



# Multivariate Statistical Modeling of Crude Oil Viscosity and Mole Percent Components for Reservoir Fluids

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## **Authors' contributions**

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## **ABSTRACT**

This study presents multivariate statistical modeling of PVT properties in a Hydrocarbon Reservoir. Traditionally, these properties are modeled by correlating them with the changes in pressure and temperature associated with them. However, these changes are often a direct corollary of the changing composition as each component's presence and/or absence contributes to the overall property of the fluid system. In this work, Multiple Linear and Multiple Nonlinear regression models were used to develop a correlation for the crude oil viscosity and the mole percent of the components as they change with pressure and temperature. A fluid system was modelled using the PVT Package of Integrated Production System Modelling (IPM) Suite. The model was then used to perform a differential liberation test simulation to predict the changes in composition of the crude oil. The composition included three lumped crude oil fractions. After the PVT modelling, the generated PVT Composition was used to perform the Multivariate statistical analysis (MVA) and modelling. Two MVA techniques were compared – the Multiple Linear Regression (MLR) and Multiple Non-Linear Regression (MLNR). Analysis of residuals generated from the prediction run based on both techniques showed that the multiple linear regression method had trending residuals, contrary to the law of parametric estimation upon which it is based. However, the multiple nonlinear regression yielded 100% correlation with adequate residual trend and is thus recommended for adaptation to

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distinct fluid systems. It is imperative to note that the accuracy of this adaptive PVT modeling and prediction is hinged primarily on the accuracy of the PVT model used to estimate the compositional variation.

*Keywords: PVT modeling; multivariable regression analysis; physical properties; pseudo components.*

## 1. INTRODUCTION

The construction of reservoir models requires accurate determination of PVT properties of reservoir fluids. These fluid properties are always required for many reservoir engineering calculations and ultimately, field management and surveillance decisions: EOR candidate screening, reserve valuation, field performance prediction and monitoring, production operation and optimization [1-9]. Several techniques are often employed in measuring reservoir fluid properties whereby the attempts have been majorly directed towards exploring a fast way of obtaining these data while considering both the economic and technical implications of the predicted data [10]. However, it must be stated that the quality of the data from the fluid properties must not be compromised. The use of some laboratory techniques such as special core analysis (SCAL) is generally employed but these techniques are mostly expensive and very time consuming [11-13]. In many cases, there are usually a lot of uncertainties subject to laboratory test conditions. This experience has necessitated the widespread use of physical models, which are often supported by laboratory tests, in constructing reservoir modes.

Attempts to construct relatively realistic models for hydrocarbon reservoirs in the past have varied depending on the reservoir being studied. A reservoir analysis that contains precisely reported values for reservoir parameters of a homogenous nature can lead to a more accurate

forecast of reservoir fluid behavior, but this only applies to reservoirs that are similar. Many circumstances, however, have played a role in the erroneous assessment of such physical behavior. The precision of the physical behavior of the reservoir fluid is affected by the data collecting techniques for reservoir parameters, the quality of the data being measured, and the way the data is interpreted.

This work aim at constructing and generating a model for oil viscosity based on fluid composition and properties rather than the previous reliance on temperature and pressure using statistical and multiple linear regression approach

## 2. METHODOLOGY

In this study, a PVT modeling approach assisted with a multivariate analysis (MVA) was employed in determining the physical behavior of reservoir fluids. The general study framework has been presented in Fig. 1 while a more detailed description of the study methodologies is presented and discussed in the following sections below.

### 2.1 Fluid PVT Model

The fluid PVT model is built using the Petroleum Experts Software PVTP. The original composition of the flow stream and the input PVT data are presented in Tables 1 and 2.



**Fig. 1. Work flow sequence**

**Table 1. Fluid PVT compositional data**

Comp.	Mol %	Weight %	MW (lb/lb-mol)
N <sub>2</sub>	0.16	0.05	28.01
CO <sub>2</sub>	0.91	0.43	44.01
C1	36.47	6.24	16.04
C2	9.67	3.1	30.1
C3	6.95	3.27	44.1
iC4	1.44	0.89	58.1
nC4	3.93	2.44	58.1
iC5	1.44	1.11	72.2
nC5	1.41	1.09	72.2
C6	4.33	3.97	86.2
C7+	33.29	77.41	218

**Table 2. Fluid Properties**

Parameter	Value	Unit
Temperature	220	°F
Depth	8692	Ft
Pressure	4100	Psig
Bubble point Pressure, Pb	2620	Psig
Density at Pb	40.967	lb/cu-ft
Specific gravity	0.8515	-
API gravity	34.5	°API

## 2.2 PVT Model Construction Algorithm

The PVT Package of Petroleum Experts was used to build the PVT EOS Model and the stepwise procedures are outlined as follows [14-15]:

- Step 1: Create a New File
- Step 2: Select Equation of State and Volume Shift Options
- Step 3: Select Components
- Step 4: Enter Composition
- Step 5: Initialize the Pseudo Component Properties
- Step 6: Match the Surface Volumetric Properties (Density, GOR etc.) using the Auto-match feature
- Step 7: Find the Pseudo Distribution (Whitson Alpha Factor) and Split the Pseudo
- Step 8: Use BI Coefficients to Improve Match on Saturation Pressure
- Step 9: Select Match Parameters
- Step 10: Use Regression to Match Fluid
- Step 11: Check and Refine the Fluid Characterization
- Step 12: Calculate and Export

The component selection and the composition entry in steps 3 and 4 respectively enables the specification of the various components of the oil package using the PCTP feature of the PVTP simulator as shown in Fig. 2.

The pseudo is the greatest unknown within the composition and is always composed of a mixture of many compounds with a wide variety of individual properties. Hence, the steps 5 to 9 were aimed at characterizing the C7+ lump (pseudo) component and establishing the corresponding EOS PVT matching as described in Fig. 3. The lumped fraction was split into three components and the final composition of the fluid sample is shown in Fig. 4.

The primary aim of building a PVT model was to generate the compositional change in the fluid with changes in pressure. These changes were estimated as a differential liberation computation. This was done in order to correlate the liquid viscosity with the changes in composition. These properties were generated between the ranges of 200 to 3000psig.

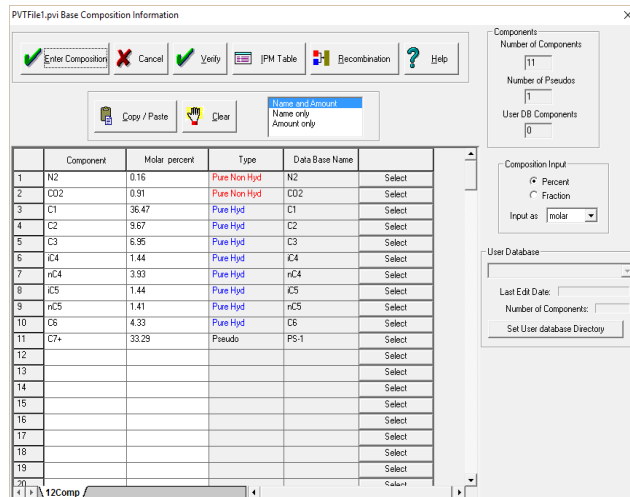


Fig. 2. Fluid Composition Input phase

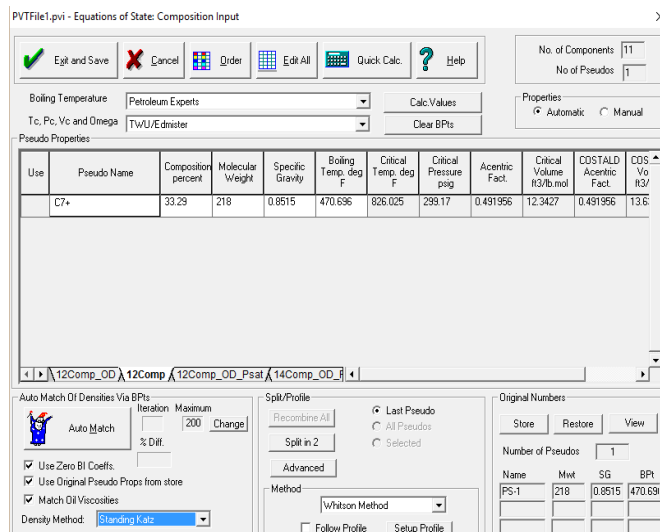


Fig. 3. Pseudocomponent Properties phase

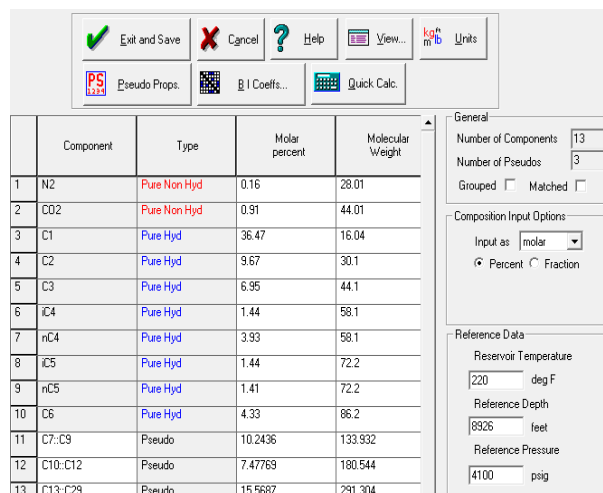


Fig. 4. Final Composition phase

### 3. RESULTS AND DISCUSSION

Following the outlined stepwise procedures in section 2.2, the resulting phase envelop from the PVT characterization of the specified fluid samples are shown in Fig. 5. The diagram suggests that the fluid sample analyzed is a typical ordinary black oil system [16-17].

#### 3.1 PVT Simulation

Following the Differential Liberation (DL) simulation run, the compositional changes were obtained. The DL was chosen as it best simulates what the oil passes through within the reservoir. The composition of the components in the liquid phase from the DL test is presented in Table 3. Table 4 shows the PVT properties variation with pressure and results indicates an increase in viscosity with increasing pressure. This is often correlated with the evolution of lighter end/fractions of the multicomponent crude oil mixture. However, whenever models of crude oil viscosity were developed based on a correlation of crude oil viscosity with pressure and temperature, primarily because they are

easier to measure than the crude composition. Viscosity prediction then relies on the application of the viscosity correlation such as Beggs and Brill which are not usually very accurate.

However, with just one compositional analysis results, we can estimate prospective changes in composition based on PVT models, tuned to match the fluid under study. The results of Table 4 are correlated with the changes in composition displayed in Table 3 to ascertain which components affect the crude oil viscosity the most. Multivariate statistical analysis is subsequently used to obtain a regression model adapted to the fluid under study and suitable for future predictions.

- **Correlation of Liquid Viscosity with Compositional Changes**

The changes in the mole percent of the components are visually analyzed in this section, to ascertain which components have similar strong correlation with the liquid viscosity as presented in Fig. 6.

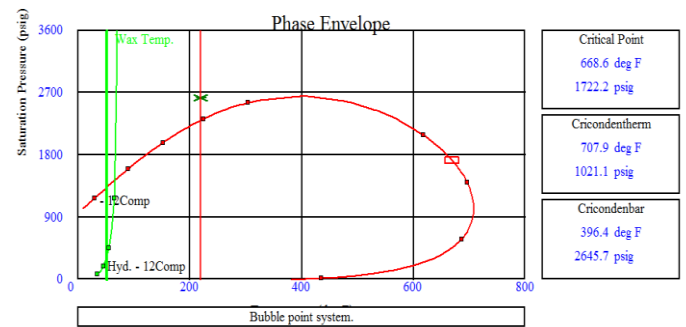


Fig. 5. Mixture Phase Envelope

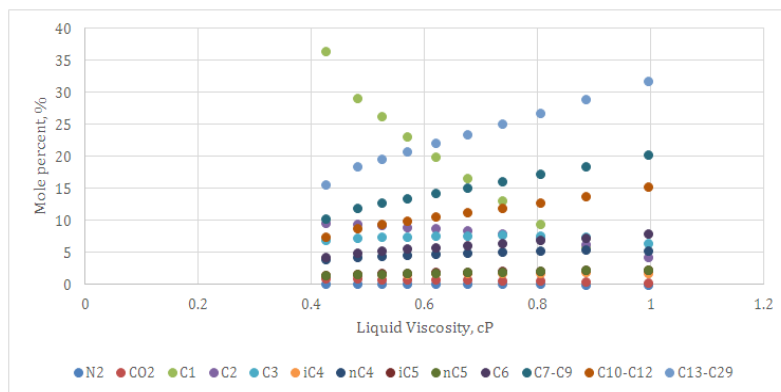


Fig. 6. Mole percent for different liquid viscosity

**Table 3. Composition in the liquid phase with Differential Liberation PVT Simulation**

Pressure (psig)	N2	CO2	C1	C2	C3	iC4	nC4	iC5	nC5	C6	C7-C9	C10-C12	C13-C29
3000	0.16	0.91	36.47	9.67	6.95	1.44	3.93	1.44	1.41	4.33	10.2436	7.4777	15.5687
1800	0.1037	0.8563	29.082	9.3505	7.2737	1.5616	4.3183	1.6188	1.5936	4.9777	12.0036	8.8299	18.4303
1600	0.0838	0.832	26.1864	9.1972	7.3905	1.6087	4.4701	1.6897	1.6664	5.2361	12.7053	9.3678	19.5661
1400	0.0653	0.8025	23.1485	8.9993	7.499	1.6571	4.6282	1.7649	1.744	5.5127	13.457	9.9429	20.7786
1200	0.0486	0.766	19.961	8.7409	7.5926	1.7064	4.792	1.8449	1.8266	5.81	14.267	10.5619	22.0821
1000	0.0338	0.7203	16.6192	8.3976	7.6602	1.7555	4.9597	1.9299	1.9148	6.1314	15.147	11.2341	23.4963
800	0.0214	0.6616	13.1242	7.9288	7.6812	1.8022	5.1277	2.0201	2.0091	6.4819	16.1152	11.9742	25.0524
600	0.0117	0.5832	9.4911	7.2586	7.6132	1.8417	5.2865	2.1155	2.11	6.8695	17.2042	12.8085	26.8063
400	0.0049	0.4713	5.7758	6.2165	7.3448	1.86	5.4075	2.2138	2.2171	7.311	18.4893	13.7989	28.889
200	0.0011	0.2897	2.2021	4.2764	6.4132	1.7889	5.3414	2.2956	2.3186	7.8521	20.2465	15.1789	31.7956

**Table 4. PVT Properties variation with pressure using Differential Liberation experiment**

Pressure (psig)	Gas Density (EOS) (Kg/m <sup>3</sup> )	Oil Density (EOS) (Kg/m <sup>3</sup> )	Interfacial Tension (dyne/cm)	Gas Viscosity (centipoise)	Oil Viscosity (centipoise)	Gas FVF (ft <sup>3</sup> /scf)	Oil FVF (RB/STB)	Gas Oil Ratio (scf/STB)
3000	107.828	686.152	0	0.0168115	0.42618	0.00888048	1.44048	784.104
1800	107.828	702.126	6.06662	0.0168115	0.480994	0.00888048	1.35483	566.38
1600	95.2921	711.104	7.13592	0.0160374	0.523487	0.0100612	1.32122	497.639
1400	83.0925	720.018	8.31828	0.0153548	0.569742	0.011597	1.28935	432.556
1200	71.249	728.903	9.61506	0.014754	0.620218	0.0136625	1.25889	370.568
1000	59.7721	737.812	11.0276	0.0142218	0.67553	0.0165705	1.22948	311.092
800	48.6562	746.826	12.5587	0.0137398	0.736627	0.0209408	1.20062	253.415
600	37.865	756.105	14.2174	0.0132785	0.805288	0.0282011	1.17156	196.43
400	27.2849	766.054	16.0329	0.0127777	0.885921	0.0425419	1.14051	137.751
200	16.4797	778.247	18.1314	0.0120557	0.99622	0.0838821	1.1008	68.711

Fig. 6 show that the Methane (C1) exhibits a negative correlation with the viscosity. Also, the lighter ends, which include Ethane (C2) to Propane (C3) and the impurities, CO<sub>2</sub> and N<sub>2</sub>, exhibit correlations with slightly variable gradients than the others. These components are sexcluded from the following multivariate analysis to reduce noisiness of results.

### 3.2 Multivariate Statistical Analysis

Two tools of Multivariate Analysis (MVA) are utilized to correlate the compositional variation with the liquid viscosity, namely multiple linear regression and nonlinear regression.

#### 3.2.1 Multiple Liner Regression (MLR)

The multiple linear regression was run to generate a linear model that incorporates the impacts of the mole composition of the various components into one. The results in Table 5 summarize the basic statistical result of the simulation.

The correlation matrix shown in Table 6 portrays the nature of the correlation between the dependent variable (DV) and the independent variables (IV) while Table 7 displays the goodness of fit coefficients of the model.

In this case, 99.2 % of the variability of the liquid viscosity is explained by the variation in composition. The remainder of the variability is due to some effects (other explanatory variables) that have not been included in this analysis. The analysis of variance results in Table 9

enable us to determine whether or not the explanatory variables bring significant information (null hypothesis H<sub>0</sub>) to the model. In other words, it's a way of ascertaining whether it is valid to use the mean to describe the whole population, or whether the information brought by the explanatory variables is of value or not.

- **Regression Model – MLR**

Table 10 gives details on the model. This table is helpful when predictions are needed, or when there is need to compare the coefficients of the model for a given set of data with the ones obtained for another set of data. The viscosity of oil model is given in Equation (1).

Following the above analysis, the standardized regression coefficients (referred to as beta coefficients) are presented in Table 11 and Fig. 7. They allow for the direct comparison of the relative influence of the explanatory variables on the dependent variable, and their significance.

Using the generated linear regression, predictions of the liquid viscosity were made and the residuals computed. These residuals, given the assumptions of the linear regression model, should be normally distributed, meaning that 95% of the residuals should be in the interval [-1.96, 1.96]. All values outside this interval are potential outliers, or might suggest that the normality assumption is wrong. The predictions and Residuals of the Oil Viscosity are presented in Table 12.

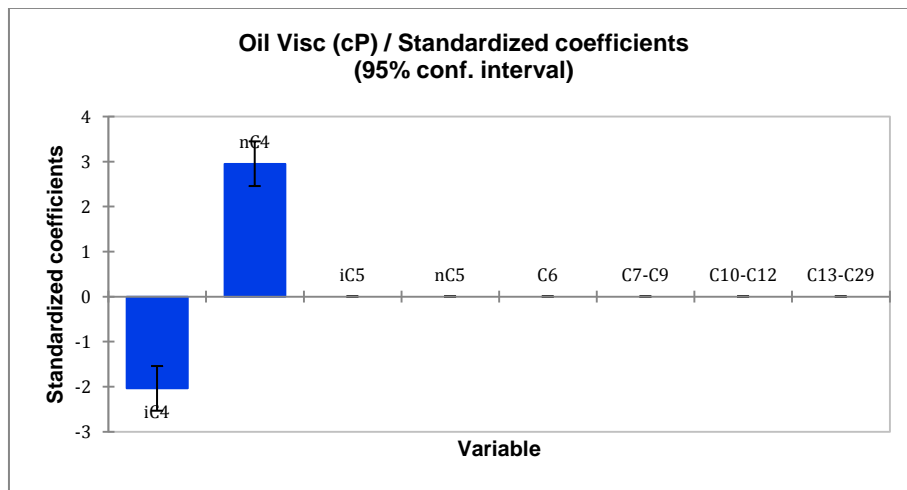


Fig. 7. Standardized Coefficients for Different Variables of MLR

Table 5. MLR Analysis

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. Deviation
Oil Visc (cP)	10	0	10	0.424	0.960	0.649	0.177
iC4	10	0	10	1.440	1.860	1.702	0.135
nC4	10	0	10	3.930	5.408	4.826	0.489
iC5	10	0	10	1.440	2.296	1.893	0.273
nC5	10	0	10	1.410	2.319	1.881	0.288
C6	10	0	10	4.330	7.852	6.051	1.096
C7-C9	10	0	10	10.244	20.247	14.988	3.084
C10-C12	10	0	10	7.478	15.179	11.117	2.369
C13-C29	10	0	10	15.569	31.796	23.247	4.990

Table 6. Correlation Matrix for MLR

	iC4	nC4	iC5	nC5	C6	C7-C9	C10-C12	C13-C29	Oil Visc (cP)
iC4	1	0.987	0.943	0.936	0.914	0.902	0.901	0.901	0.874
nC4	0.987	1	0.984	0.980	0.968	0.960	0.959	0.959	0.940
iC5	0.943	0.984	1	1.000	0.997	0.994	0.994	0.994	0.983
nC5	0.936	0.980	1.000	1	0.998	0.996	0.996	0.996	0.986
C6	0.914	0.968	0.997	0.998	1	1.000	0.999	0.999	0.992
C7-C9	0.902	0.960	0.994	0.996	1.000	1	1.000	1.000	0.994
C10-C12	0.901	0.959	0.994	0.996	0.999	1.000	1	1.000	0.994
C13-C29	0.901	0.959	0.994	0.996	0.999	1.000	1.000	1	0.994
Oil Visc (cP)	0.874	0.940	0.983	0.986	0.992	0.994	0.994	0.994	1

Table 7. Goodness of Fit for MLR

Observations	Sum of weights	DF	R <sup>2</sup>	Adjusted R <sup>2</sup>	MSE	RMSE	MAPE	DW	Cp	AIC	SBC	PC
10	10	7	0.992	0.99	0	0.018	2.309	1.529	3	-77.933	-77.025	0.015



**Table 8. Analysis of Variance (Oil Visc, cp) – MLR**

Source	DF	Sum of squares	Mean squares	F
Model	2	0.279	0.139	431.312
Error	7	0.002	0.000	
Corrected Total	9	0.281		

Computed against model  $Y=Mean(Y)$ **Table 9. Model Parameters (Oil Visc, cp) for MLR**

Source	Value	Standard error	T	Pr >  t	Lower bound (95%)	Upper bound (95%)
Intercept	0.043	0.122	0.354	0.734	-0.245	0.331
iC4	-2.669	0.275	-9.719	< 0.0001	-3.319	-2.020
nC4	1.067	0.076	14.073	< 0.0001	0.888	1.246
iC5	0.000	0.000				
nC5	0.000	0.000				
C6	0.000	0.000				
C7-C9	0.000	0.000				
C10-C12	0.000	0.000				
C13-C29	0.000	0.000				

$$\mu_{oil} = 4.316888733429061 \times 10^{-2} - 2.66928717451177iC_4 + 1.06694810925145nC_4 \quad (1)$$

**Table 10. Standardized coefficients (Oil Visc (cP)) for MLR**

Source	Value	Standard error	t	Pr >  t	Lower bound (95%)	Upper bound (95%)
iC4	-2.039	0.210	-9.719	< 0.0001	-2.535	-1.543
nC4	2.952	0.210	14.073	< 0.0001	2.456	3.448
iC5	0.000	0.000				
nC5	0.000	0.000				
C6	0.000	0.000				
C7-C9	0.000	0.000				
C10-C12	0.000	0.000				
C13-C29	0.000	0.000				

Table 11. Predictions and Residuals (Oil Visc, cp) for MLR

Observation	Wt	Oil Visc (cP)	Pred (Oil Visc (cP))	Residual	Std. residual	Std. dev. on pred. (Mean)	Lower bound 95% (Mean)	Upper bound 95% (Mean)	Std. dev. on pred. (Observation)	Lower bound 95% (Observation)	Upper bound 95% (Observation)
Obs1	1	0.424	0.393	0.032	1.774	0.013	0.361	0.424	0.022	0.340	0.445
Obs2	1	0.459	0.482	-0.023	-1.282	0.008	0.462	0.502	0.020	0.435	0.529
Obs3	1	0.502	0.518	-0.017	-0.942	0.007	0.501	0.536	0.019	0.473	0.564
Obs4	1	0.547	0.558	-0.010	-0.583	0.007	0.542	0.574	0.019	0.513	0.603
Obs5	1	0.597	0.601	-0.004	-0.208	0.007	0.585	0.617	0.019	0.556	0.647
Obs6	1	0.652	0.649	0.003	0.158	0.008	0.631	0.667	0.019	0.603	0.695
Obs7	1	0.712	0.704	0.008	0.447	0.008	0.684	0.723	0.020	0.657	0.750
Obs8	1	0.778	0.768	0.011	0.597	0.009	0.747	0.789	0.020	0.720	0.815
Obs9	1	0.856	0.848	0.008	0.443	0.009	0.826	0.869	0.020	0.800	0.895
Obs10	1	0.960	0.967	-0.007	-0.403	0.017	0.927	1.007	0.025	0.909	1.026

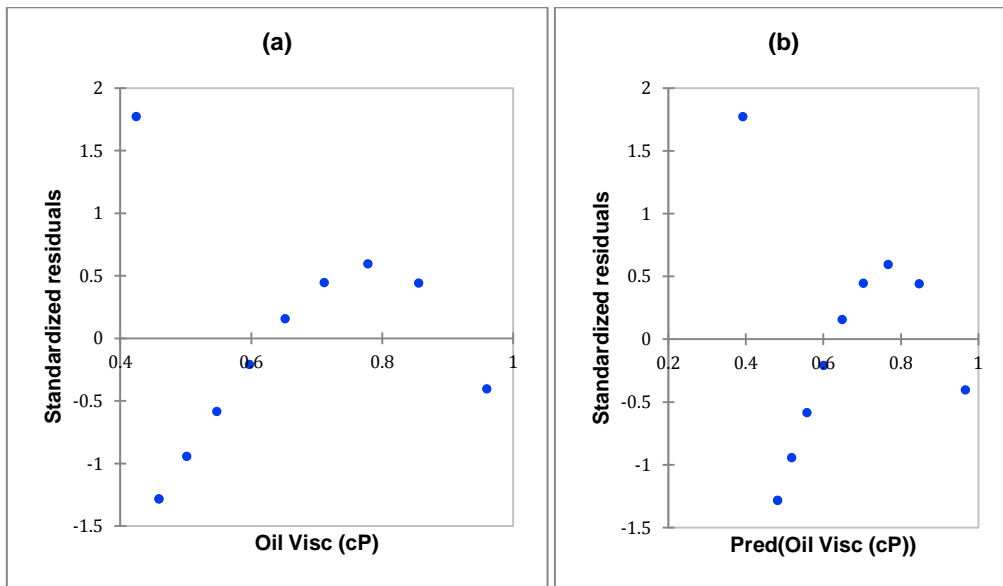


Fig. 8. Standard Residuals for(a) observed Oil Viscosity (b) Predicted Oil Viscosity (MLR)

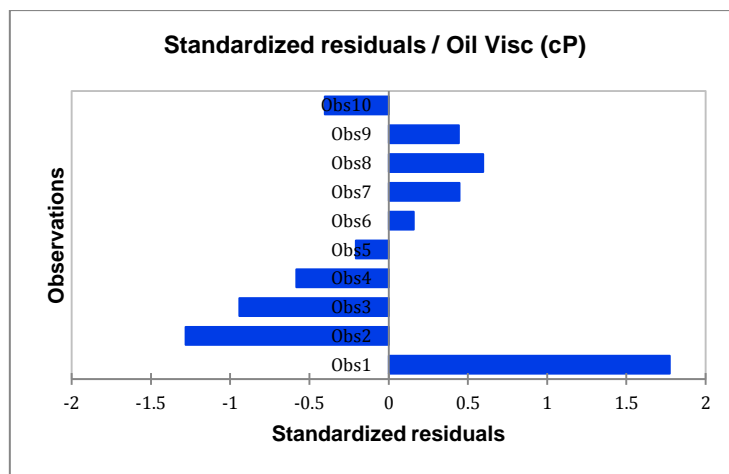


Fig. 9. Standardized Residuals for Each Observation (MLR)

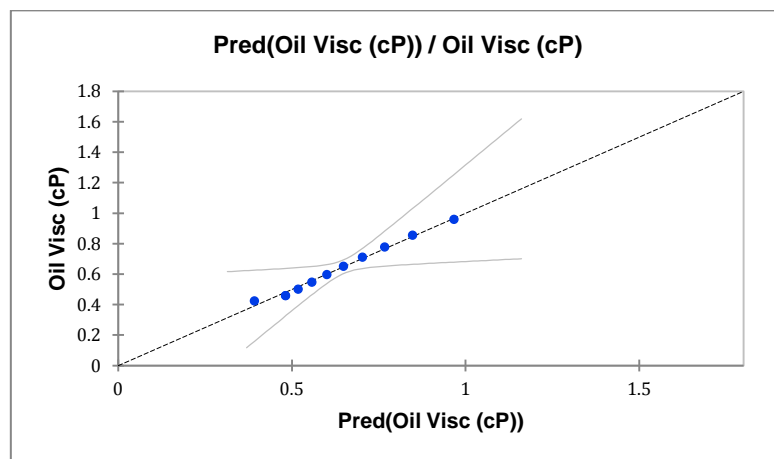


Fig. 10. Actual Oil Viscosity versus Predicted Oil Viscosity (MLR)

**Table 12. Statistical Analysis for MNL**

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Oil Visc (cP)	10	0	10	0.426	0.996	0.672	0.184
iC4	10	0	10	1.440	1.860	1.702	0.135
nC4	10	0	10	3.930	5.408	4.826	0.489
iC5	10	0	10	1.440	2.296	1.893	0.273
nC5	10	0	10	1.410	2.319	1.881	0.288
C6	10	0	10	4.330	7.852	6.051	1.096
C7-C9	10	0	10	10.244	20.247	14.988	3.084
C10-C12	10	0	10	7.478	15.179	11.117	2.369
C13-C29	10	0	10	15.569	31.796	23.247	4.990

**Table 13. Correlation Matrix for MNL**

Variables	iC4	nC4	iC5	nC5	C6	C7-C9	C10-C12	C13-C29	Oil Visc (cP)
iC4	1.000	0.987	0.943	0.936	0.914	0.902	0.901	0.901	0.880
nC4	0.987	1.000	0.984	0.980	0.968	0.960	0.959	0.959	0.944
iC5	0.943	0.984	1.000	1.000	0.997	0.994	0.994	0.994	0.986
nC5	0.936	0.980	1.000	1.000	0.998	0.996	0.996	0.996	0.989
C6	0.914	0.968	0.997	0.998	1.000	1.000	0.999	0.999	0.995
C7-C9	0.902	0.960	0.994	0.996	1.000	1.000	1.000	1.000	0.997
C10-C12	0.901	0.959	0.994	0.996	0.999	1.000	1.000	1.000	0.997
C13-C29	0.901	0.959	0.994	0.996	0.999	1.000	1.000	1.000	0.997
Oil Visc(cP)	0.880	0.944	0.986	0.989	0.995	0.997	0.997	0.997	1.000

**Table 14. Goodness of Fit for MNL**

Observations	DF	R <sup>2</sup>	SSE	MSE	RMSE
10	-7	1	0		

**Table 15. Model Parameters**

Parameter	Value	Standard error
pr1	-10.556	65535.000
pr2	37.420	65535.000
pr3	10.248	65535.000
pr4	-24.491	65535.000
pr5	-8.632	65535.000
pr6	-36.366	65535.000
pr7	19.523	65535.000
pr8	3.683	65535.000
pr9	-6.357	65535.000
pr10	-6.928	65535.000
pr11	0.000	0.000
pr12	0.000	0.000
pr13	0.000	0.000
pr14	0.402	65535.000
pr15	0.000	0.000
pr16	0.000	0.000
pr17	0.000	0.000

**Table 16. Prediction and Residuals Based on Fit Regression Model for MNL**

Observations	iC4	nC4	iC5	nC5	C6	C7-C9	C10-C12	C13-C29	Oil Visc (cP)	Pred(Oil Visc (cP))	Residuals
Obs1	1.440	3.930	1.440	1.410	4.330	10.244	7.478	15.569	0.426	0.426	0.000
Obs2	1.562	4.318	1.619	1.594	4.978	12.004	8.830	18.430	0.481	0.481	0.000
Obs3	1.609	4.470	1.690	1.666	5.236	12.705	9.368	19.566	0.523	0.523	0.000
Obs4	1.657	4.628	1.765	1.744	5.513	13.457	9.943	20.779	0.570	0.570	0.000
Obs5	1.706	4.792	1.845	1.827	5.810	14.267	10.562	22.082	0.620	0.620	0.000
Obs6	1.756	4.960	1.930	1.915	6.131	15.147	11.234	23.496	0.676	0.676	0.000
Obs7	1.802	5.128	2.020	2.009	6.482	16.115	11.974	25.052	0.737	0.737	0.000
Obs8	1.842	5.287	2.116	2.110	6.870	17.204	12.809	26.806	0.805	0.805	0.000
Obs9	1.860	5.408	2.214	2.217	7.311	18.489	13.799	28.889	0.886	0.886	0.000
Obs10	1.789	5.341	2.296	2.319	7.852	20.247	15.179	31.796	0.996	0.996	0.000

Fig. 8 shows the standardized residuals versus the predicted oil viscosity. A trend been identified indicates that the model is not correct as there is an auto correlation in the residuals, which is contrary to one of the assumptions of parametric linear regression. This would imply that there is a hidden “trending” error in the model predictions. Fig. 9 shows the standardized residuals for each observation. It is used primarily to identify outliers and no one is observed.

Fig. 10 shows a plot of the actual liquid viscosity against the predicted liquid viscosity. The predicted is in agreement with the actual viscosity.

### 3.2.2 Multiple Non-Linear Regression (MNL) Results

The summary of the statistical parameters obtained from the simulation of the Multiple Non-linear regression is presented in Table 13. The number of observations, missing values, the number of non-missing values, the mean and the standard deviation (unbiased) are displayed for the dependent variables (in blue) and the quantitative explanatory variables. The corresponding correlation matrix is presented in Table 14. It shows a very strong correlation between the dependent variable, oil viscosity and independent variables, the components’ mole percent.

The nonlinear regression was run with a convergence criterion of 0.00001 and maximum iterations of 200. The R<sup>2</sup> (coefficient of determination) indicates the % of variability of the dependent variable which is explained by the explanatory variables. The closer to 1 the R<sup>2</sup> is, the better the fit. The Goodness of fit is presented in Table 15

Table 15 shows that 100% of the variation in the liquid viscosity can be explained by the variation in the composition of the components. Consequently, the model to be fit would give a “statistically” perfect prediction of liquid viscosities.

#### • Regression Model – MNL

The regression takes the form displayed in Equation 2 below.

$$Y = Pr_1 + X_1Pr_2 + X_2Pr_3 + X_3Pr_4 + X_4Pr_5 + X_5Pr_6 + X_6Pr_7 + X_7Pr_8 + X_8Pr_9 + X_1^2Pr_{10} + X_2^2Pr_{11} + X_3^2Pr_{12} + X_4^2Pr_{13} + X_5^2Pr_{14} + X_6^2Pr_{15} + X_7^2Pr_{16} + X_8^2Pr_{17} \quad (2)$$

The parameters that fit the data used for this study are tabulated in Table 16 and the stop iteration condition was set at 200 iterations and 0.00001 convergence.

$$\begin{aligned} \mu_{oil} = & -10.559298514411 + 37.4204046018315iC_4 + \\ & 10.2484865732932nC_4 - \\ & 24.4913346604639iC_5 - \\ & 8.63182580540697nC_5 - 36.3656238777595C_6 + \\ & 19.5227042940771C_{7-9} + \\ & 3.68284551753329C_{10-12} - \\ & 6.35682264979521C_{13-29} - \\ & 6.9283730700242iC_4^2 + 0.401830336219369C_6^2 \end{aligned} \quad (3)$$

Equation (3) is used to make predictions of the oil viscosity. It is important to note that this equation was based on the lumping rule selected during the PVT model building. The results of the prediction are given in Table 17.

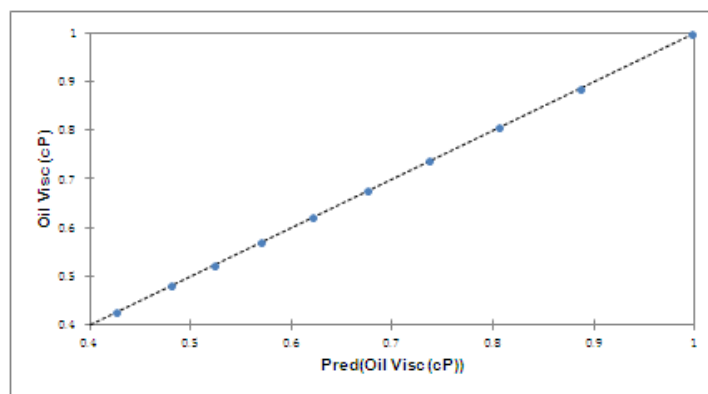
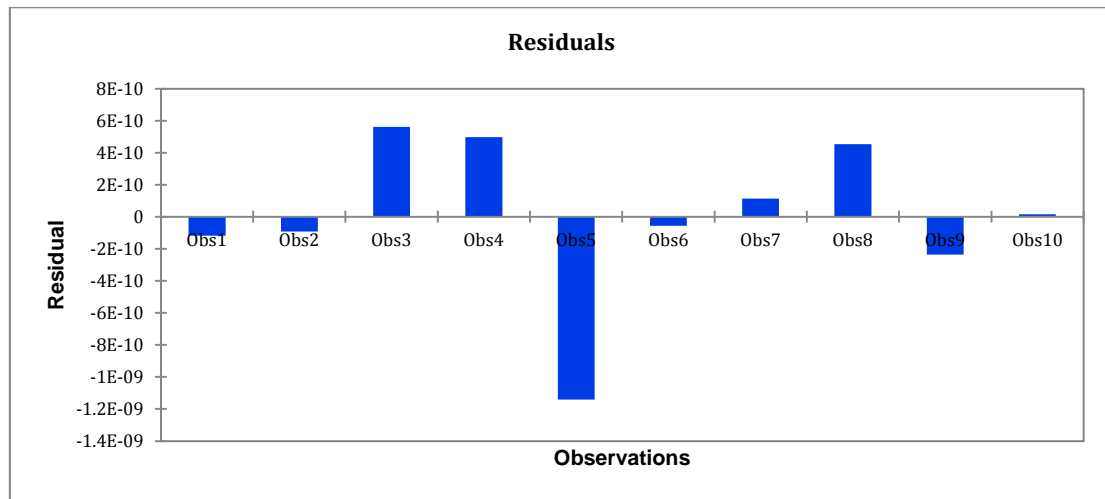


Fig. 11. Actual Liquid Viscosity versus Predicted Liquid Viscosity Based on MNL



**Fig. 12. Residuals from MLNR prediction**

Fig. 11 shows the predicted values versus the observed values. Confidence intervals allow identifying potential outliers. There is obviously an excellent prediction of the liquid viscosity with the computed model.

Fig. 12 shows the residuals. These residuals, given the assumptions of the linear regression model, should be normally distributed, meaning that 95% of the residuals should be in the interval  $[-1.96, 1.96]$  which the predicted was within the range.

It can be seen that the residuals are well within the accepted limits. They are very minute to be precise, implying very little difference between measured viscosity and simulated viscosity.

#### 4. CONCLUSION

This work has modeled the oil viscosity from reservoir fluid composition and properties using the Multiple Linear and Nonlinear regression techniques. These properties are often modeled primarily based on their dependence on temperature and pressure. However, variation in these properties is often a direct corollary of the changes in the inherent component composition. Such a model, when built, can be adapted to any reservoir fluid system. When built, PVT simulation results of compositional variations can be used to predict future viscosity changes, accurately. Two MVA techniques were compared – the Multiple Linear Regression (MLR) and Multiple Non-Linear Regression (MLNR). The MLR model revealed that 99.2% of the variation in the crude oil viscosity could be

explained by the variation in mole percent of the heavier ends. Subsequently, the generated linear model was used to predict the viscosity as a QC technique. The residuals generated were found to follow a pattern when standardized and plotted against the oil viscosity. This revealed that there was an inherent error propagated through the prediction. As such the MLR model was not ideal although it correlated highly positively. On the other hand, the MLNR model revealed a 100% correlation between the crude oil viscosity and composition. Further analysis revealed a “statistically” perfect prediction of crude oil viscosity. Summarily, the Multiple Non-Linear Model is the most ideal to model the effects of changes in composition on crude oil viscosity.

#### COMPETING INTERESTS

Authors have declared that no competing interests exist.

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