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Development of a Predictive Model for Wax Content in Crude Oil Using Experimental Data from the Niger Delta Basin

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Abstract: *Waxy crude oils pose major flow assurance challenges during production and transportation due to wax crystallization, which increases viscosity, elevates the pour point, and can lead to pipeline blockages. This study presents a predictive regression model for estimating wax content in crude oils from the Niger Delta Basin using experimentally measured properties. Ten crude oil samples were analyzed based on resin, asphaltene, pour point, density, and viscosity. The Box–Behnken Design (BBD) approach in Design Expert software was employed to develop and optimize the model, with statistical validation conducted using Analysis of Variance (ANOVA). Results revealed a strong correlation between measured and predicted wax contents, with a high coefficient of determination (R^2 = 0.985) and prediction errors below 1%. The model demonstrated excellent accuracy and robustness in forecasting wax content using easily obtainable crude oil parameters. This predictive framework reduces dependence on time-consuming and costly laboratory analyses such as gravimetric or chromatographic techniques. Consequently, it provides a rapid and reliable tool for flow assurance planning, enabling timely mitigation of wax deposition risks and improving production efficiency across Niger Delta oilfields.*

Keywords: *Waxy crude oil, Wax content prediction, Niger Delta, Flow assurance, Regression modeling, ANOVA*

1. INTRODUCTION

Waxy crude oils are characterized by the presence of long-chain paraffinic hydrocarbons (C18–C36) and naphthenic hydrocarbons (C30–C60), which crystallize under certain flow conditions, temperatures, and pressures (Aiyejina et al., 2011). When crude oil cools below the cloud point or wax appearance temperature (WAT), wax molecules lose solubility and form crystals that alter the fluid's rheological behavior. This transition causes the oil to behave as a non-Newtonian fluid with significantly increased viscosity and pour point (Pires, Góis, & Santos, 2016; Yao et al., 2021). Such changes pose serious flow assurance problems during production, transportation, and storage, particularly in subsea pipelines where rapid heat loss accelerates wax precipitation and deposition.

The economic impact of wax deposition is substantial. Wax accumulation restricts flow, reduces pipeline throughput, and may eventually lead to partial or complete blockage of production facilities. These challenges result in increased operational costs, production downtime, and the need for costly remediation such as pigging, hot oiling, or the use of chemical inhibitors (Behbahani, 2014; Makwashi et al., 2018). Globally, wax deposition is estimated to cost the petroleum industry billions of dollars annually, underscoring the need for predictive and preventive approaches.

Traditionally, wax content in crude oil has been determined through experimental methods such as gas chromatography, differential scanning calorimetry (DSC), gravimetric methods, and standardized UOP procedures (Chen et al., 2004; Jokuty et al., 1996). While these methods provide accurate results, they are often time-consuming, expensive, and labor-intensive, making them impractical for routine field applications. Recent studies have therefore emphasized the need for rapid and reliable predictive techniques that can estimate wax content based on readily measurable crude oil properties (Outlaw & Ye, 2011; Ragunathan, Husin, & Wood, 2020).

This study addresses this research gap by developing a regression-based model for predicting wax content in Niger Delta crude oils using experimental data. Key crude oil parameters such as viscosity, density, pour point, resin, and asphaltene content were analyzed to establish correlations with wax concentration. The model was validated using statistical techniques, including analysis of variance (ANOVA), to assess its predictive accuracy and reliability. By providing a simplified yet accurate predictive tool, this study contributes to improved flow assurance management and cost reduction in crude oil production and transportation.

2. RELATED WORKS

2.1 Wax Crystallization and Flow Assurance Challenges

Wax precipitation occurs when crude oil cools below its wax appearance temperature (WAT) or cloud point, reducing the solubility of high-molecular-weight paraffins (C18–C36) and naphthenic hydrocarbons (C30–C60). The resulting wax crystals form networks that increase viscosity, raise pour point, and may lead to gelling (Aiyejina et al., 2011; Pires, Góis, & Santos, 2016).

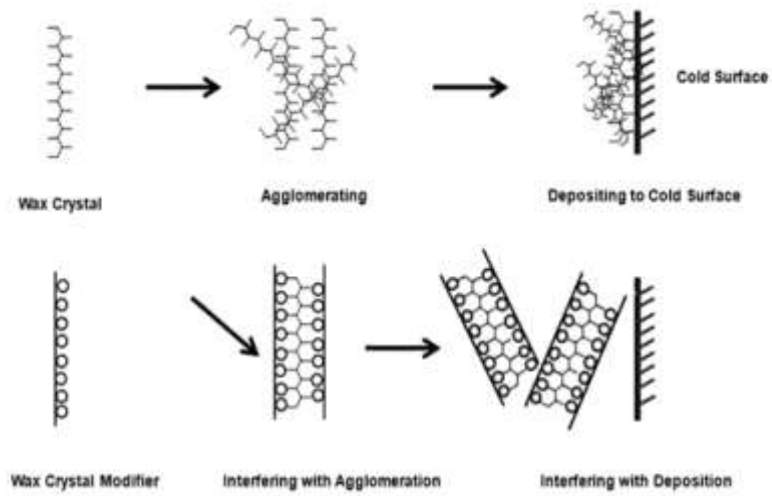

Fig.1: Wax Formation

In subsea environments, where heat transfer to the surroundings is rapid, wax deposition on pipeline walls is a common cause of flow restriction and production downtime (El-Dalatony et al., 2019; Yao et al., 2021). These phenomena pose severe operational and economic challenges for oil producers.

2.2 Economic Implications of Wax Deposition

The petroleum industry incurs billions of dollars annually due to wax deposition, which reduces pipeline capacity, damages facilities, and necessitates frequent remediation such as pigging, solvent washing, or chemical treatment (Behbahani, 2014; Makwashi et al., 2018).

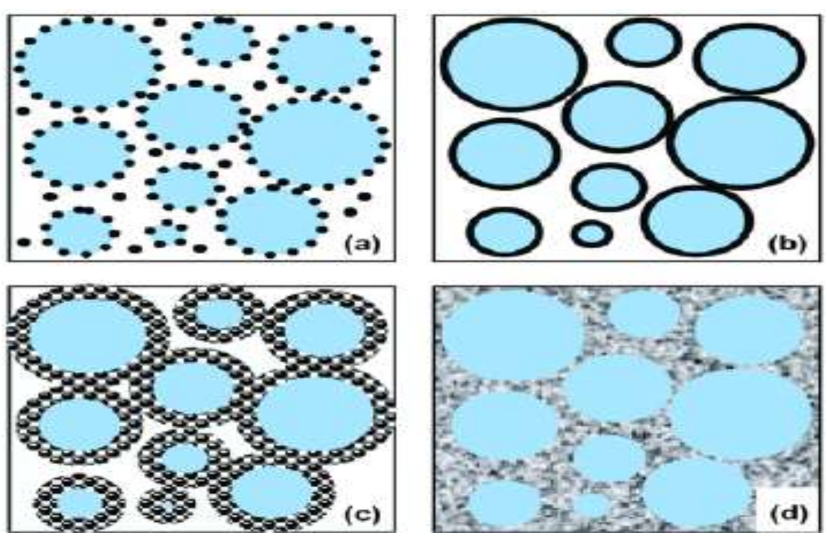

Fig. 2: Gel Formation

At the reservoir scale, wax deposition also contributes to formation damage by clogging pore spaces and reducing permeability (Hao, Al-Salim, & Ridzuan, 2019). These impacts highlight the importance of timely wax prediction and prevention strategies in flow assurance planning.

2.3 Wax Types and Characteristics

Petroleum waxes are broadly classified as paraffin wax and microcrystalline wax. Paraffins are straight- or branched-chain alkanes with melting points ranging from 23 to 67 °C, depending on chain length. They are insoluble in water but soluble in organic solvents, and their crystallization releases latent heat that significantly alters crude oil rheology (Parkash, 2003; Speight, 2011).

Fig. 2: Micro-Crystalline Structure

Microcrystalline waxes, on the other hand, have smaller crystal structures, higher viscosity, and contribute to stronger gel formation in crude oils (El-Dalatony et al., 2019). Both wax types complicate production and transport but are valuable feedstocks for lubricants and specialty products.

2.4 Wax Inhibition and Remediation Strategies

To mitigate wax deposition, several strategies are employed, including thermal methods (heating), dilution with light hydrocarbons, and chemical inhibitors such as pour point depressants and dispersants (Ruwoldt et al., 2019). Chemical treatment is often considered the most practical approach, although its effectiveness depends on crude oil composition, flow regime, and operating temperature (Ragunathan, Husin, & Wood, 2020). Nonetheless, determining the optimal dosage of inhibitors requires accurate knowledge of wax content, underscoring the importance of predictive modeling.

2.5 Conventional Wax Content Determination Methods

Several laboratory methods have been developed for quantifying wax in crude oils:

a. Gas chromatography (GC): separates hydrocarbon groups and quantifies wax fractions above C18 (Jokuty et al., 1996).
b. Differential scanning calorimetry (DSC): measures thermal transitions associated with wax crystallization, providing accurate WAT and wax content values (Chen, Zhang, & Li, 2004).
c. Gravimetric methods: rely on solvent precipitation of wax and weighing of dried samples (Jokuty et al., 1996).
d. UOP standard methods: employ adsorption and solvent recovery for wax determination.

While these methods are reliable, they are time-consuming, costly, and not suited for rapid field application.

2.6 Research Gap

Despite extensive work on wax characterization and inhibition, limited attention has been given to predictive models that estimate wax content based on simple crude oil properties such as viscosity, density, resin, and asphaltene content. Existing methods remain highly experimental, limiting their practicality in real-time production scenarios (Outlaw & Ye, 2011). Therefore, the development of a regression-based predictive model offers a valuable alternative for the petroleum industry by enabling timely and cost-effective wax management.

3. Materials and Methods

3.1 Data Source

Ten crude oil samples were obtained from different wells in the Niger Delta Basin, Nigeria. For each sample, the following properties were measured: resin content, asphaltene content, pour point, density, viscosity, and wax content. These parameters were selected based on their relevance to crude oil rheology and wax precipitation tendencies. Table 1 summarizes the dataset used in this study.

Table 1: Properties of Niger Delta crude oil samples used for model development.

Oil Samples	Resin	Asphaltene	Pour point	Density	Viscosity	Wax Content
A	7.98	3.72	-7	879.5	71.25	3.5
B	8.04	1.1	29	856.6	16.3	12.6
C	1.61	3.96	-9	872	11.91	3.78
D	7.94	2.92	36	863.8	24.97	22.01
E	0.64	0.81	-1	839.4	3.4	6.52
F	5.75	2.18	1	864.9	17.26	7.53
G	1.46	6.79	18	835.9	7.65	10.63
H	0.11	6.11	17	818.7	3.06	9.39
I	9.45	2.38	11	864.3	17	14.13
J	10.2	3.1	13	868.9	28.72	14.29

3.2 Model Development

A regression-based model was developed to predict wax content using Design Expert 12 software. The Box–Behnken Design (BBD), a response surface methodology, was employed to generate input parameter combinations and evaluate their effects on wax content.

a. Response variable: wax content (%)
b. Input factors: resin, asphaltene, pour point, density, viscosity

The dataset was fitted to a second-order polynomial model, with both coded and actual factor equations generated. Model selection considered hierarchy preservation and significance of interaction terms.

3.3 Statistical Analysis

Analysis of variance (ANOVA) was used to compare and analyze a number of regression models in order to determine which one best fits the input and output data. In design expert, different transformation functions are available. Each transformation function was assessed as follows.

a. The highest coefficient of determination value should be produced by the suggested transformation function.
b. It is advised to use a transformation function that produces an adjusted to predicted difference between the two that is less than 0.2.
c. It is advised to use the transformation function that produces the highest Adequacy in Precision (Adeq Precision) value. A desirable value of more than 4 on the Adeq Precision signal-to-noise ratio indicates that the model can be used to navigate the design space. The higher the value, the more useful the model is.
d. Assessing the standard deviations obtained using various transformational functions. It is advised to use the transformation function that produces the smallest standard deviation result.

The equations below are used in validating and comparing the model;

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{sim} - Y_{pred}\right)^2}{\sum_{i=1}^{n}\left(Y_{pred} - Y_{sim}\right)^2} \tag{1}$$

$$AAPE = \frac{1}{N}\sum_{i=1}^{n}\left(\sqrt{\left(\frac{Y_{sim} - Y_{pred}}{Y_{sim}}\right)^2}\right) \times 100 \tag{2}$$

$$AAPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(\frac{Y_{sim}-Y_{pred}}{Y_{sim}}\right)^2\right)} \quad (3)$$

The Box-Cox plot for power-law transformations can also be used to find the appropriate transformation function for a set of input and output data. An equation or proxy model for forecasting the time and recovery factor at water breakthrough was built from the suggested transformation function after it had been chosen based on the mentioned criteria. To ascertain the model's performance within the experimental design space, the model was validated.

Table 2: ANOVA for reduced 2F1 Model

Source	Sum of Squares	df	Mean Square	F-value	P-value	
Model	6.8200	5	1.3600	52.07	0.0010	significant
A-X1	0.5557	1	0.5557	21.21	0.0100	
B-X2	0.1520	1	0.5120	19.54	0.0115	
C-X3	2.1300	1	2.1300	81.14	0.0008	
D-X4	0.7653	1	0.7653	24.21	0.0057	
AB	0.5013	1	0.5013	19.13	0.0119	
Residual	0.1048	4	0.0262			
Cor Total	6.9300	9				

Factor coding is **Coded**

Sum of squares is **Type III – Partial**

The model is suggested to be significant by the Model F-value of 52.07. An F-value this large might happen owing to noise just 0.10% of the time.

Model terms are considered significant when the P-value is less than 0.0500. In this instance, key model terms include A, B, C, D, and AB. Model terms are not significant if the value is higher than 0.1000. Model reduction may enhance the model if there are numerous unnecessary terms (excluding those needed to support hierarchy).

4. Results and Discussion

4.1 Results

A Model Equation is developed using the fit statistics to balance and validate the model for a proper fitting and high predictability.

1. Fit Statistics

Table 3: Fit Statistics run obtained in the model

Std. Dev.	0.1619	**R^2**	0.9849
Mean	3.12	**Adjusted R^2**	0.9660
C.V. %	5.19	**Predicted R^2**	0.7801
		Adeq Precision	22.0864

2. Coefficients in terms of Coded Factors

Table 4: Coefficient in terms of coded factors

Factor	**Coefficient Estimate**	**Df**	**Standard Error**	**95% CI Low**	**95% CI High**	**VIF**
Intercept	131.12	1	27.64	54.36	207.87	
A-X1	35.89	1	7.79	14.25	57.53	1438.87
B-X2	56.49	1	12.78	21.01	91.97	942.14
C-X3	0.4535	1	0.0503	0.3137	0.5933	1.94
D-X4	-0.7776	1	0.1439	-1.18	-0.3782	3.11
AB	15.78	1	3.61	5.76	25.79	1341.26

3. Final Equations in terms of Coded Factors and Actual Factors

$$\sqrt{WC} = 131.119 + 35.8931X_1 + 56.4901X_2 + 0.453531X_3 - 0.77645X_4 + 15.7786X_5 \quad (4)$$

$$\sqrt{WC} = 2.75992 - 0.0615752X_1 - 0.090977X_2 + 0.453531X_3 - 0.025915X_4 + 0.07012X_5 \quad (5)$$

4. Power Transformation Report

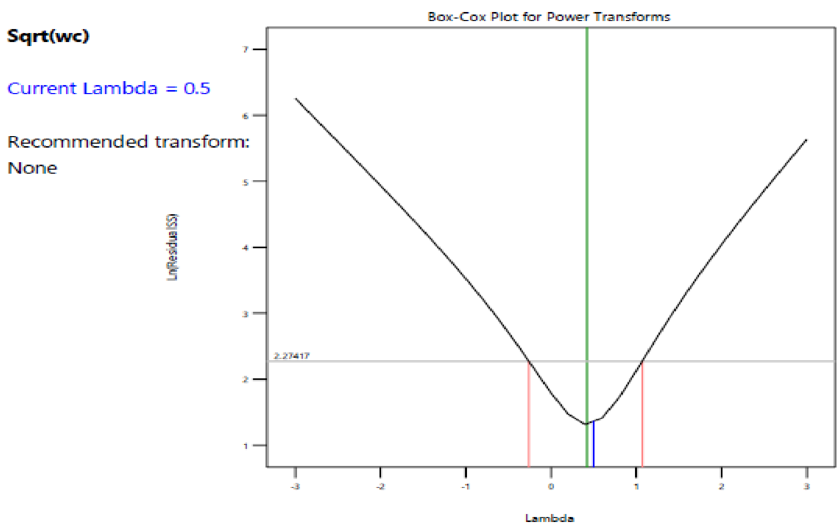

Fig. 3: Wax Content plot for Power Transformation

5. Comparison Report

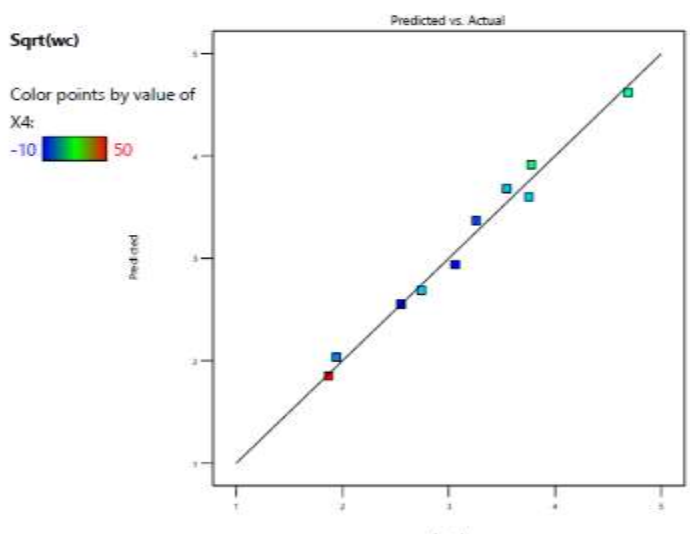

Fig. 4: Graph of Predicted vs Actual Value

Table 5: Cumulative report of the actual and predicted value

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Influence on Fitted Value (DFFITS)
1	1.87	1.85	0.0233	0.97	0.826	0.785	4.433(1)
2	3.55	3.68	-0.1281	0.829	-1.913	-5.682	-12.509(1)
3	1.94	2.03	-0.0865	0.38	-0.679	-0.625	-0.489
4	4.69	4.62	0.0748	0.708	0.855	0.819	1.275
5	2.55	2.55	0.004	0.859	0.065	0.057	0.14
6	2.74	2.68	0.0596	0.247	0.424	0.376	0.215
7	3.26	3.37	-0.1052	0.509	-0.928	-0.907	-0.924
8	3.06	2.94	0.1282	0.514	1.136	1.195	1.229
9	3.76	3.6	0.162	0.463	1.366	1.62	1.504
10	3.78	3.91	-0.1322	0.521	-1.18	-1.266	-1.322

Table 6: Show the results of the errors obtain in comparison of the model

Run Order	Actual (x-axis)	Predicted (y-axis)	R^2	AAPE	RMSE
1	1.87	1.85	0.0004	-1.27	1.6129
2	3.55	3.68	0.0169	0.56	0.3136
3	1.94	2.03	0.0081	-1.09	1.1881
4	4.69	4.62	0.0049	1.5	2.25
5	2.55	2.55	0	-0.57	0.3249
6	2.74	2.68	0.0036	-0.44	0.1936
7	3.26	3.37	0.0121	0.25	0.0625
8	3.06	2.94	0.0144	-0.18	0.0324
9	3.76	3.6	0.0256	0.48	0.2304
10	3.78	3.91	0.0169	0.79	0.6241
	3.12		0.1029		6.8325
					0.98493963

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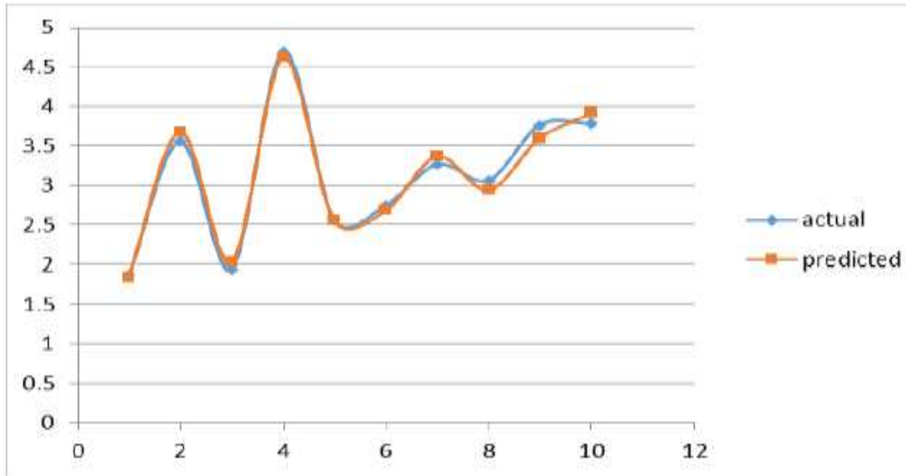

Fig 5: Actual value Vs predicted validation

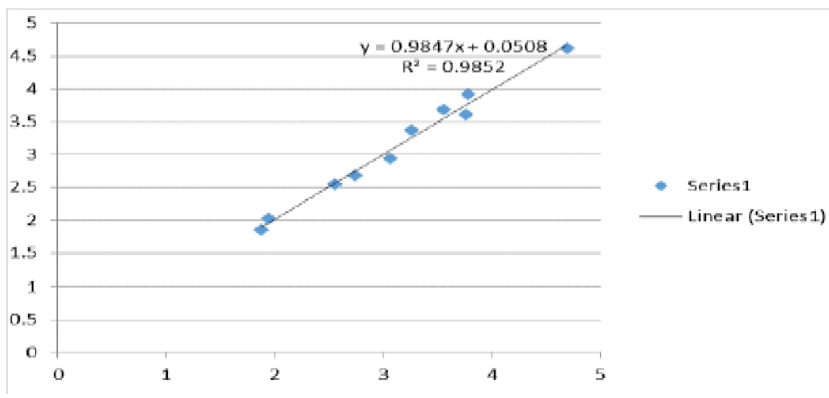

Fig 6: Plot of actual Vs predicted value after validation

4.2 Discussion

1. Fit Statistics

From table 3, the **Predicted R^2** of 0.7801 is in reasonable agreement with the **Adjusted R^2** of 0.9660; i.e. the difference is less than 0.2. **Adeq Precision** measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 22.086 indicates an adequate signal. This model can be used to navigate the design space.

2. Coefficients in terms of Coded Factors

The coefficient estimate shows the anticipated change in response for each unit change in factor value when the other factors are held constant as shown in table 4. The average overall reaction across all runs constitutes the intercept in an orthogonal design. Depending on the parameters for the factors, the coefficients are adjustments made to that average. The VIFs are 1 when the factors are orthogonal; VIFs higher than 1 imply multi-collinearity, and the higher the VIF, the more severe the correlation of the components is. VIFs under 10 are typically acceptable.

3. Final Equations (Coded and Actual Factors)

Eqn. 4 shows that, it is possible to anticipate the reaction for specific levels of each element using the equation expressed in terms of coded factors. By default, the factors' high levels are coded as +1 and their low levels as -1. By contrasting the factor coefficients, the coded equation can be used to determine the relative importance of the elements.

While making predictions about the response for specific levels of each element can be done using the equation expressed in terms of actual factors as shown in eqn. 5. Here, the levels for each factor should be stated in their original units. Because the coefficients are scaled to account for the units of each element and the intercept is not at the center of the design space, this equation should not be used to estimate the relative importance of each factor.

4. Selection of Transformation Function

To identify which transformation function provides the highest value, the smallest difference between Adjusted and Predicted, the highest value of Adeq Precision, and the lowest standard deviation, various transformation functions were tested using a modified quadratic regression model. A comparison of several wax content transformation functions is shown in Table 3. Table 5's findings demonstrate that, in contrast to other transformation functions, Natural Log and JYZ both satisfy the given criteria. However, the JYZ" was chosen since it produced a lower standard deviation for RS.

The Box-Cox Plot for Power-law transformations was generated for the wax content as shown in Table 3. These plots gave recommendations of the best transformation function for the response using the modified quadratic model

Overall, the results from the model developed was validated using the Excel Sheet as shown in table 6. Results from figures 5 and 6 show that the actual and predicted values for the response obtained which are in close agreement with each other depicted by coefficients of determination of 0.9852 for wax content. Also, the percentage errors of each data point for both cases were found to be less than 1%. This implies that the developed models are accurate and reliable

5. Conclusion and Recommendations

5.1 Conclusion

Using Design Expert of tests, a reservoir crude oil model for predicting wax content was created. This numerical model was developed using data from experimental parameters and a transformation function that satisfies certain requirements or is suggested by the Box-Cox plot of power-law transformations.

The models in this study demonstrated the connection between density, pour point, asphaltenes, resin, and viscosity. Comparing predicted and actual results for the two situations allowed the models to be validated and found to be consistent. Since a little percentage inaccuracy was seen in every case, the actual and predicted results likewise agreed well with one another. This demonstrates the capability of the created model to navigate the crude samples and forecast wax content.

5.2 Recommendations

Many different kinds of crude oil contain dissolved waxes that, given the right climatic conditions, can precipitate and deposit, reducing production rates, clogging machinery, stopping production, and causing other issues. Thus, prevention of wax deposition must take part and remove properly, if need be, immediately it formed, making this study more advantageous to the oil producing company.

In this study, it is also necessary to take into account a reservoir model that will calculate the WAT and wax content along with other parameters related to highly heterogeneous wax. This will help the production staff overcome the difficulties of wax clogging the pipe flow and take preventive action to minimize damage to production equipment.

NOMENCLATURES/ABBREVIATION

ANOVA	Analysis of Variance
R2	Coefficient of Determination
COP	Cumulative Oil Produced
X1	Resin
X2	Asphaltene
X3	Pour point
X4	Density
X5	Viscosity
Y_{sim}	Actual Values
Y_{pred}	Predicted Values

n	Number of Simulation runs
AAPE	Average Absolute Percentage Error
RMSE	Root Mean Square Error
BBD	Box Behnken Design

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