique is able to capture the influence of non-ideality of asphaltene and resin molecules in PVT studies.

Prediction of asphaltene precipitation by conventional tools generally leads to considerable error despite the fact that these techniques have been broadly employed. Smart techniques such as artificial neural network (ANN) could be an effective solution for this problem because ANN optimisation is well suited to model ill-defined, ambiguous, and non-linear problems. The authors of this paper have previously predicted thermodynamic properties such as condensate gas ratio (CGR) [7].

A series of dynamic experimental runs were carried out in this study to investigate the effect of temperature, dilution ratio, pressure, and fluids' composition on asphaltene precipitation. A thermodynamic framework using a solid model approach was developed to obtain the equilibrium mole fractions of the components involved in asphaltene precipitation/deposition. Subsequently, three ANN smart techniques; back-propagation (ANN-BP), particle swarm optimisation (ANN-PSO), and imperialist competitive algorithm (ANN-ICA) were applied to the experimental data to predict the target function. Statistical analysis was used to evaluate the predictive performance of the ANN models.

SOLID MODEL

According to Pan and Firoozabadi (2000), the solid fugacity (f_S) for a pure component under isothermal conditions is given as follows [5]:

$$\ln f_S = \ln f_S^* + \frac{V_S(P - P^*)}{RT} \tag{1}$$

$$\ln f_{ij} = \ln f_{ij}^{EOS} + \frac{S_i b_i P}{RT}, \; i = 1,\ldots,nc \; ; \; j = v, l \tag{2}$$

where f_{ij} and f_{ij}^{EOS} are the fugacities with and without translation, respectively; S_i is the dimensionless volume shift parameter, and b_i represents binary interaction parameter of the EOS for the i^{th} component.

The fugacities of each component are the same in all phases at equilibrium condition as shown by the following relationship:

$$\ln f_S^i = \ln f_L^i = \ln f_G^i \tag{3}$$

Based on Nghiem and Coombe (1997), the solid phase exists in the solution if the following relationship is established [8]:

$$\ln f_S^{nc} \geq \ln f_L^{nc} \tag{4}$$

The asphaltene precipitation model should satisfy Equation (4). The mole fraction of each component is determined using K-values equations written below [5,8]:

$$K_i^{GL} = \frac{x_i^G}{x_i^L} = \frac{\ln \phi_i^L}{\ln \phi_i^G} = \frac{f_i^L}{f_i^G} \tag{5}$$

$$K_i^{LS} = \frac{x_i^L}{x_i^S} = \frac{\ln \phi_i^S}{\ln \phi_i^L} = \frac{f_i^S}{f_i^L} \tag{6}$$

LABORATORY INVESTIGATION

Asphaltene deposition dynamic tests incorporate core flooding with and without CO_2. A physical model (D = 10 cm and L = 30 cm) was used in this part of study. The experimental setup is shown in Figure 1. The main components of the setup are a core, a core holder, accumulators, inline analytical instruments, flow meters, pressure and temperature gauges, and a pump. First, the porous system is saturated with the oil using the vacuum method. After that, the CO_2 gas is injected while the gas flow rate is being recorded. During the flooding process, the pressure difference between the input and output is controlled by a backpressure regulator installed on the outlet. Hence, the pressure drop along the porous medium length remains constant throughout the injection. A gradual cylinder is employed to collect the produced fluid. After around 5.5 PV gas injected, the core flooding is ended where no oil is produced from the core. Then, the pressure of the physical model is declined slightly. When the pressure approaches zero, the core is taken out from the core holder. The core is dried in an oven under vacuum condition which is different from the process conditions. The magnitude of asphaltene deposited during the production process was obtained based on the difference between mass of the dried porous system before saturation and after injection process. It is important to note that the process pressure and temperature varies in the ranges of [0, 9000 psia] and [20, 100 °C], respectively.

ARTIFICIAL NEURAL NETWORK (ANN)

ANN has been made on the basis of the information processing system of brain. ANN builds a non-linear relationship between input and output parameters through its inherent properties [9]. The ANN consists of three different layers, namely; input, hidden and output layers [9]. The data used are categorized into two groups: training and testing data series. The main purpose in the training stage is to determine the optimum values of weights connecting layers to each other.

Particle swarm optimization (PSO)

PSO is a stochastic optimization technique on the basis of social behavior of fish education and/or bird collection [10]. This algorithm has capability to optimize the ANN variables and avoid trapping in local optima.

Imperialist Competitive Algorithm (ICA)

ICA is recognized as a new algorithm in the evolutionary computation system based on the human's socio-political evolution. There are two kinds of countries in ICA: colony and imperialist [11]. The ICA in the form of an optimization algorithm is joined to the ANN model to construct a suitable structure. The Mean Squared Error (MSE) is taken into account as a cost function in the ANN-ICA system. The goal is to minimize the cost function throughout the computation process.

RESULTS & DISCUSSION

In this paper, asphaltene deposition is studied through experimental, modeling and connectionist modeling. Based on the data obtained from the solid model and the experimental work, the two-phase asphaltene precipitation/deposition envelope is plotted as demonstrated in Figure 2.

When CO_2 injection is conducted for EOR operation, the amount of deposited asphaltene will exhibit a decrease for the oil sample used in our study (light oil with API ^{o}33) as the concentration of CO_2 in the oil sample increases (See Figure 3a). This behaviour will proceed until bubble point pressure (BPP) is attained. However, asphaltene deposition increases for the pressures greater than (BPP). The main reason for this trend is high density of CO_2 compared to the oil sample that may have significant effect on the solubility of asphaltene particles in the mixture.

Figure 3b demonstrates the influence of pressure drop along the length of porous medium on the amount of asphaltene deposited. As clear indicated in Figure 3b, the higher pressure drop causes more asphaltene deposition on the surface of rocks or particles in the porous media. It is also can be concluded the pressure drop exhibits higher effects in contrast with the flowing pressure throughout on the asphaltene deposition.

This study employs various ANN structures (number of hidden layers and neurons). The optimum parameters for the ANN structure are obtained based on the R^2 value and MSE through trial and error. The algorithm to train the network is the back propagation (BP) algorithm. Two evolutionary algorithms including ICA and PSO are used to predict AD and BPP. The ANN systems consider temperature, pressure, solvent/oil ratio, CO_2mole fraction, pressure drop, flow rate and molecular weight as inputs. Temperature, molecular weight, and gas/oil ratio are the input parameters for BPP.

As Figure 4 depicts, a comparison is made between the measure amounts of asphaltene deposited and estimated values obtained from Hu et al. (2000)'s model [12] and the testing stage in the BP-ANN, ANN-PSO and ANN-ICA systems. It is found that the ANN-PSO with [R^2 = 0.969; MSE = 0.0296] and ANN-ICA with [R^2 = 0.976; MSE = 0.0248] predict asphaltene deposition with reasonable accuracy, while the conventional ANN with [R^2 = 0.9247; MSE = 0.2213] has lower performance in terms of precision compared to the hybrid ANN systems. However, Hu et al. (2000)'s model [12] with [R^2 = 0.857; MSE= 0.9835] fails to accurately estimate asphaltene deposition at particular thermodynamic and process conditions. The same qualitative conclusion is drawn for BPP while predicting this parameter using ANN-BP, ANN-PSO and ANN-ICA models. It is important to mention here that the ANN-ICA shows greater performance in terms of the number of iterations for convergence and execution time, compared to the ANN-PSO.

An ANOVA analysis was performed. The most important parameters affecting asphaltene deposition was found to be the pressure drop and temperature. Gas-to-oil ratio and temperature were found to be important in predicting the bubble point pressure.

Better understanding of PVT behaviour and precise estimation of asphaltene precipitation/deposition for hydrocarbon mixtures offers petroleum and chemical engineers appropriate rules of thumb for optimization of process conditions in order to minimize pressure drops in the production and surface facilities, resulting in separating the mixture into the heavy component, oil, and gas.

CONCLUSION

Asphaltene deposition and bubble point pressure were investigated through experimental studies, a solid model and predictive connectionist modeling. The following main conclusions are drawn:

1. The predictive performance of the hybrid smart technique is appreciably superior to the conventional ANN system and the model developed by Hu et al. (2000).
2. The relative importance of the input variables indicated that pressure drop and temperature pressure are the most important variables contributing in the magnitude of the AD. It was also concluded that the BPP is mostly affected by the temperature and GOR among the input parameters.
3. Both ANN-PSO and ANN-ICA systems benefit from global and local searching abilities that help avoid optimization results getting stuck in a local minimum. However, the convergence speeds of the ANN models are in the order of ANN-ICA, ANN-PSO and ANN-BP.
4. The optimum structure of the ANN models was manually determined. An alternative procedure is recommended to be combined with PSO and/or ICA for this purpose.
5. The effects of pressure and temperature on the amount of asphaltene deposition are strongly dependent on the magnitudes of these variables with respect to the bubble point pressure of the oil mixture.

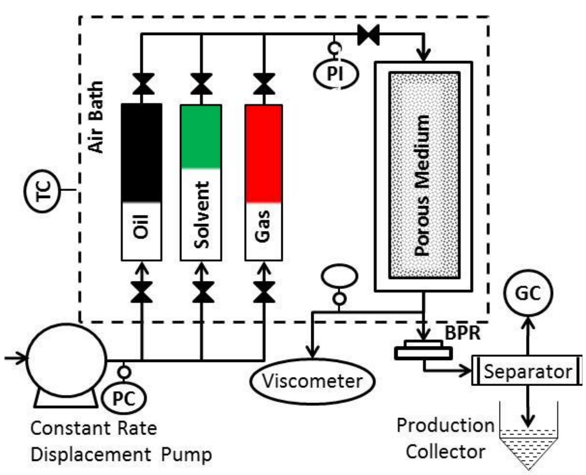

Figure 1: Experimental Setup

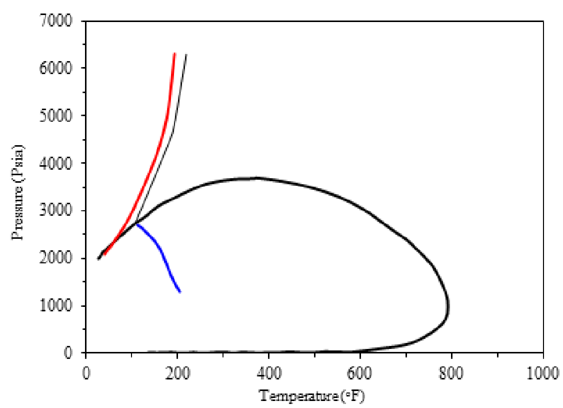

Figure 2: Asphaltene Precipitation Envelope

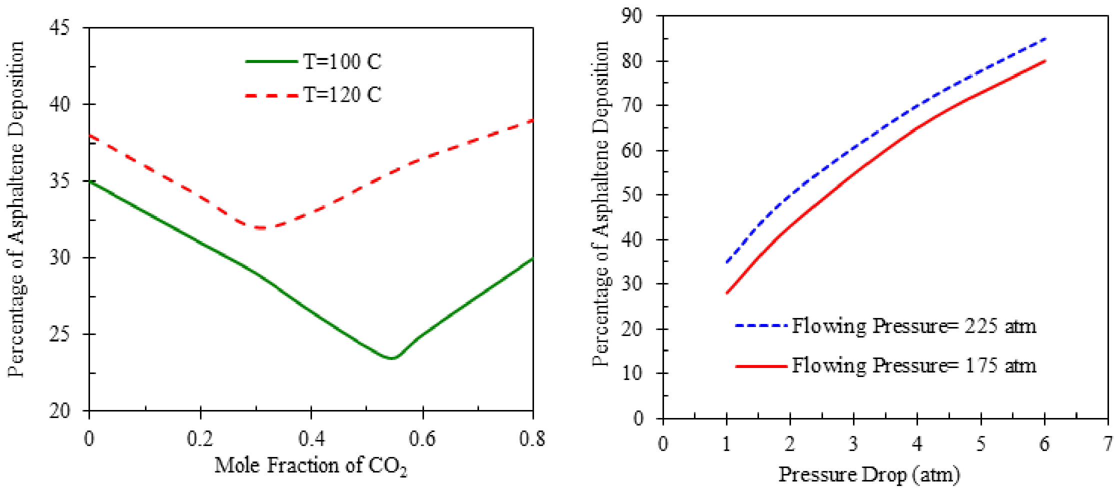

Figure 3: Effect of a) CO_2 Concentration and b) Pressure Drop on Asphaltene Deposition

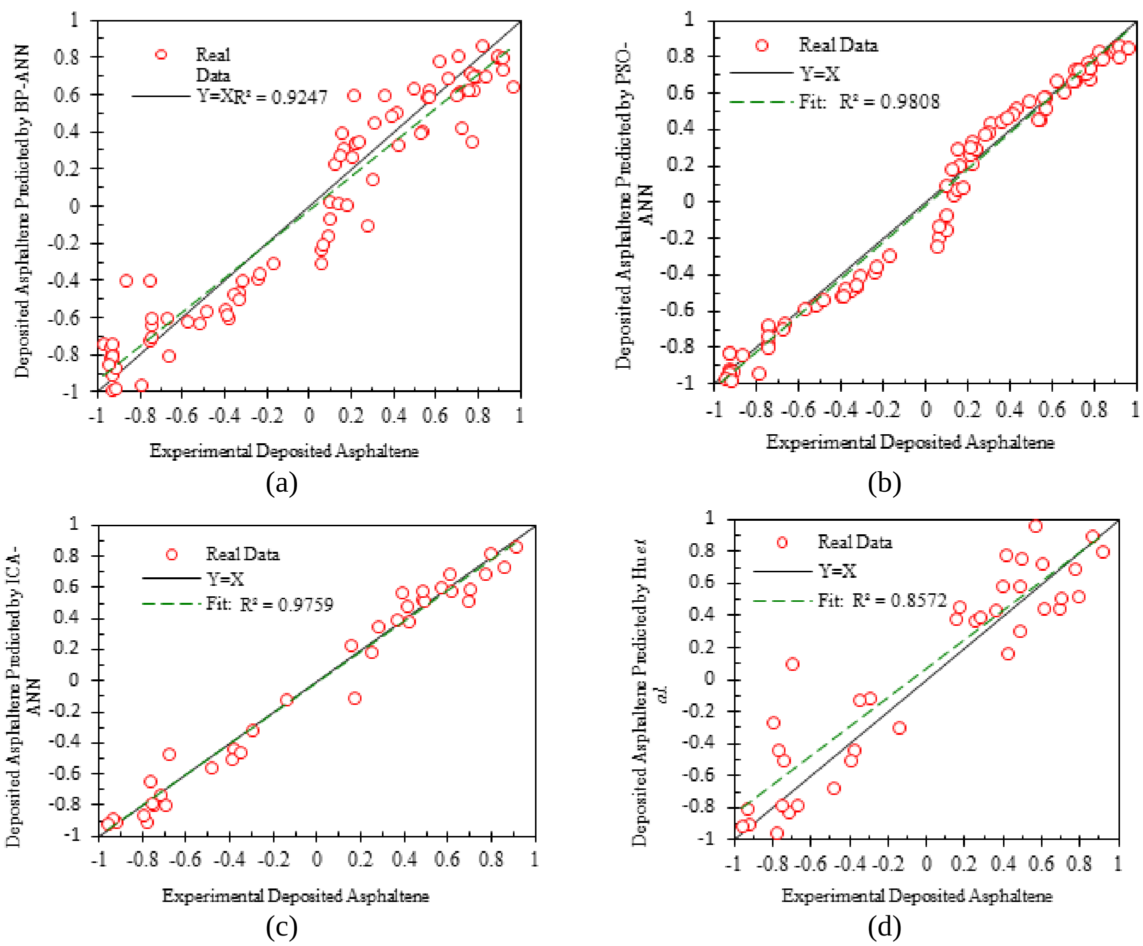

Figure 4: Predictive performance of various models: a) ANN-BP; b)ANN-PSO ; c) ANN-ICA; d) Hu *et al.* (2000)

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