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Optimal Annular Frictional Loss Modelling In Constant Bottom Hole Pressure Variant of Managed Pressure Drilling

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ABSTRACT

Managed pressure drilling (MPD) as a drilling system is the product of elevated cost of Non Productive Time(NPT) caused by the closeness of formation pore pressure and fracture pressure which is regular in deep off shore, off shore, high pressure and high temperature and depleted reservoirs as well as some onshore drilling operations. Proper computation of AFL in constant bottom-hole pressure CBHP variation of MPD was studied in this work. An empirical model was derived to efficiently estimate the AFL value that will form part of the BHP term required to maintain the BHP constant between the pore pressure and the fracture pressure. The generated empirical AFL correlation was built using response surface methodology (RSM) where annular friction loss as the response variable was subjected to well depth(D), annular mud weight (MW), annular flow rate (Q_o) and annular hydraulic diameter (D_o) as predictor variables. The surface responses were modelled with and without variable interactions to minimise model errors, based on goodness of fit criteria, surface response modelled with predictor variable interaction fitted field data better with a correlation coefficient of 0.998. Model verification was performed to confirm the prediction capability and compared with existing rheological model (Power law and API RP 13D). The AFL correlation developed performed better in the estimation of AFL and Optimisation Study on the Proposed AFL Model was carried out From the result obtained, the degree of responsiveness of AFL to the predictors is in the order M_w > Q_o > D_a > D.

Index Terms – Managed Pressure Drilling, Non Productive Time, Annular Flow Rat, Snnular Gydraulic Diameter, Annular Friction Loss.

1. INTRODUCTION

The application of science and engineering to drill a hole from the surface to hit a geologic target in the subsurface has encountered several difficulties. In an attempt to overcome these difficulties, drilling operations have gone round a lot of evolutionary stages and numerous methods have been engaged by practicing drilling engineers in a bid to profitably drill formations at diverse pressures. For many years now, underbalanced, overbalanced and balanced drilling techniques have been discussed and the resolution of which is suitable and for which situation have depended on many factors, some of which are expertise (or technical knowhow), down-hole pressure limits, health safety and environment constraints, formation damages possibilities etc, (Elliot *et al*.,2011).

However, managed pressure drilling (MPD) is an emerging drilling technology used primarily to drill wells that are neither amenable to overbalanced nor underbalanced drilling method (Hannegan, 2005). The primary objective of MPD is to mitigate drilling related challenges, thereby optimising drilling processes by decreasing non-productive time (NPT) (Malloy *et al.*, 2009).The main idea behind MPD is that it violates the basic conventional assumptions of zero surface pressures and an open mud circulation system, yet the MPD concept has been exploited and employed in handling difficult wells with commendable efficiency.

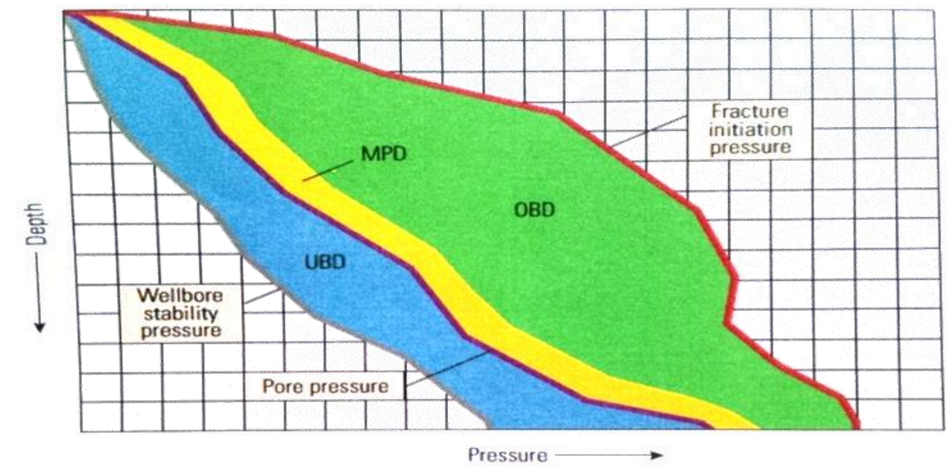

Figure 1 Managing Pressure Profiles (Elliot et al.,2011)

The advantage of MPD in addressing NPT and its application to marine (offshore) environment will prove valuable in reducing the associated cost of oil exploration (Aadnoy *et al.*, 2009).Depending on the nature of the formation, the down-hole conditions and the reservations for health and safety, Hannegan (2015) stated the different variations of MPD as follows:

i. Constant Bottom-hole Pressure (CBHP)

ii. Pressurised Mud Cap Drilling (PMCD)

iii. Dual Gradient (DG)

iv. Returns Flow Control (HSE) Variation.

The above MPD variations may be implemented alone or in combination. However priority will be given to the constant Bottom-hole Pressure (CBHP) variation as it is the principal focus of this research.

Constant Bottom-hole Pressure (CBHP) MPD

Tercan (2010) described the CBHP MPD as a collection of techniques whose primary objective is to maintain a constant bottom-hole pressure which must be within a predetermined drilling window usually defined by pore pressure and fracture gradient. According to Tercan (2010) CBHP can be achieved using any of the following techniques:

- CBHP using Surface Back Pressure Application
- CBHP by Friction Management
- CBHP by Continuous Circulation

CBHP Using Surface Back Pressure Application

As previously mentioned, this is the technique adopted for this research work. CBHP describes all the actions taken to correct or reduce the effect of circulating friction loss or Equivalent Circulating Density (ECD) in an effort to stay within the limits imposed by the formation pressure and fracture pressure.

MPD solves the problem with CBHP because effective BHP (equivalent mud weight, EMW) is under precise control at all times. The relationship between Bottom-hole Pressure (BHP) and Annular Friction Loss (AFL), Surface Back Pressure (SBP) and Hydrostatic Pressure (HP) for a CBHP MPD is as follows

$$:BHP = HP + AFL + SBP \qquad (1.)$$

From equation 1 above, AFL term will be the major focus in this research work.

Down-hole Measurements

Measurement While Drilling (MWD) tool, the Pressure While Drilling (PWD) tool both of which constitutes part of the bottom-hole assembly (BHA) and the coriolis flow-meter which is a surface equipment was used to obtain the values in Table 1 below from fields in Niger Delta.

	Surface Data	Down-hole Data
Mud Data	I. Pit volume II. Mud temperature III. Mud weight IV. Flow rate	N/A
Geologic Data	Cuttings analysis	i. Density ii. Porosity iii. Resistivity iv. Gamma
Well Data	i. Temperature ii. pressure iii. Gas measurement	Temperature Pressure
Drilling Mechanics	i. RPM ii. Weight on bit iii. Torque iv. Bending Moment v. Rotary torque vi. Hook load vii. ROP	RPM Weight on bit Torque on bit Bending moment Down-hole vibration

Table 1 Summary of Types of Drilling Operation Data during MPD

Statistical Data Treatment: Time Weighted Averaging (TWA)

The real time data obtained from the MPD operation were displayed in terms of properties measured in micro-seconds and data smoothened for easier processing and clear appreciation during analysis. Arithmetic time-weighted averaging was performed on the real time data using Microsoft excel package. With this, the data set were properly tailored by removing misleading trends; hence

$$X_k = \frac{\sum_i^k x_i}{h}, \quad (i,k) = \{(1 + h(n-1), nh)\} \text{ for } n \in \text{ I} \qquad (2)$$

Where h= desired stepsize, X_i =Average property after the k^{th} finite time interval, X_i = Drilling property measured in real time.

This treated data set was afterwards subjected to modelling.

2. MODELLING PROCEDURE

The model was generated using the surface response method. The model generated is a non linear model of 2^{nd} Order, hence quadratic, with predictor variables interaction where one predictor variable can interact (multiply) another predictor variable. non-linear modelling could have being used instead of modelling with variable interaction, but a more encompassing term ('with variable interaction') was used to incorporate both the usual non-linear terms which is called SELF INTERACTION and other kinds of non-linear terms which is called OTHER INTERACTION. The modelling will comprise three terms basically, the linear terms, the conventional non-linear terms which is referred to as self-interaction terms and the other interaction terms. The intercept term has been eliminated by the assumption made for the modelling which states that the annular friction loss should be zero when all the predictor variables are zero, because at zero depth, without drilling mud (there is no mud-weight). The other interaction terms are generated when one predictor variable is allowed to interact (multiply) with another predictor variable. Since there are four predictor variables and the predictor variable interactions is restricted to not more than two predictor variables at a time, which implies one predictor variable can interact with only but one other predictor variable at a time, to avoid variable repetitions (i.e

$x_1x_2 = x_2x_1$), four predictor variables will interact, two at a time. This is a combination problem, hence the number of other interaction terms in the equation will be $4C_2$ which gives 6 other interaction terms.

Hence the equation is represented mathematically as:

$$F_L = b_1D + b_2M_{wo} + b_3Q_O + b_4D_A + b_5D^2 + b_6M_{wo}^2 + b_7Q_O^2 + b_8D_A^2 + b_9DM_{wo} + b_{10}DQ_O + b_{11}DD_A + b_{12}M_{wo}Q_O + b_{13}M_{wo}D_A + b_{14}Q_OD_A \tag{3}$$

In the equation above, the terms with coefficients b_1 *to* b_4 represent the linear terms of the equation. The terms with coefficients b_5 *to* b_8 represent the conventional non-linear terms which in this modelling it is referred to as the self interaction terms, and the remaining six terms with coefficients b_9 *to* b_{14} represents the other interaction terms. To better appreciate and vividly illustrate the categorisation, below is a condensed form of this equation written using conventional mathematical notation Linear.

linear terms

Conventional Non-linear terms (self interaction term)

Other Interaction terms

$$F_L = \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{i+k} x_i^2 + \sum_{i=1}^{k-2} b_{2i+j+k+1} x_i x_j + b_{2k+kC_2} x_{k-1} (\$) \tag{4}$$

The above equation helps present the modelled equation in the three basic terms which was outlined earlier to be the linear terms, self-interaction terms and other interaction terms. In the above equation, the subscript j appears only in the other interaction term. This interaction must be such that one predictor variable can interact once and only once with another predictor variable to avoid repetition of terms, that is, x_1x_3 is the same with x_3x_1 and should not be repeated twice. Having generated the general format of the equation, the values of the unknowns was established such that a model with the only unknown being the input parameters is obtained. The value of these input parameters can be read and the AFL calculated. There are fourteen (14) unknowns, the b(s) in the model. The unknowns can be obtained through the following steps:

1. Generating a set of linear equations called the normal equations.
2. Representing the generated normal equations in matrix format.
3. Solving for the unknown using any of the techniques for solving multiple linear equation

A set of Linear Equations called the Normal Equations are represented in matrix format by the equation below

$$bX = Y \tag{5}$$

Where b = matrix of unknown, X = matrix of coefficients. Y = matrix of constants

Representing the generated equations above using matrix notations as shown below.

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \\ b_6 \\ b_7 \\ b_8 \\ b_9 \\ b_{10} \\ b_{11} \\ b_{12} \\ b_{13} \\ b_{14} \end{bmatrix} \begin{bmatrix} 5.35E6 & 5.77E3 & 3.37E3 & 5.44E3 & 7.15E9 & 8.43E3 & 2.33E5 & 8.07E3 & 7.74E6 & 4.06E7 & 7.22E6 & 4.39E4 & 7.62E3 & 4.12E4 \\ 7.15E9 & 7.74E6 & 4.06E7 & 7.22E6 & 9.58E13 & 1.13E8 & 3.11E9 & 1.66E8 & 1.04E11 & 5.43E11 & 9.59E10 & 5.88E8 & 1.01E8 & 5.46E8 \\ 7.74E6 & 8.43E3 & 4.40E4 & 7.61E3 & 1.04E11 & 1.24E5 & 3.37E6 & 1.10E5 & 1.13E8 & 5.88E8 & 1.01E8 & 6.43E5 & 1.08E5 & 5.79E5 \\ 4.06E7 & 4.39E4 & 2.33E5 & 4.12E4 & 5.43E11 & 6.42E5 & 1.8E7 & 6.05E5 & 5.88E8 & 3.11E9 & 5.46E8 & 3.37E6 & 5.79E5 & 3.16E6 \\ 7.22E6 & 7.61E3 & 4.12E4 & 8.07E3 & 9.59E10 & 1.08E5 & 3.16E6 & 1.28E5 & 1.01E8 & 5.46E8 & 1.06E8 & 5.79E5 & 1.1E5 & 6.05E5 \\ 9.6E13 & 1.04E11 & 5.43E11 & 9.59E10 & 1.28E18 & 5.3E12 & 4.16E13 & 1.4E12 & 1.39E15 & 7.27E15 & 1.27E15 & 7.9E12 & 1.35E12 & 7.26E12 \\ 1.13E8 & 1.25E5 & 6.42E5 & 1.08E5 & 5.3E12 & 1.86E6 & 4.9E7 & 1.12E5 & 1.68E9 & 8.63E9 & 1.44E9 & 9.49E6 & 1.55E6 & 8.24E6 \\ 3.11E9 & 3.37E6 & 1.8E7 & 3.16E6 & 4.16E13 & 4.9E7 & 1.39E9 & 4.46E7 & 4.51E10 & 2.39E11 & 4.19E10 & 2.6E8 & 4.55E7 & 2.45E8 \\ 1.66E8 & 1.1E5 & 6.05E5 & 1.28E5 & 1.4E12 & 1.12E5 & 4.46E7 & 2.12E6 & 1.45E9 & 1.99E9 & 1.68E9 & 8.33E6 & 1.7E6 & 9.44E6 \\ 1E11 & 1.13E8 & 5.88E8 & 1E8 & 1.39E15 & 1.68E9 & 4.5E10 & 1.45E9 & 5.3E12 & 7.9E12 & 1.35E12 & 7.9E12 & 1.44E9 & 7.7E9 \\ 5.43E11 & 5.88E8 & 3.1E9 & 5.46E8 & 7.27E15 & 8.63E9 & 2.39E11 & 7.99E9 & 7.9E12 & 4.6E13 & 7.26E12 & 4.51E10 & 7.7E9 & 4.2E10 \\ 9.59E10 & 1E8 & 5.46E8 & 1.66E8 & 1.27E15 & 1.44E9 & 4.2E10 & 1.68E9 & 1.35E12 & 7.26E12 & 1.41E12 & 7.7E9 & 1.45E9 & 8E9 \\ 5.88E8 & 6.42E5 & 3.37E6 & 5.79E5 & 7.9E12 & 9.5E6 & 2.6E8 & 8.33E6 & 8.63E9 & 4.51E10 & 7.7E9 & 4.9E7 & 8E3 & 4.55E7 \\ 1E8 & 1E5 & 5.8E5 & 1.1E5 & 1.35E12 & 1.55E6 & 4.55E7 & 1.7E6 & 1.44E9 & 7.7E9 & 1.45E9 & 8.24E6 & 1.16E5 & 8.33E6 \end{bmatrix} = \begin{bmatrix} 1.31E4 \\ 1.78E8 \\ 2.07E5 \\ 9.84E5 \\ 1.36E5 \\ 2.45E12 \\ 3.31E6 \\ 7.45E7 \\ 1.56E6 \\ 2.48E9 \\ 1.35E10 \\ 1.85E9 \\ 1.5E7 \\ 2.12E6 \end{bmatrix}$$

Solving for the value of the unknowns using any desired multiple linear equations technique, probably Gaussian elimination or Gauss Jordan row reduction, the following values for the unknowns are obtained

$$b_1 = 7.22;\ b_2 = -5791;\ b_3 = 85.4\ ;\ b_4 = -1379\ ;\ b_5 = -0.000695\ ;\ b_6 = -60\ ;$$
$$b_7 = -0.3591;\ b_8 = 0;\ b_9 = 0.621;\ b_{10} = 0;\ b_{11} = 0.1581;\ b_{12} = 0;\ b_{13} = -43.33;$$
$$b_{14} = -1.676;$$

Substituting these values into equation (3) the equation becomes:

$$F_{\mathbf{L}} = 7.22D - 5791M_{wo} + 85.4Q_O - 1379D_A - 0.000695D^2 - 60M_{wo}^2 - 0.3591Q_O^2 + 0D_A^2 + 0.621DM_{wo} + 0DQ_O + 0.1581DD_A + 0M_{wo}Q_O - 43.33M_{wo}D_A - 1.676Q_OD_A \quad (6)$$

Removing the terms multiplied by zero in equation (6) above,

$$F_{\mathbf{L}} = 7.22D - 5791M_{wo} + 85.4Q_O - 1379D_A - 0.000695D^2 - 60M_{wo}^2 - 0.3591Q_O^2 + 0.621DM_{wo} + 0.1581DD_A - 43.33M_{wo}D_A - 1.676Q_OD_A \quad (7)$$

Refactoring the above equation, the final equation is given as:

$$AFL = D(7.22 - 0.000695D + 0.621M_w) + q_o(85.4 - 0.3591q_o - 1.676d_a) + d_a(0.1581D - 1379) - M_w(5791 + 60M_w + 43.33d_a)$$

Goodness of Fit

The accuracy and constancy of the regression model is ascertained by method of goodness of fit. The accuracy criteria used for this work were coefficient of correlation (R) and standard error (SE). If R = 1, all plotted data aligns to form a smooth curve, if R < 1, then some of the plotted points are out of the curve, but if R = 0, no correlation and a case of highly scattered data is evident.

Empirical Estimation of Coefficient of Determination (R)

From the models generated by surface response methodology (SRM) for drilling operations data generated by method of managed pressure drilling technique (MPD) in Hilong-27 rig platform, the coefficient of determination (or Correlation), R was estimated using the statistical formula given as.

$$R^2 = P_{xy} = \frac{N(\sum xy) - (\sum x \sum y)}{\sqrt{N(\sum x^2) - (\sum x)^2 (N \sum y^2) - (\sum y)^2}} \quad (8)$$

Where X = experimental value .Y = predicted value .N = number of sampling points

Model Verification and Validation

The proposed annular friction pressure model was verified by comparing its predictions with real time data. The correlation coefficient, standard deviation and other model accuracy indicators were considered. Validation of the proposed model was performed by comparing the model with pre-existing rheological models such as Power Law and API 13D models which are industrially recommended. Graphical plot was generated to better illustrate the comparisons.

Empirical Modelling of Drilling Operations Data

The empirical relationships for drilling operations data were established using method of surface response methodology (SRM), for which bottom-hole pressure, friction loss and apparent viscosity were considered as response variables. The following empirical models were developed as shown in tables .2 and 3.

S/N	**Model Expression** (Without Variable Interaction)	**Correlation Coefficient (R)**	**Standard Error (S)**
1	$P_{BH} = F_L + P_H + P_{SB}$	1.000	0.000
2	$F_L = -903 - 0.35D + 2002M_{wo} - 0.4464Q_0 + 35.6D_A$	0.935	86.346

3	$\mu_{APP} = 53.08 + 0.710\mu_P + 0.00899F_L - 0.329Y_P - 0.1196T_{BH}$	0.928	2.280

Table 2 Surface Response Models without Variable Interaction

S/N	**Model Expressions** **(With Variable Interaction)**	**Correlation Coefficient** **(R)**	**Standard Error(S)**
1	$P_{BH} = F_L + P_H + P_{SB}$	1.000	0.000
2	$AFL = D(7.22 - 0.000695D + 0.621M_w) + q_o(85.4 - 0.3591q_o - 1.676d_a) + d_a(0.1581D - 1379) - M_w(5791 + 60M_w + 43.33d_a)$	0.998	16.506
3	$\mu_{APP} = 41.0 + 2.64\mu_P - 0.0142F_L + 1.15Y_P - 0.470T_{BH} - 0.1434\mu_P^2 - 8 * 10^{-6}F_L^2 + 0.265{Y_P}^2 + 4.35 * 10^{-3}{T_{BH}}^2 - 4.42 * 10^{-3}\mu_P F_L - 0.401\mu_P Y_P - 0.0288\mu_P T_{BH} + 5.64 * 10^{-3}F_L Y_P + 5.67 * 10^{-4}F_L T_{BH} + 0.0256Y_P T_{BH}$	0.957	2.088

Table 3 Surface Response Models with Variable Interactions

The adopted modelling technique allowed for modelling of the response variable with and without predictor variables interactions. The performances of the models were evaluated based on their goodness of fit results.

Table 2 shows the goodness of fit output for the modelling without variable interaction. The coefficient of correlation (R) for the annular friction loss (AFL) model without variable interaction was estimated to be 0.935 while the standard error value was 86.4. Table 3 displays the model performance for models developed with variable interactions. The goodness of fit for the annular friction loss (AFL) model shows a coefficient of correlation (R) of 0.998 with a standard error value of 16.5 which is within the engineering practice acceptance tolerance.

Comparatively, although both models appear to fit the data satisfactorily judging from their goodness of fit criteria, the models developed with variable interactions each had a better goodness of fit as seen in Tables 2 and 3. Therefore the AFL model generated based on variable interactions was deemed necessary for further considerations.

Model Verification with Actual Data

The most accurate generated AFL model (with variable interaction) was verified by comparing its estimations with actual data. From figure 2, the plot shown below is a verification of the generated model by the developed software. The verification is achieved by plotting the model's predicted frictional pressure with the actual pressure obtained from the rig data for several depths. The blue line indicates the actual frictional pressure, while the orange line dictates the model's predicted pressure; the model performance while making a connection and during circulation as indicated by the orange coloured line on the plot below is shown to be almost exact with measured AFL indicated by the blue coloured line. This justifies the goodness of fit values.

A good correlation of the model's prediction with actual data was observed, even at the depth of 13380 ft, a sudden spike in pressure which is due to the increased mud weight and reduced hydraulic diameter was caused by the drilling of a new hole section, precisely the 8.5 inch hole. The model correlated well with the actual data. Furthermore at depths of 13880 [ft] up to 14040 [ft], there are pressure fluctuations which indicate abrupt variations in the annular frictional pressure; here, the model was observed to predict with a reasonable accuracy the pressure spikes and correlated well with actual data. The implication of this is that the model would be able to achieve constant bottom-hole pressure at all points. This is because the BHP has a strong dependence on AFL as implied by the BHP equation. Such increase or decrease in AFL will create a corresponding change in the BHP, this is the major reasons for the impossibility of achieving constant BHP. The other component, HP is virtually equivalent to the mud column and density mud which can be static for a section, hence the AFL is the changing variable which brings variations in the BHP. The other term of the BHP equation which is the SBP is strongly dependent on the AFL; as the AFL has to be determined and the SBP reacts to cancel out the actions of the AFL(pressure surprises), hence accuracy in predicting the AFL infers that accurate SBP can be applied to counter the effect of the variable AFL. This is the working principle of achieving a constant BHP. Hence the accuracy of the model in regions of pressure surprises that accurate SBP can be applied and as such constant BHP will be achieved at all times.

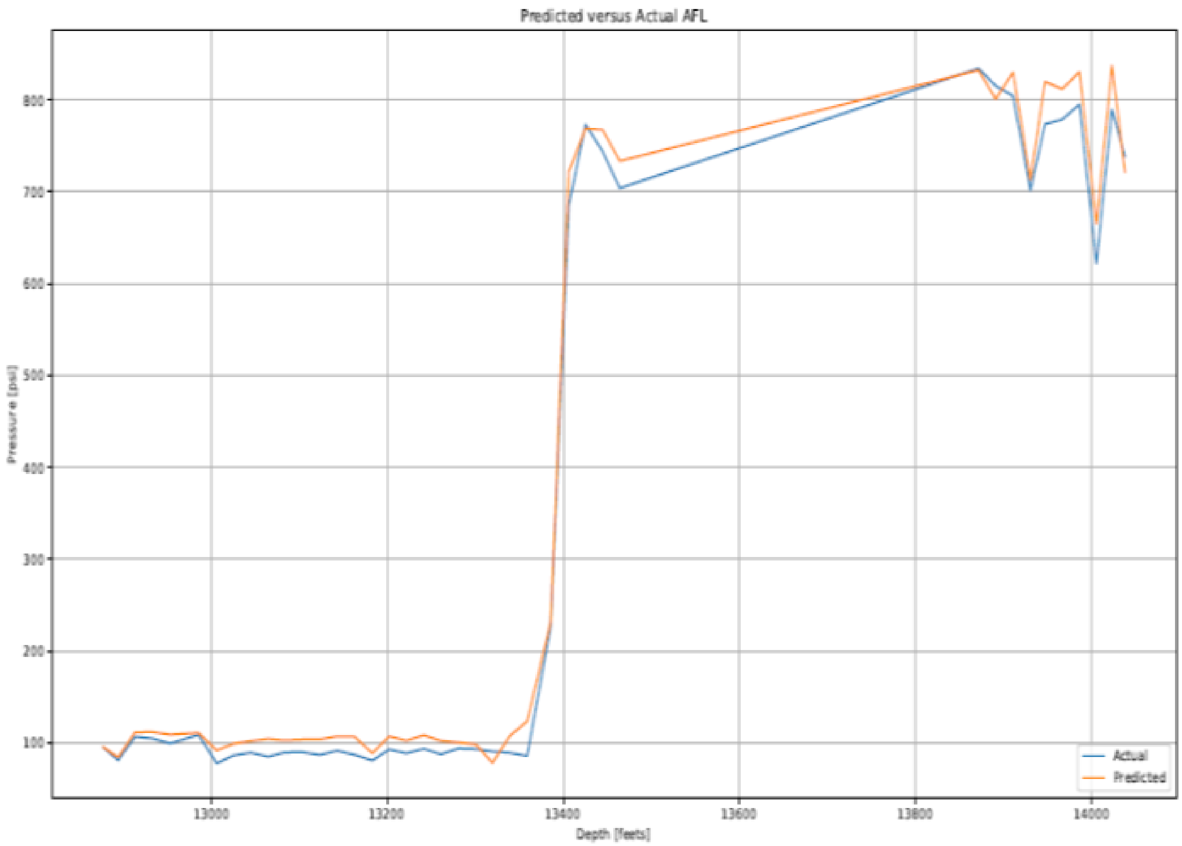

Figure 2 A Plot of Measured vs Predicted AFL

Model Verification with Existing Rheological Models

The proposed model was compared with two pre-existing industrial models namely the Power law model and API 13D Recommended Practice model. The choice of the power law model for the verification follows from the study findings of Oriji and Marcus (2017) and Dermidal and Cunha (2007), who independently carried out a comparative analysis using three rheological models to both compute the AFL and predict the SBP, they concluded that the Power law model was best suited for AFL computation and the API RP-13D model was selected because it is the recommended practice model by the American Petroleum Institute (API) regarding drilling issues. More-so it is a more recent model derived by modifying the power law equation.

From the plot that follows, the comparison vividly shows that the proposed model fitted better and estimates the AFL most accurately compared with the pre-existing rheological models. Table 4.2 shows the coefficient of correlation for the respective models.

S/N	MODELS	R
1	Proposed Model	0.998
2	API RP 13D	0.376
3	Power Law	0.307

Table 4 Model Comparison

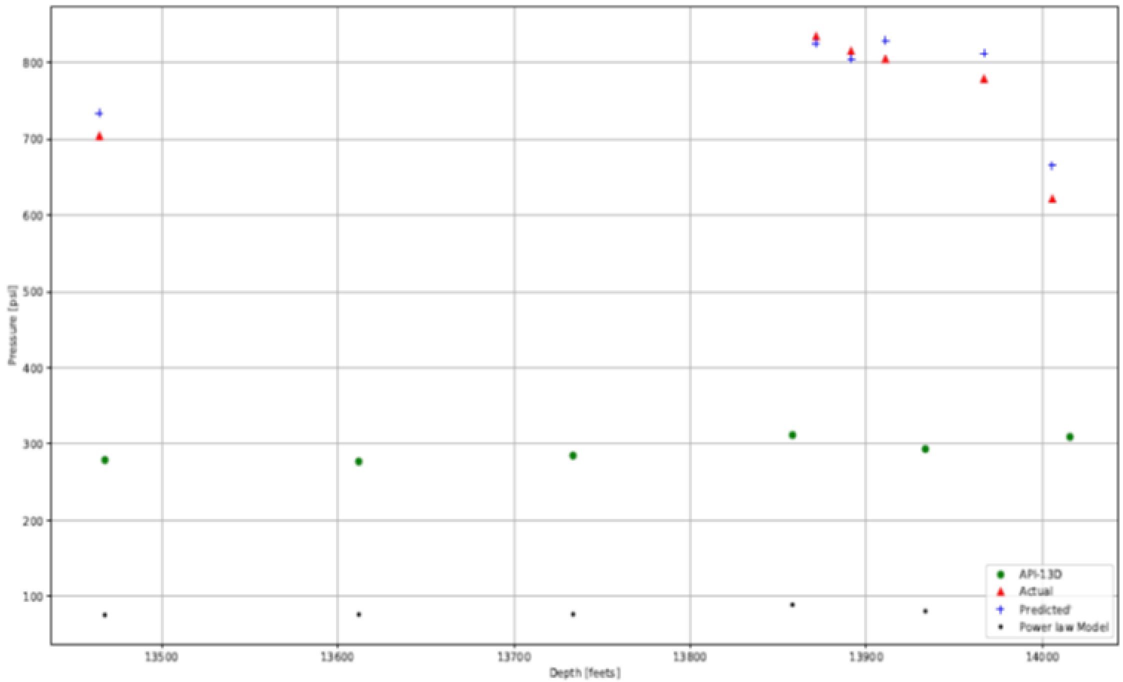

Figure 3 Comparison between Proposed and Existing Models

The plot shown above is a validation of the model, by comparing the model with other standard rheological models with the actual field data; the green circular markers indicate the API- recommended practice model, the red triangular markers indicate the actual pressure from the rig, the blue cross marker indicates the proposed model's prediction for this study, and the other dark circular marker represents the power law rheological model. Mathematically, error is given as the actual value less estimated value, thus the deviations (closeness or distance) of similar points between any model and the actual data indicate the error in measurement. Hence the deviations between point 1 of the actual pressure data and point 1 of any other model is the error of that model's first measurement, hence deviation or distance between point 1 of actual pressure data and point 1 of the power law model, is the error in the power law's first measurement; the sum of all the errors in all six points indicate the total error in the model. This dictates that the closer the model points (the shorter the distance) is to the corresponding actual data points, the more accurate the model.

Beginning with the API RP-13D Model, at a depth of 13400 ft, the Model records a pressure of 280 psi when the actual reads 700 psi, an error of 60% with a numerical value of 420 psi, about 0.6ppg equivalent, the implication of this in an MPD candidate well whose operating window may not exceed $\pm 1\ ppg$ pressure equivalent is that we most likely would exceed the margins and suffer the due unfavourable effects.

For the power law model, it estimates a value of around 70 psi, when the actual reads 700 psi at a depth of 13400 ft, a pressure error of about 90%, in numerical value, 630 psi equivalent to 0.9ppg, again this is unfavourable for MPD candidate wells because of the close drill margin, however for the proposed model, it records 721 psi when the actual reads 700 psi, an error of 21 psi, equivalent to 0.03 ppg, which is very tolerable for MPD candidate wells and thus the model is suitable for MPD wells relative to pre-existing correlations.

Hence based on the closeness, with the actual data points as the reference or datum, the model has the shortest distance depicting hat it is the most accurate, trailing the proposed model is the API- recommended practice model and at the bottom of the graph with the furthest distance is the power law model.

Optimisation Study on the Proposed AFL Model

The proposed model was further analysed by subjecting it to optimisation analysis in order to ascertain the redundant variables as different from the abundant variables, as regards the measure of impact a slight change in the predictor variables can have on the response variable as well the optimal variable settings that ensure minimal annular friction losses. The results of the optimisation study on the proposed model are shown in Tables 4 to 8 and figures 4 to 6 for different hole sections as follows;

Response Optimization: AFL for 12-1/2 inch Hole Section

Response	Goal	Lower	Target	Upper
AFL (psi)	Target	77.941	334.802	834.476

Table 4 Optimization Parameters

Response Prediction of AFL

S/N	Depth, D(Ft)	Qo (Cuft/Sec)	Da(Inch)	Mw(Ppg)	Composite Fit	Desirability
1	12877.3	80.465	22.6374	11.3143	334.802	1

Table 5 Optimal Variable Settings

Response	Fit	SE Fit	95% CI	95% PI
AFL	334.8	83.2	(164.8, 504.8)	(160.6, 509.0)

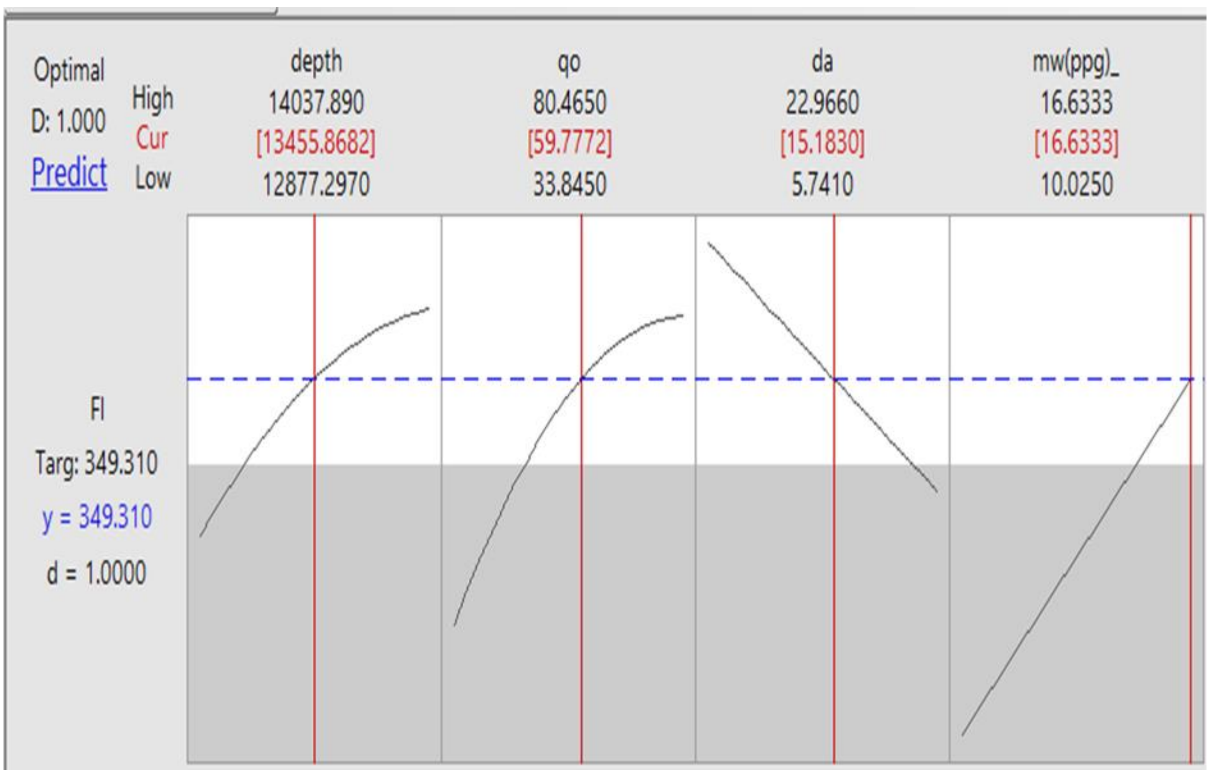

Figure 4 Optimization Plot of AFL at 12-1/2 Inch Hole Section

Table 4 shows the optimization parameters, the optimization objective (which is to ascertain the variable settings that are required to maintain a target AFL) and the maximum AFL interval permissible during the drilling of the 12-1/2 hole-section whose TD is 12877ft.

The optimization plot in figure 4, helps carry out the sensitivity analysis. The relationship or dependence of each predictor variable to the response variable can be determined by the slope and nature of the graph for each predictor variable. The steepness or slope of the plot indicates the relationship of the predictor variable with the response variable, the slope indicates if the predictor variable has a direct proportionality or inverse proportionality with the response variable. This implies an increase in the predictor variable would increase or decrease the response variable. More-so the nature of the plot indicates the order of the relationship with the response variable. If the plot is a straight line or a curve, this help indicate if the relationship between the predictor variable and the response variable is linear or quadratic. From the result obtained, the degree of responsiveness of AFL to the predictors is in the order $M_w > Q_o > D_a > D$.

The optimal solution in terms of variable settings needed to achieve a target AFL as estimated by the proposed model response optimization is given in table 4.8.

Response Optimization: AFL for 10-5/8 inch Hole Section

Response	Goal	Lower	Target	Upper
AFL (psi)	Target	77.941	334.8	834.476

Table 6 Table of Optimization Parameters

Response Prediction of AFL

S/N	Depth, D(Ft)	Qo (Cuft/Sec)	Da(Inch)	Mw(Ppg)	Composite Fit	Desirability
1	13500	63.7772	15.1830	15.6	334.8	1

Table 7 Optimal Variable Settings

Response	Fit	SE Fit	95% CI	95% PI
AFL	349.3	68.5	(209.3, 489.3)	(204.2, 494.4)

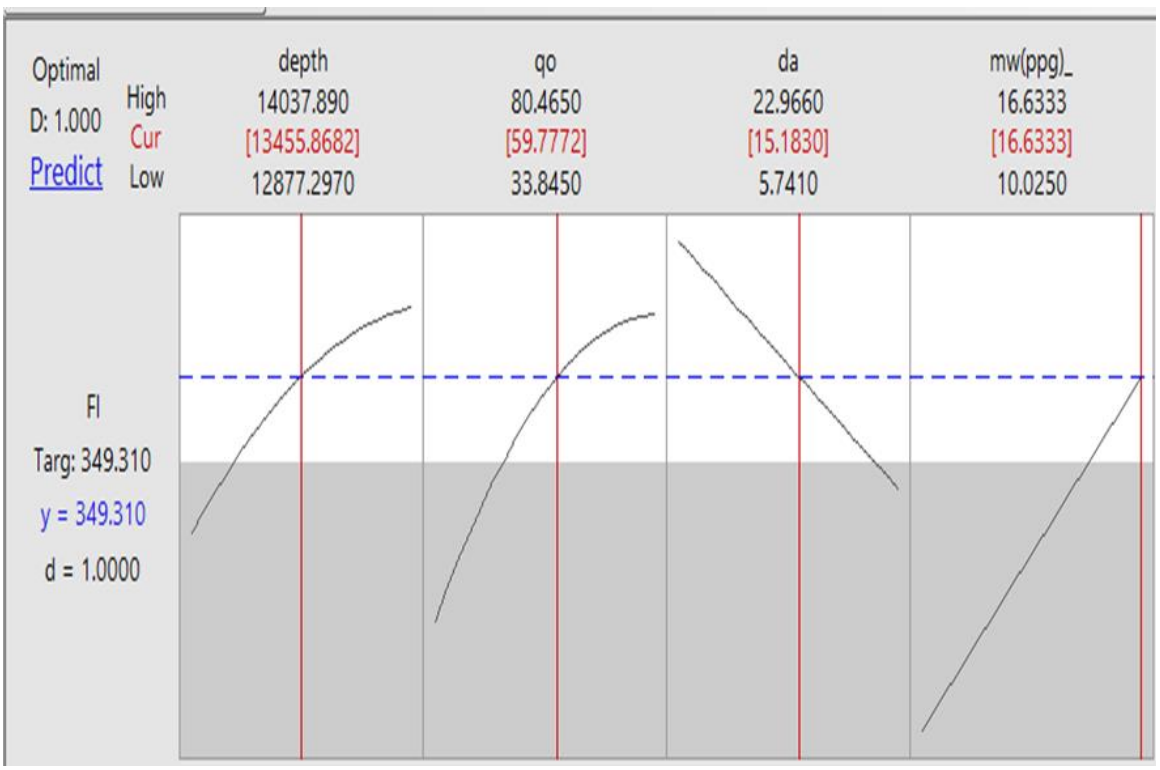

Figure 5 Optimization Plot of AFL for 10-5/8 Inch Hole Section

Given the prevailing annular friction loss AFL boundaries and the optimization parameters in table 6, the required variable settings needed to obtain a target AFL at a total depth (TD) of 13456ft are tabulated in table 7. Again the behavior of the predictor variable with the response variable was such that depth and flow rate exhibited direct non-linear variation whereas mud weight had a direct linear relationship with the response variable. Only the hydraulic diameter was inversely proportional.

Response Prediction for 8-1/2 inch Hole Section

S/N	Depth, D(Ft)	Qo (Cuft/Sec)	Da(Inch)	Mw(Ppg)	Composite Fit	Desirability
1	14037.9	58.9	5.741	16.6	351	1

Table Optimal Variable Settings

Response	Fit	SE Fit	95% CI	95% PI
AFL	351	3.5	(293.6, 438.6)	(284.1, 448.1)

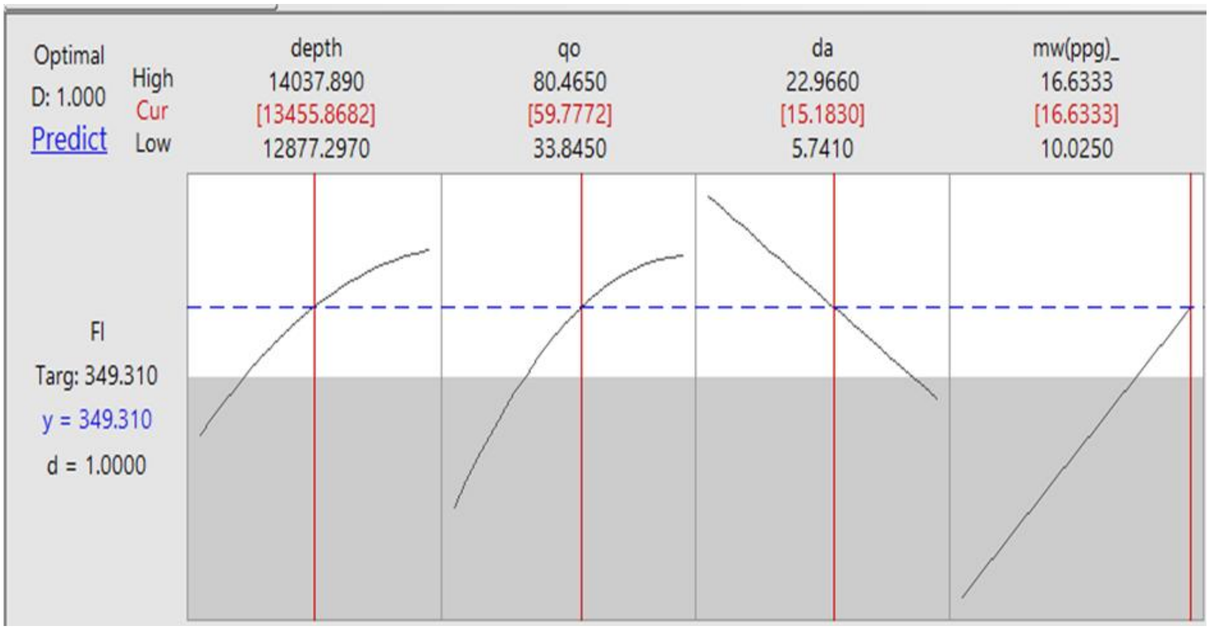

Figure 6 Optimization Plot of AFL at 8-1/2 Inch Hole Section

The plot shown above visualizes the results of the sensitivity analysis carried on the variables. The first thing to note is that this is a four in one plot composite plot as seen above, since it is a multi-variable model, with each of this plot representing a plot of the frictional loss on the Y-axis against the corresponding predictor variable on the X-axis indicated directly overhead each plot.

The red coloured values for each of the predictor variables indicates the current values of the directly overhead predictor variable depicted by the abbreviated cur to the left top end of the plot, the value above and below the red values represents the maximum and minimum limits for each variables abbreviated as high and low on the plot. The blue value on the FL depicts the current FL value, while the black value with a label Targ denotes the target value which could be the desired value of AFL.

On the plot the red continuous vertical line indicates the current predictor variable value, while the dotted blue line represents the current response variable value. The intersection of the two lines denotes the current coordinates of the corresponding predictor variable and the response variable.

The second thing worthy of note is the nature of the graph, the graph is the black line on each variable, the graph is what shows the relationship between the response variable and the corresponding predictor variable; the nature of the graph, means the shape, if it is linear or quadratic and how it slopes whether positively indicated by left to right slope (which means that the response variable increases with a corresponding increase in that particular predictor variable) or negatively indicated by right to left slope of the black line (which implies that the response variable decreases with an increase in that particular predictor variable).

For the first predictor variable, depth; the graph is a non-linear graph as depicted by the parabolic shape of the black line. This depicts that the FL has a non-linear relationship with depth, and the slope is from left to right indicating a positive slope, which is logically correct, for the FL should increase with a corresponding increase in the depth of the hole-section. This indicates the frictional losses would continue to increase as depth is gained during drilling.

For the next predictor variable, flow-rate; the graph is a non-linear graph as depicted by the parabolic shape of the black line. This depicts that the FL has a non-linear relationship with flow-rate, and the slope is from left to right indicating a positive slope, which is logically correct for the FL should increase with a corresponding increase in the flow rate of the mud. This indicates that reducing the flow-rate of the mud is one way to minimize frictional losses.

For the next predictor variable, hydraulic annular diameter; it is seen that the graph is a linear graph as depicted by the straight-line shape of the black line. This depicts that the FL has a linear relationship with hydraulic annular diameter, and the slope is from right to left indicating a negative slope, which is logically correct, for the FL should decrease with a corresponding increase in the hydraulic annular diameter of the hole-section. This indicates that expanding the hole-diameter for a section would reduce the frictional losses and vice versa.

For the next predictor variable, mud-weight; the graph is seen to be a linear graph as depicted by the straight-line shape of the black line. This depicts that the FL has a linear relationship with mud-weight, and the slope is from left to right indicating a positive slope, which is logically correct, for the FL should increase with a corresponding increase in the mud-weight. This implies that increasing the mud-weight would increase the frictional pressure losses.

3. CONCLUSION

1. The generated empirical AFL correlation estimated the Annular Friction Loss more precisely than the existing rheological models.
2. Modelling with predictor variable interactions performed better than without interactions.
3. From the result of the sensitivity analysis, it was concluded that in the order of relative impact on annular friction loss generation, the predictor variables are ranked as follows: mud weight > flow rate > hydraulic diameter > well depth. The result of the optimisation studies reveals that the maximum flow-rate should be applied at shallower sections and the flow-rate should be reduced as depth is gained. This is because as depth is gained, the annular diameter becomes smaller, the mud-weight increases and the depth also increases. All these conditions result in increase in the friction loss. From the results of the sensitivity analysis, a good way to cushion this effect will be to reduce the flow-rate as depth is gained.

4. RECOMMENDATION

Even though the developed friction loss correlation in this work appears to fit perfectly with the majority of the data, there are still uncertainties in the accuracy of the model under intense down-hole conditions. The following recommendations regarding these uncertainties can be addressed to improve the accuracy of the model.

- Geothermal considerations – The Obiafor field under study had a regular geothermal temperature trend and therefore the proposed annular friction model may only work exclusively for such fields. Hence a consideration on higher geothermal wells will reduce the accuracy uncertainties.
- Higher order multiple regression analysis will produce a stronger model.

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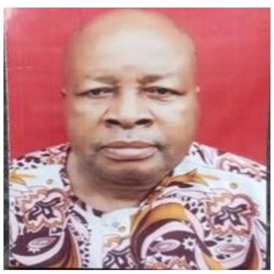

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