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Bayesian Belief Network Method for Predicting Asphaltene Precipitation in Light Oil Reservoirs

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ABSTRACT: *- Asphaltene precipitation is caused by a number of factors including changes in pressure, temperature, and composition. The two most prevalent causes of asphaltene precipitation in light oil reservoirs are decreasing pressure and mixing oil with injected solvent in improved oil recovery processes. This study focused on predicting the amount of asphaltene precipitation with increasing Gas-Oil Ratio in a light oil reservoir using Bayesian Belief Network Method. These Artificial Intelligence-Bayesian Belief Network Method employed were validated and tested by unseen data to determine their accuracy and trend stability and were also compared with the findings obtained from Scaling equations. The obtained Bayesian Belief Network results indicated that the method showed an improved performance of predicting the amount of asphaltene precipitated in light oil reservoirs thus reducing the number of experiments required.*

Keywords: *(Asphaltene Precipitation, Bayesian Belief Network, High Gas-Oil Ratio, Light Oil Reservoirs, Scaling Equation).*

I. INTRODUCTION

Asphaltene precipitation and deposition in petroleum reservoirs fluids during production has proved to be a difficult problem to define and study as it can cause plugging of reservoir formation, wellbore, tubing and production facilities. Field conditions conductive to asphaltene precipitation include primary depletion, acid stimulation, gas-lift operations and miscible flooding, just to mention a few. Asphaltene precipitation during primary depletion of highly undersaturated reservoirs due to changes in pressure, temperature and compositions or during application of any of the improved oil recovery processes was described by many authors ***[Kokal and Sayegh, 1995; Michell and Speight, 1973; Leontaritis and Mansoori, 1989; Mofidi and Edalat, 2006 and Rassamdana, 2006].***

Asphaltenes comprises the heaviest and the most polar fraction of crude oil ***[Kokal and Sayegh, 1995; Michell and Speight, 1973]***. Asphaltenes exist in the form of colloidal dispersions and are stabilized in solutions by resins and aromatics that act as peptizing agents. Asphaltene precipitation and deposition may occur deep inside the reservoir, near the wellbore and/or in processing facilities ***[Leontaritis and Mansoori, 198]***. Asphaltene precipitation is a function of pressure, temperature and live crude oil composition. Asphaltene have a tendency to precipitate as the pressure is reduced, especially near the bubble point (however, precipitation can occur even at higher pressures than the bubble point, depending on the crude). Another important reason for precipitation is the stripping of crude oil by gas. When gas is added to the crude (as may be happening during the production from the gas-cap wells) the composition of the crude changes and may lead to precipitation. This is the same mechanism during de-asphalting of crude in a refinery where propane and butane are used for stripping the asphaltenes. The precipitated asphaltenes then deposit near, or in the wellbore. This may lead to increase in formation damage (skin), and subsequently more precipitation.

1.1. Aims of the study: The aims of this study are to investigate the effects of increasing gas-oil ratio on the stability of asphaltene in light oil reservoirs and to select the best Bayesian Belief Network predictor for asphaltene precipitation.

1.2. Objective of the study: A numerical model "(Bayesian Belief Network Model) for predicting the amount of asphaltene precipitated in light oil reservoirs was developed instead of using approximate and complex analytical equation. Factors affecting asphaltene precipitation in light oil reservoirs like temperature, pressure, crude oil composition, gas gravity, oil gravity, ^{0}API, and dilution ratio which are believed to have effects on asphaltene stability are included in the model to determine their effects on asphaltene precipitation.

II. SCALING EQUATION AND BAYESIAN BELIEF NETWORK METHOD

2.1. Scaling Equation: The use of aggregation/gelation phenomena in the scaling model first presented by ***[Rassamdana et al., 1989]*** led to model independency on asphaltene properties. They claimed that asphaltene precipitation is similar to aggregation/gelation phenomena and thus used the scaling/fractal theory to describe asphaltene precipitation. The scaling model is a simple model that requires the dilution ratio, $_{m}$, and molecular weight of injected fluid (called diluents), to predict the amount of asphaltene precipitation, ***[Hirschberg et. al., 1984; Hu et al., 2000; Hu and Guo, 2001).*** These variables were combined into two dimensionless variables and, defined as follows:

$$X = \frac{Rm}{Mw^{Z}} \tag{2.1}$$

and

$$Y = \frac{wt\%}{Rm^{Z'}} \tag{2.2}$$

Where with numerical value of -2 is recommended as a constant exponent that is independent of the type of crude oil and the precipitating agent and is considered as an adjustable parameter with the numerical value in the range of 0.25-0.6 depending upon the type of crude oil and precipitant.[24] the scaling equation has been represented in terms of and by polynomial function.

$$Y = A_1X + A_2X + A_3X^2 + A_4X^3 \tag{2.3}$$

The coefficients A_{1}-$_{4}$ should be determined through data fixing using experimental data. The development of scaling model by ***(Rassamdana et al**., **1989; Hirschberg et al., 1984; Hu, et al., 2000)*** was based on data from Iranian southwest oil reservoirs. Later on, ***(Hu et al., 2004)*** applied a tuned scaling model to predict asphaltene precipitation for two kinds of heavy oils from Canada and U.S.A.

The effects of the temperature, molecular weight of -alkane precipitants, and dilution ratio on asphaltene precipitation in a Chinese crude oil have been studied experimentally by ***[Meshad et al., 2008]. Hu et al., (2004)*** have also studied asphaltene precipitation because of CO_2 injection ***[Floridi, 2004]*** they proposed a generalized corresponding state principle (CSP) for the prediction of asphaltene precipitation. The CSP theory complemented the scaling equation for asphaltene precipitation under the influence of -alkane precipitant. In their study, their parameters and exponents of a corresponding state equation was capable of describing the asphaltene precipitation behaviour in the studied high-pressure CO_2 injected crude oil systems. They indicated that the generalized corresponding state theory was suitable for prediction of asphaltene precipitation from petroleum fluids as a result of the addition of miscible solvents at various temperatures and pressures. Thermodynamically, asphaltene precipitation is not dependent of the reservoir pressure. However, the effect of pressure is not included in the scaling model developed by ***[Rassamdana et al., 1996].***

[Pearl et al., 2000; Meshad et al., 2008] included the effect of pressure on the nucleation onset and the amount of asphaltene precipitation in the scaling model. In the new scaling model, the relation between the dilution ratio and the molecular weight of diluents and the amount of asphaltene precipitation has been presented in two variables and as follows:

$$x = \frac{Rm}{Mw^{Z}} \tag{2.4}$$

And

$$y = \frac{wt\%}{Rm^{Z'}} \tag{2.5}$$

To include the effect of reservoir pressure and asphaltene precipitation in the new scaling model, the variables and, defined as follows:

$$X = \frac{x}{P^{C1}} \quad \textbf{(2.6)}$$

And

$$Y = \frac{y}{x^{C2}} \quad \textbf{(2.7)}$$

In the new scaling equation, similar to the original scaling equation has been expressed in terms of by a polynomial function of eq. 3. Thus, the new scaling equation includes seven adjustable parameters of A_{1}-$_{4}$, c_1, c_2, and Z. These parameters should be estimated using experimental data. Scaling models to a less degree than thermodynamic models require parameter tuning to predict asphaltene precipitation for different oil and reservoir conditions assuming that necessary laboratory data are available. Therefore, the need for parameter tuning for each specific oil and reservoir condition is the limitation of scaling models.

To remove such limitation, this study presents a comprehensive model that investigates the effect of increasing gas-oil ratio on the stability of asphaltene in light oil reservoirs and to define and select the best BBN predictor that predicts the asphaltene precipitation in a gas-cap well instead of approximate and complex analytical equation under the prevailing conditions of temperature, pressure, oil composition, gas gravity, oil gravity, ^{0}API, and dilution ratio which are believed to have effects on asphaltene stability. The presented model is based on an artificial intelligence (AI) method that is still in the primary stages of development and presents promising results that still require extensive study to be matured. A BBN is applied particularly when the fundamentals of the model structure, cause-effect relation between variables, are faced with problems of conceptual uncertainty ***(Langseth, 2008; Pourret, 2008; Norsys, 1996).*** The preference of BBN among AI methods was due to the facts that: **(1)** Asphaltene precipitation is causative in nature, **(2)** BBN is capable of extracting an interrelation between causes and effects quantitatively, **(3)** BBN algorithms can learn from experiments, and are also fault tolerant in the sense that they can handle inaccurate and incomplete data, **(4)** fast response, simplicity and capacity to learn are the advantages of BBN compared to classical (conventional) methods, and **(5)** there is no limitation in the flow of information in a BBN model from causes to effects and vice versa. The latter fact allows one to predict the dilution ratio at nucleation onset for a given pressure and diluents and trivial asphaltene weight percent. Moreover, the BBN model training using a complete databank covering oil conditions of interest removes the limitation associated with the scaling model. Because the required data for training does not include asphaltene properties, one does not face difficulties associated with thermodynamic models in applying a trained BBN model. Avery brief introduction to fundamentals of BBN is includes as a background, and then the BBN model was developed to predict the asphaltene precipitation in a light oil reservoir. A comparison was made between the BBN model predictions and the scaling predictions.

2.2. Bayesian Belief Network (BBN) Method: A BBN is a graphical probabilistic model to represent and study an uncertain domain. A BBN can also be used to deal with the systems that are of a cause-nature. However, a BBN is a mathematical Structure that uses conditional independences for the speed of inference, instead of real model of causalities. Historically speaking, a suggested link between causality and conditional independence indeed goes back to Reichenbach.[18] representing conditional independences, which can be obtained as consequences of the causal relationships, provides a natural and consistent way to express what is known about the different phenomena. Probabilistic relationships, such as conditional independences, can be used to investigate the causal structure dealing with uncontrolled observations ***[Pourret, 2008].***

A BBN consists of a set of nodes and directed edges between nodes. Nodes represent uncertain events or variables ***[Pourret, 2008].*** Nodes can be either continuous or discrete random format. The states bin ranges of a discretized node are exclusive. The directed edges are the links between a pair of nodes, and their direction represent causal influence of one node (parent node) on the other one (child node). In the context of BBN, each node is associated with a probability distribution. Nodes without parents are called root nodes and have an associated prior probability (PP) distribution. For child nodes, the probability distribution takes the form of conditional probability (CP) that represents the correlation between a parent and a child node. The edges of a bin represent the statement that each variable is conditionally independent of its non-descendent in the graph given its parent in the same graph ***[Norsys, 1996].*** A BBN requires four basic elements to represent knowledge of the process under consideration: set of nodes, directed edges, conditional probability distribution, and the prior probability distribution. New information for a variable, called evidence, can be used to instantiate the node representing the variable by setting the probability of one of the states of that node to 100 (on a percentage basis). The number of nodes receiving evidence can be different from one to many at different times depending upon the information availability. Introducing evidence to a model allows for the updating probability distribution of uninstantiated nodes that can be used to calculate numerical values for such nodes as predictions. The mathematical procedure to update probability distribution is called "inference", and 'Bayes' rule is the basis for carrying out the inference in a BBN. When there is a shortage of information, the evidence of the probabilistic BBN model help us update our knowledge of the process, even in the case of inaccurate data. This is an advantage of BBN over other modeling methods that do not deliver any result when a set of input is not complete.

III. RESEARCH METHODOLOGY

3.1. Data Acquisition Analyses: The **250** data sets used in this work were collected from the static asphaltene precipitation tests conducted on the North Arab-D reservoir of Ghawar field in Saudi Arabia containing undersaturated light oil[1]. Data are further extrapolated from the existing ones in order to have a more extensive database for the network. Of the **250** data points, **175** ***(70%)*** of the data points were used to train the network, **10** ***(4%)*** of the data sets were used to cross-validate the relationships established during training process and the remaining **65** ***(26%)*** data points were used to test the network and to evaluate their accuracy through statistical analysis.

3.2. Simulating API Gravity and Gas Specific Gravity of the Mixture

The data given does not reflect the gravity of the resulting mixture which is also believed to have a serious influence on whether a particular fluid will experience asphaltene precipitation or not and these was simulated using the Glaso's (1980) correlation for estimating the gas solubility as a function of the API gravity, pressure, temperature, and gas specific gravity.

$$R_s = \gamma_g\left[\left(\frac{°API^{0.989}}{(T-460)^{0.172}}\right)(Pb^*)\right]^{1.2255} \quad \textbf{(3.1)}$$

Where $P_b^* = 10^x$ is a correlating number with the parameter x defined thus as:

$$x = 2.8869 - [14.1811 - 3.3073\, log(P)]0.5 \quad \textbf{(3.2)}$$

3.3. Statistical analyses used for model performance and validation.

The statistical inferences below were used to evaluate the model performance and validation:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(ei)^2 = \frac{1}{N}\sum(Ti - Outi)^2 \quad \textbf{(3.3)}$$

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{m}(Ti - Outi)^2} \quad \textbf{(3.4)}$$

$$R^2 = 1 - \frac{(Ti-Outi)^2}{\sum_{i=1}^{m} Ti^2} \quad \textbf{(3.5)}$$

$$\sigma = \sum_{i=1}^{n} |(Yi^{exp} - Yi^{model})/Yi^{exp}| \quad \textbf{(3.6)}$$

$$\sigma_{ave} = \sum_{i=1}^{n}(|(Yi^{exp} - Yi^{model})|/Yi^{exp})/n \quad \textbf{(3.7)}$$

$$Ei = \frac{Outi - Ti}{Ti} \times 100 \quad \textbf{(3.8)}$$

$$\%MAE = \frac{1}{N}\sum_{i=1}^{n}|Ei| \quad \textbf{(3.9)}$$

$$R = \sqrt{1 - \sum_{i=1}^{n}(Y^e - Y^m)/\sum_{i=1}^{n}(Y^e - Y')} \quad \textbf{(3.10)}$$

$$\text{Where } Y' = \frac{1}{n} i \sum_{i=1}^{n} Y^e \quad \textbf{(3.11)}$$

IV. ANALYSES OF RESULTS AND INTERPRETATION

Ghawar Field Record: The Arab-D reservoir of Ghawar field is situated in the North East province in the Kayaker desert in the North West of Saudi Arabia.

Crude Oil and Gas Properties of Ghawar Field: The crude oil was sampled using a conventional bottomhole sampler. The crude oil fluid composition is shown in **Table A1** and **A2**. It has a bubble point pressure of ~1900psia at a reservoir temperature of 215°F and a GOR of 580scf/stb. The crude oil properties do not vary significantly across the area of interest. The dead crude has an asphaltene content of ~3.0 wt. %.

The composition of the injected gas (that was injected in the 1960s and 1970s) is presented in **Table A1.** This was the associated gas from the crude after processing at the gas oil separating plant (GOSP). The gas used in the experiment was prepared from the high pressure production trap (HPPT) gas after flashing it at 1,300 psia and 75°F. The model was validated using the input parameters in **Table A1** and **A2** from Ghawar field, one of the major fields in Saudi Arabia.

4.1. Results

Table A: Fluid Properties of North Ghawar-Arab D Reservoir in Saudi Arabia, Kokal et al. (1995).

Table A1: Crude Oil and Gas Properties

Component	Mole %			
	Molecular Weight	Reservoir Fluid	Injected Gas (Actual)	Injected Gas (Experiment)
N_2	28.01	0.14	0.41	0.34
CO_2	44.01	5.89	12.30	12.62
H_2S	34.08	1.82	1.91	2.49
C_1	16.04	24.01	56.00	56.00
C_2	30.07	9.79	17.45	16.23
C_3	44.10	7.49	8.20	8.39
C_4	58.12	4.92	2.64	2.86
C_5	72.15	3.95	0.84	0.83
C_6	86.18	3.14	0.25	0.25
C_{7+}	100.20	38.85	0.00	0.01
C_{7+}MW	100.20	240		
C_{7+}SG		0.8652		
BPP (psia)		~1900@220°F		

Table A2: Bulk Deposit Test

GOR (scf/stb)	550	597	643	736	125	195
Oil charged (cc)	60	60	60	60	60	60
Gas charged (cc)	0	2	4	8	30	60
Pressure (psia)	30	30	300	300	300	300
Temp.	21	21	215	215	215	215
Amount Precipitated (mg)	17.	33	58	62	81.1	132
Precipitated asphaltene (ppm)	43	73	13	13	182	29

Table 4.1: Statistics of the R-values on network performance for the training, testing, and the entire data sets.

EM Learning Algorithm	Mean	Max. Absolute Error	Min. Absolute Error	Standard deviation (σ_{ave})	Ave. Standard deviation (σ)	Correlation coefficient R
Training data sets	0.50056448	0.7823412	0.47112483	0.348197	0. 002106	0.99889887
Testing data sets	0.00461453	0.0049139	3.8788E-07	0.1678	0.001864	0.99428189
Entire data sets	0.00465241	0.0075961	5.7153E-07	0.76423	0.0027981	0.99907533

Table 4.1a: Validating the trained data sets.

Best Network	Training Data Sets		Validating Data Sets	
	Training	Cross-Validation	Training	Cross-Validation
Runs #			2	2
Period	100	100	99	100
Min. MSE	0.000195835	0.000448607	0.000122137	0.000211566
Max. MSE	0.000195835	0.000448607	0.000505758	0.000211565

Table 4.1b: Validating the trained data sets

All Runs #	Training Minimum	Cross-Validation Minimum
Minimum MSE	7.1183E-06	5.20314E-06
Average Minimum MSE	0.000201394	0.000340931
Average Maximum MSE	0.000329268	0.000380287

Table 4.1c: Validating the trained data sets

All Runs #	Min	Cross Validation		Cross Validation
Average Min. MSE	0.000201394	0.000340931	6.89124E-05	0.000124135
Average Max. MSE	0.000329268	0.000380287	0.000152968	0.000146175

Table 4.2: Best Network Performance.

Network Performance	Correlation coefficient (R-value)					
	MSE	MAE	MAE (Max.)	MAE	(σ)	R
Training data sets	7.1183E-06	0.00069148	0.00930148	4.01298-06	0.2579	0.99849887
Testing data sets	1.1214E-06	0.00055299	0.00491395	3.8788E-06	0.1678	0.99398189

Table 4.3: Relative absolute deviation (σ) and average relative absolute deviation (σ_{ave}) for simulated data.

Scaling Methods	Rassamdana et al. (1996)	Yu-Feng et.al. (2000)	Ashoori et.al. (2003)	BBN Model (This study)		
				Training data sets	Testing data sets	Entire data sets
(σ)	1.071688	4.9586	68.8602	0.1678	0.248194	0.76423
(σ_{ave})	0.003897	0.018031	0.2504	0.001864	0.0013062	0.00279818

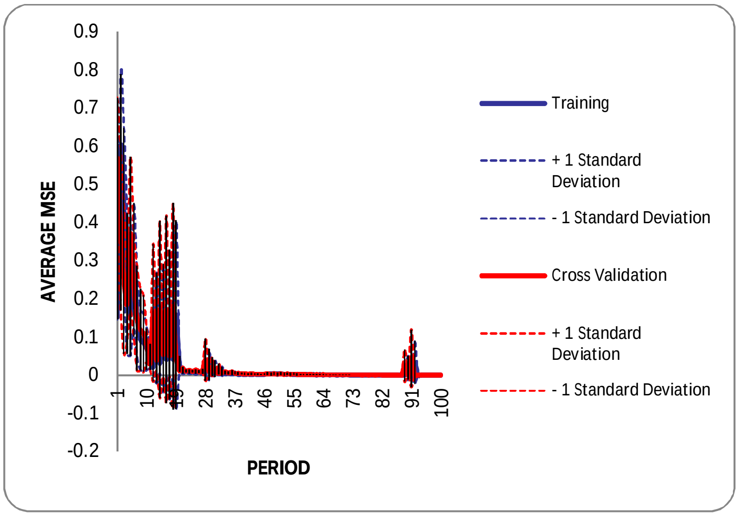

Figure 4.1: Average MSE with standard deviations boundaries for 3 Runs

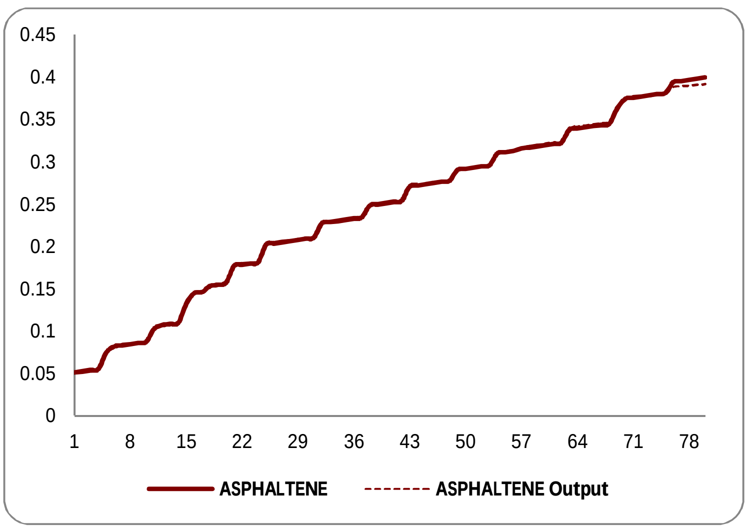

Figure 4.2: Bayesian Belief Network testing the desired output and actual network output

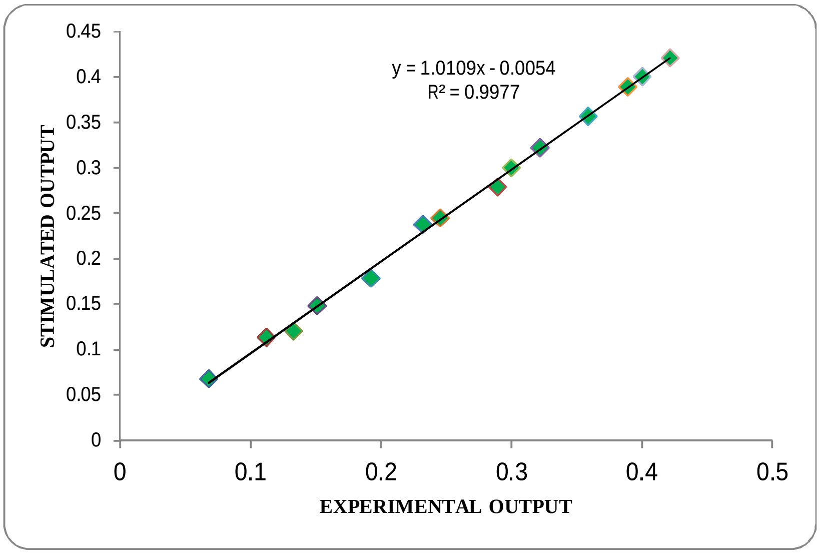

Figure 4.3 Comparison of experimental data with stimulated values that used to train the network.

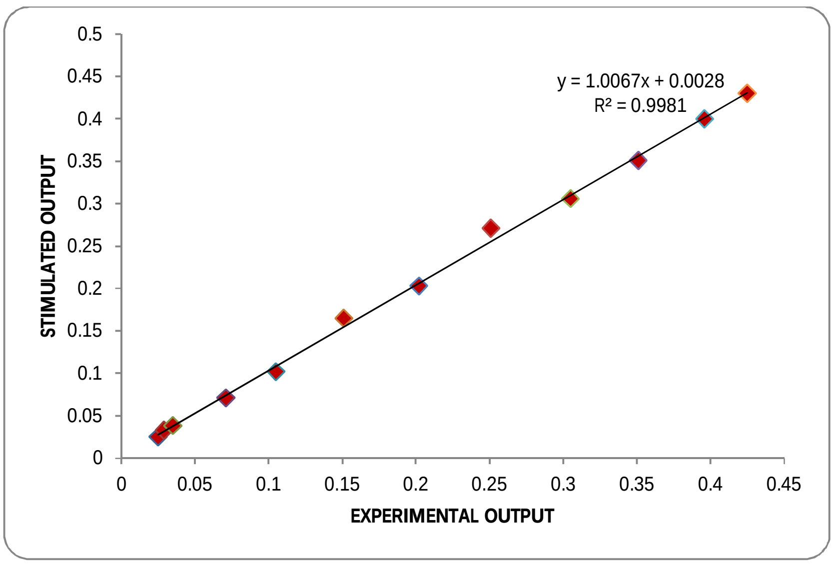

Figure 4.4 Comparison of experimental data with stimulated values of the entire data used in the network

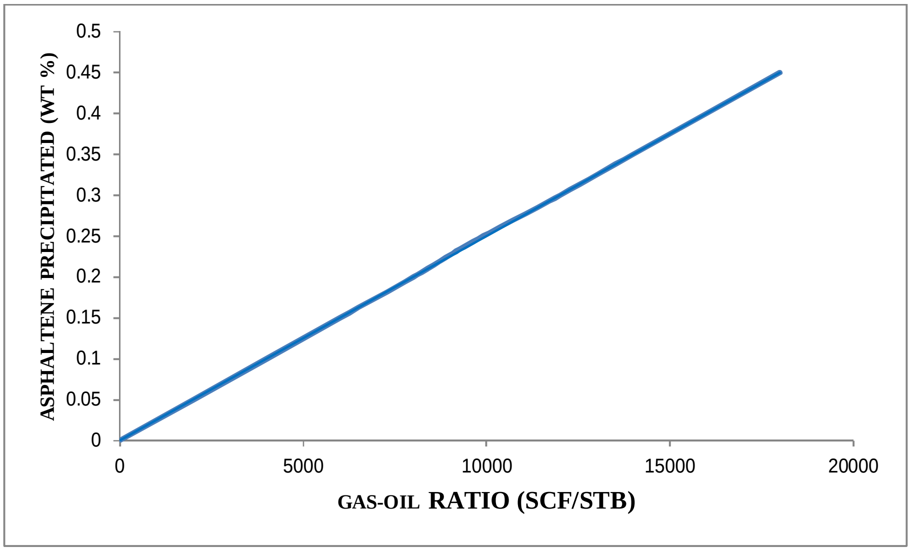

Figure 4.5: Asphaltene precipitated as a function of Gas-Oil Ratio (GOR)

4.2. Interpretation of Results

Table 4.1 shows the results of the optimization of the networks. The network of correlation coefficient, **R.** of **0.9985** trained with the EM learning algorithm gave the best performance and was shown in **Fig. 4.3.**

Table 4.3 illustrates the accuracy of each method to predict the amount of asphaltene precipitation by comparison the relative absolute deviation **(**and average relative absolute deviation $_{\mathbf{ave}}$**)** are defined as shown in equation (3.6) and (3.7) respectively. As it is apparent, the deviation is the less for BBN model, while it is much higher for scaling equations as shown in **Table 4.3.** This analyses shows that the BBN model is more accurate than the other methods to simulate the asphaltene precipitation.

Fig. 4.1, and **Fig. 4.2** shows the training processes, its validations and the testing process on the used data points, respectively. The correlation coefficient **R**-values between the predicted and the actual values of the measured asphaltene weight percent are shown in **Fig. 4.3 and 4.4**. This shows that the BBN predicted asphaltene precipitation values are very close to the actual values of all data sets. **Fig. 4.5** has shown that asphaltene precipitation is a function of gas injection and increases with increasing gas-oil ratio. However, the amount of asphaltene precipitated is relatively small. There is evidence that some of the asphaltene dissolve as the pressure is reduced below the bubble point. These effects have resulted in preventing severe asphaltene build ups in the well. In **Table 4.3** shown, the BBN model showed dominance over scaling equations when their absolute deviations and relative absolute deviations are compared.

V. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

In this study, A Bayesian Belief Network (BBN) model was developed to predict and simulate the amount of asphaltene precipitation in a high-gas oil ratio well as a function of dilution ratio, temperature, oil volume, gas volume, gas-oil ratio, gas gravity, stock tank oil gravity, and pressure. The results of this study clearly indicate that asphaltene precipitation is a function of gas injection and increases with increasing gas-oil ratio. The results from BBN model were compared with predicted values using some scaling equations. The performance of the BBN model was measured using correlation coefficients (R), Mean Squared Error (MSE), and absolute error. The reported results confirmed that BBN approach used for asphaltene precipitation prediction have good statistical performance values of correlation coefficient with Minimum Absolute Mean Squared Error and Mean Squared Error values.

5.2. Recommendations

The main recommendations of this study are:

- Produce the oil wells at as low a GOR as possible. This will reduce the amount of asphaltene precipitation and subsequent deposition.
- Constant monitoring of asphaltene build-up in the wellbores should be maintained

- Constant monitoring of the cleanout procedures to improve processes for future cleanouts should be sustained.
- Solvent should be injected into the oil reservoir to prevent plugging.
- Examine the use of asphaltene dispersants in severe deposition cases.
- Examine the suspended asphaltenes in the crude and increase demulsifier dosage to prevent the asphaltene turning to emulsion and causing production problems.

NOMENCLATURES
Symbols

Rm	Dilution ratio
Mw	Molecular weight of the diluents
P	Pressure
T	Temperature
V_o	Oil volume
V_g	Gas volume
γ_g	Gas gravity
γ_o	Stock tank oil gravity
°API	American Petroleum Institute
GOR	Gas-Oil Ratio
Wi	Weight percent of asphaltene precipitation
Z	Adjustable parameter constant
Z'	Constant exponent
c_1, c_2,	Constants
n	Constant
A_i	Scaling equation coefficients of equation (2.3)
X	Function defined by equation (2.1)
Y	Function defined by equation (2.2)
x	Function defined by equation (2.4)
y	Function defined by equation (2.5)
BBN	Bayesian Belief Network
R_s	Dissolved gas specific gravity of the mixture
BPP	Bubble point pressure
MSE	Mean Squared Error defined by equation (3.3)
MAE	Mean Absolute Error
MAE (Max.)	Maximum Absolute Error of the Mean
RMSE	Root Mean Squared Error defined by equation (3.4)
Ei	Absolute Error function defined by equation (3.8)
%MAE	Percent mean error defined by equation (3.9)
R	Correlation coefficient defined by equation (3.10)
Greeks	
σ	Absolute Deviation defined by equation (3.6)
σ_{Ave}	Average Deviation defined by equation (3.7)

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