*American Journal of Sciences and Engineering Research*

*E-ISSN -2348 – 703X, Volume 6, Issue 2, 2023*

# Determining Annular Frictional Losses for Accurate Surface Back Pressure using a Stepwise Multiple Linear Regression

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***ABSTRACT:*** *The oil industry has evolved, in recent times, the increased need for petroleum products as well as the exploitation of shallower wells has made drillers to start considering deep offshore regions and other regions hitherto considered "undrillable". One of such difficult to drill region prior to now are wells with narrow drill margins, however with the advent of MPD, this wells can now be safely harnessed. This paper focuses on optimizing the efficiency of the CBHP variant of MPD. The CBHP-MPD aims to achieve constant BHP throughout drilling process by manipulating SBP as required to supplement or counter the Frictional losses ensuring the BHP remains steady all through the drilling process. Therefore accurate SBP requires that accurate Frictional losses be determined. In this project, we will be determining the frictional loss using a stepwise Linear Regression and then using the frictional losses so obtained in supplying adequate surface back pressure for steady BHP management throughout the entire drilling process of this delicate MPD wells.*

***Keywords:*** *Annular friction loss, Surface back pressure, managed pressure drilling, stepwise multiple linear regression.*

## I. INTRODUCTION

Managed Pressure Drilling, a seemingly old reformed conventional drilling technique which refers to all methods of drilling that focuses on efficient management of the bottom hole pressure is a very potent tool in drilling safely and efficiently these days, considering that majority of the wells that are been exploited are wells requiring stringent pressure management, MPD has prospered with several variants like the Pressurized Mud Cap Drilling- PMCD which seeks to monitor the pressure by simulating an overburden formation weight using pressured drilling fluid just above the drilled region like a cap, giving it the name pressurized mud cap.There is also an Equivalent Circulating Density MPD which seeks to maintain the drilling pressure by ECD manipulations. However this project focuses on the Constant Bottom Hole Pressure Managed Pressure Drilling Variant, CBHP-MPD, which seeks to maintain steady drilling pressure by achieving constant bottom hole pressure. The pressure at the bottom of the hole (BHP) is due to several factor, first, the hole is filled with a column of fluid called the drilling mud, therefore the BHP is a function of the hydro-static pressure of the mud in the hole, furthermore, there are pressures surges and swabs that arises due to friction as circulation of the fluid increases or is halted, increasing or reducing the Hydro-static Pressure consequently producing an overall increased BHP. However because the frictional losses are unsteady, the BHP shall be unsteady, this means that achieving constant BHP would involve canceling out the effect of the pressure fluctuations arising from the frictional losses. This is achieved in CBHP-MPD by introducing another pressure called the surface back pressure, SBP. The SBP is a fall back pressure that act as an additive inverse to the frictional pressures this

 Received-03-03-2023, Accepted- 09-03-2023

implies that when there's an increase or a decrease in the frictional pressure, the SBP will be reduced or increased respectively by exactly the same amount of the frictional pressure increase, annulling the overall effect of the increased pressure consequently a constant Bottom Hole Pressure is achieved and maintained all through the drilling process.

This means the efficiency of the CBHP-MPD is determined by the accuracy of the applied Surface Back Pressure, SBP which is just a reflective of the accuracy of the frictional loss estimation. Fares (2018). This is where the need for a model to accurately estimate the frictional loss in the drilling fluid and the well-bore annular geometry arises. Determining the frictional losses in the annular geometry of the well-bore prior to this paper is done using models which requires high level of computations. Models like the Herschel Buckley, API-13D and the Power law models are the widely used model in petroleum industry. Furthermore the drilling fluid being a complex mixture of several components exhibits rheological behaviour which cannot be accurately modeled because it exhibits different rheological properties under different conditions, for instance every good drilling fluid should possess a gelling or thixotropic properties at quiescent which is required to suspend drilled cuttings from slipping during periods of no circulations and should behave like a fluid under conditions of plasticity making the drilling fluid difficult to be modeled exactly using a single fluid model. Furthermore the current drilling fluid models do not directly model the annular frictional loss but requires tedious indirect computations of other parameters, therefore this project seeks to produce a model that computes the frictional pressure losses directly as a function of the drilling fluid parameters.The Stepwise Linear regression model (SLRM) is a new breed of regression models, They function like an hybrid, in the sense that the SLRM possesses the simplicity of the linear model yet potent in estimating any nonlinear trend with proper knowledge of it application. SLRM was developed to aid estimation of non linear trend using a linear regression, this regression model seeks to accurately fit nonlinear trends yet maintaining the simplicity of a linear model. To estimate a nonlinear trend using a linear model, the SLRM employs the fact that a curve is basically made up of infinite small straight lines, therefore the SLRM breaks down the curved sections accurately modeling these sections by series of straight lines giving the SLRM efficiency and unmatched accuracy in modelling non linear trends.

## II. Materials and Methods

In parameters selection, from comprehensive research from previous literature, it's determined that friction in fluid is affected by certain properties of the fluid and the conduit through which the fluid flows. The four most stringent fluid and flow properties was selected for this study. Bern.et al (2006) agreed that the frictional loss is affected by the mud weight. The frictional loss is also affected by a flow property termed the annular diameter of the pipe or the hole containing the drilling fluid, for friction is the resistance in motion due to shearing stress in liquids, this shearing stress is always inversely affected by the effective flow area such that the smaller the pipe or conduit, the smaller the effective flow area leading to increased shearing stresses in the fluid.The rate at which the fluid is flowing through the conduit will also determine the shearing stress, for the shearing stress is directly related to the pressure of the fluid and at higher flow rates the fluids pressure is higher, therefore the shearing stress will be higher assuming constant effective flow area. Finally, the effective area of the pipe is also determined by the effective length of the pipe, translating this in petroleum, this will be the effective length of the hole section which is the depth as measured from a standard or reference elevation like the KB or DFE . Therefore the Model will be built on these four parameters. The SLRM involves the conventional linear modeling carried out in a predetermined number of steps. In generating this model, data was obtained from an MPD candidate Oil well in Niger Delta field, the name of the well withheld for confidential purposes.The data comprises over a thousand data points of real time drilling data at depth interval of (12800-13464)ft. This depth was characterized by very close drill windows hence the need for the CBHP-MPD intervention. The data includes properties like frictional loss, mud-weight, flow rate, depth, plastic viscosity etc. First, only the required parameters were mined from the data, which are the frictional loss, mud-weight, depth, flow-rate and effective annular diameter parameters. Afterwards, because real time data comprises several data points in a fraction of a second, it is difficult working with as you have clusters of data at one point, which means the trend will not be visible, therefore statistical averaging using time trend analysis was carried out on the real time drilling data, smoothening the data to a representative 40 data points suitable for the linear modeling.The SLR modelling is carried out using a step of 4 points, for a 40 data point, this translates into 10 steps and then a sample of the modelling procedures is carried out on two of the steps as shown below. This modeling process is repeated to cover all the data. In this model, the independent variables are outlined below:

Mw = Mud-weight [lbs/cu-ft], Qo = flow-rate [cu-ft/s], D= True vertical Depth [ft], Da= Annular diameter [ft], Fl = Frictional loss [psi]

The value of the frictional loss would be modeled as a function of all these variables, therefore:

$$\mathrm{Fl} = \mathrm{f}(\mathrm{Mw}, \mathrm{Qo}, \mathrm{D}, \mathrm{Da}) \qquad (1)$$

For a linear model, assuming no frictional loss at conditions of no flow with a drilling fluid of zero lb/cu-ft mud-weight at a footage of zero foot and in a well-bore with effective annular diameter of zero:

$$\mathrm{Fl} = \mathrm{b}_0\mathrm{Mw} + \mathrm{b}_1\mathrm{Qo} + \mathrm{b}_2\mathrm{D} + \mathrm{b}_3\mathrm{Da} \qquad (2)$$

With $\mathrm{b}_0$,$\mathrm{b}_1$,$\mathrm{b}_2$ and $\mathrm{b}_3$ as constants whose value shall be determined in the following steps.

1. Generating the normal equations, we obtain the following equations:

$$\sum \mathrm{Fl} = \mathrm{b}_0 \sum \mathrm{Mw} + \mathrm{b}_1 \sum \mathrm{Qo} + \mathrm{b}_2 \sum \mathrm{D} + \mathrm{b}_3 \sum \mathrm{Da} \qquad (3)$$

$$\sum \mathrm{Fl.Mw} = \mathrm{b}_0 \sum \mathrm{Mw}^2 + \mathrm{b}_1 \sum \mathrm{QoMw} + \mathrm{b}_2 \sum \mathrm{DMw} + \mathrm{b}_3 \sum \mathrm{DaMw} \qquad (4)$$

$$\sum \mathrm{Fl.Qo} = \mathrm{b}_0 \sum \mathrm{MwQo} + \mathrm{b}_1 \sum \mathrm{Qo}^2 + \mathrm{b}_2 \sum \mathrm{DQo} + \mathrm{b}_3 \sum \mathrm{DaQo} \qquad (5)$$

$$\sum \mathrm{Fl.Da} = \mathrm{b}_0 \sum \mathrm{MwDa} + \mathrm{b}_1 \sum \mathrm{QoDa} + \mathrm{b}_2 \sum \mathrm{DDa} + \mathrm{b}_3 \sum \mathrm{Da}^2 \qquad (6)$$

2. Translating equations 3,4,5 and 6 into matrices using matrix notation:

The General format is:

$$\mathrm{b.X} = \mathrm{C}$$

With b = the vector of the to be determined constants,

X = the matrix of the drilling parameters (Mw, Qo, D, Da)

C = Matrix of the left hand side constants.

$$\begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} \begin{bmatrix} & \sum \mathrm{Mw} & \sum \mathrm{Qo} & \sum \mathrm{D} & \sum \mathrm{Da} \\ \sum \mathrm{Mw}^2 & \sum \mathrm{QoMw} & \sum \mathrm{DMw} & \sum \mathrm{DaMw} \\ \sum \mathrm{MwQo} & \sum \mathrm{Qo}^2 & \sum \mathrm{DQo} & \sum \mathrm{DaQo} \\ \sum \mathrm{MwDa} & \sum \mathrm{QoDa} & \sum \mathrm{DDa} & \sum \mathrm{Da}^2 \end{bmatrix} = \begin{bmatrix} \sum \mathrm{Fl} \\ \sum \mathrm{Fl.Mw} \\ \sum \mathrm{Fl.Qo} \\ \sum \mathrm{Fl.Da} \end{bmatrix} \qquad (7)$$

3. To obtain this sums in the matrix above, the regression table is prepared using a multiple regressor statistical tool developed specifically for this project, screenshot of the regression output is displayed below :

| FILE | OPTIONS | DATA | MULTIPLE LINEAR REGRESSOR | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| R.Mw | R.Qo | R.Da | R | D | Mw | Qo | Da | Mw^2 | Qo^2 | Da^2 |
| 954.906 | 3225.905 | 2188.088 | 95.3 | 12877.3 | 10.02 | 33.85 | 22.96 | 100.4004 | 1145.8225 | 527.1616 |
| 1065.344 | 5838.28 | 1364.16 | 81.2 | 12894.2 | 13.12 | 71.9 | 16.8 | 172.1344 | 5169.61 | 282.24 |
| 1395.9834 | 8583.267 | 1795.752 | 106.89 | 12913.4 | 13.06 | 80.3 | 16.8 | 170.5636 | 6448.09 | 282.24 |
| 1368.5535 | 8200.834 | 1761.816 | 104.87 | 12933.2 | 13.05 | 78.2 | 16.8 | 170.3025 | 6115.24 | 282.24 |
| **4784.7869** | **25848.286** | **7109.816** | **388.26** | **51618.1** | **49.25** | **264.25** | **73.36** | **613.4009** | **18878.7625** | **1373.8816** |
| 3364.04 | 15117.723 | 2113.89 | 227.3 | 13385.6 | 14.8 | 66.51 | 9.3 | 219.04 | 4423.5801 | 86.49 |
| 11092.14 | 51811.249 | 6710.06 | 684.7 | 13406.2 | 16.2 | 75.67 | 9.8 | 262.44 | 5725.9489 | 96.04 |
| 12499.1136 | 60948.648 | 7579.908 | 773.46 | 13425 | 16.16 | 78.8 | 9.8 | 261.1456 | 6209.44 | 96.04 |
| 12016.4075 | 58593.9375 | 7291.69 | 744.05 | 13444.5 | 16.15 | 78.75 | 9.8 | 260.8225 | 6201.5625 | 96.04 |
| 11336.01 | 53983.347 | 6900.18 | 704.1 | 13464 | 16.1 | 76.67 | 9.8 | 259.21 | 5878.2889 | 96.04 |
| **50307.7111** | **240454.9045** | **30595.728** | **3133.61** | **67125.3** | **79.41** | **376.4** | **48.5** | **1262.6581** | **28438.8204** | **470.65** |

Figure 1: Multiple linear regression statistical tool output

The statistical tool reads data in excel format and is designed to perform regression modelling in steps, the output of the sums are generated and displayed in matrix format as shown below.

$$\begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} \begin{bmatrix} 49.3 & 264.3 & 51618.1 & 73.4 \\ 613.4 & 3551.7 & 635629.7 & 889 \\ 3551.7 & 18878 & 3411311 & 4648 \\ 889 & 4648 & 946508 & 1374 \end{bmatrix} = \begin{bmatrix} 388.2 \\ 4784.8 \\ 25848 \\ 7109.8 \end{bmatrix}$$

The results for the unknown coefficients is obtained as displayed below.

$$\begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} 0.644 \\ -0.0018 \\ 0.007 \\ -0.013 \end{bmatrix}$$

Substituting the values for the coefficients in equation 2, the frictional loss model for the first step is obtained as shown below.

$$\mathrm{Fl} = 0.644\mathrm{Mw} - 0.0018\mathrm{Qo} + 0.007\mathrm{D} - 0.013\mathrm{Da}$$

## III. Results and Discussion

The annular frictional loss predictions from the generated model is compared with the actual data for the first step, the standard error is also computed and the result displayed on a graph as shown below.

Table 1. Model prediction against actual annular friction losses

| AFL [ Field data] (psi) | AFL [Model] (psi) | Standard Error (%) |
|---|---|---|
| 95.3 | 93.7 | 1.67 |
| 81.2 | 83.5 | 4.30 |
| 106.8 | 102.3 | - 4.20 |
| 104.9 | 107.1 | 2.09 |

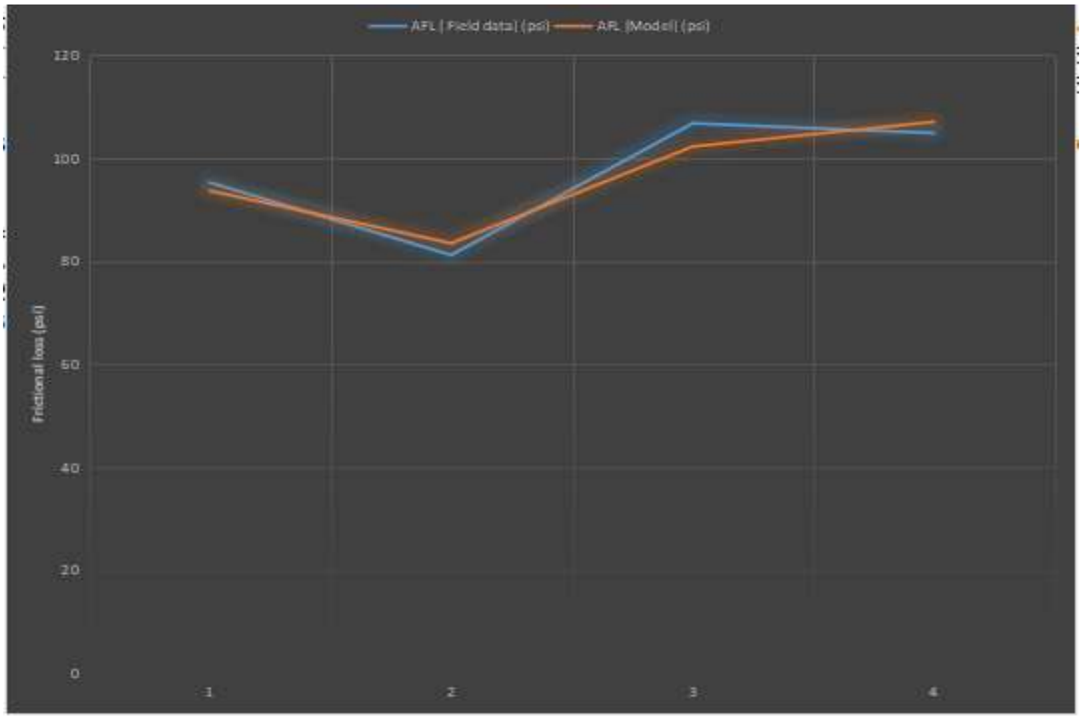


Figure 2. Graphical plot of model estimation against field data friction loss.

In the plot above, the blue trend line indicates the obtained annular pressure loss from field data, whilst the solid orange trend line dictates the generated model frictional loss predictions. The plot reveals precise estimation of the frictional losses by the model.

The generated frictional loss model is also compared against other existing models, two model was employed: the Herschel Buckley and the API-13D model. The reason for the choice of this two is that based on previous literature, these two models have been proven to yield a higher accuracy in annular frictional loss prediction for drilling fluids (oriji et marcus 2014). The result is displayed in tabular form with graphical output as seen below.

Table 2. Model against HB and API-13D friction loss estimation.

| AFL [ Field data] (psi) | AFL [Herschel Buckley] (psi) | AFL [ API-13D] (psi) | AFL [ Model] (psi) |
|---|---|---|---|
| 95.3 | 45.4 | 75.5 | 93.7 |
| 81.2 | 98.9 | 69.9 | 83.5 |
| 106.8 | 65.3 | 98.7 | 102.3 |
| 104.9 | 59.6 | 88.6 | 107.1 |

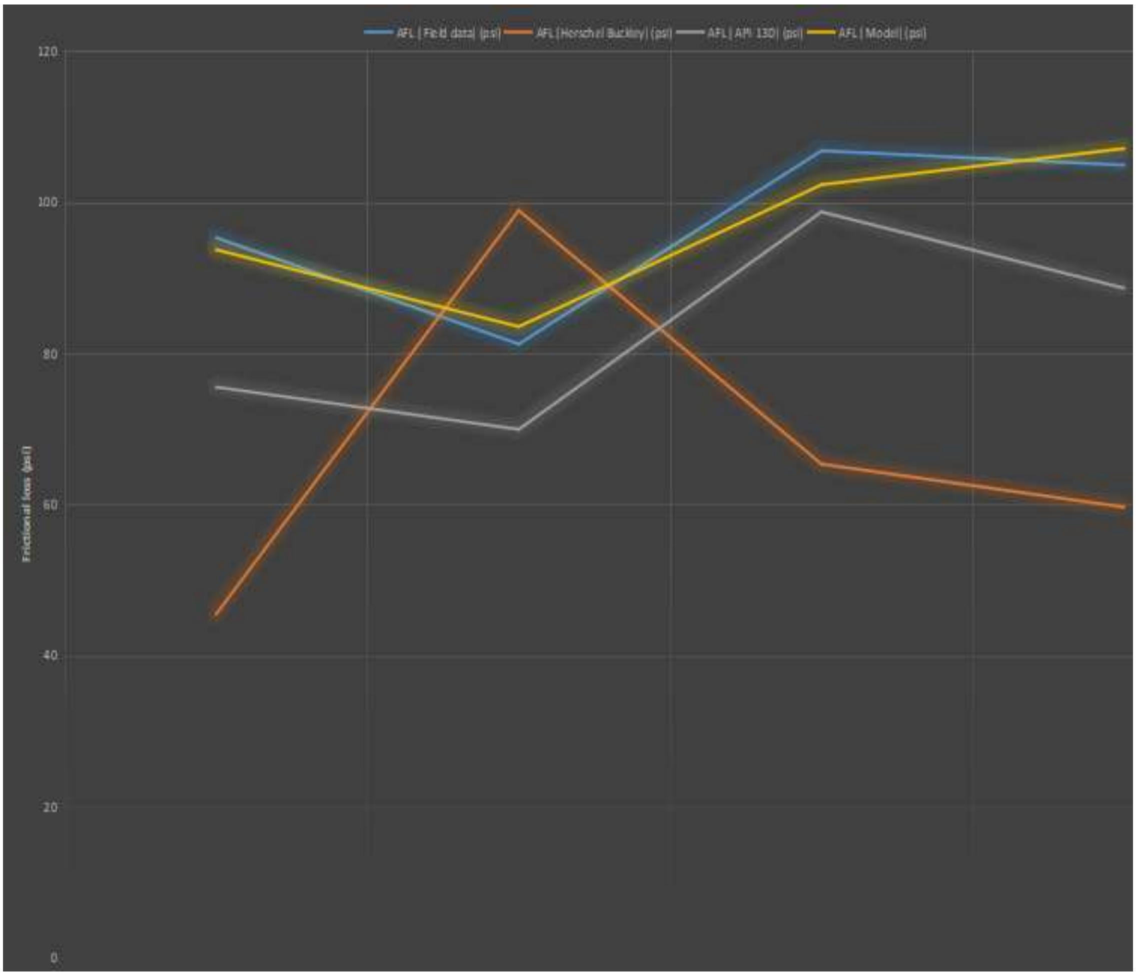


Figure 3. Comparison plot of SLR model with preexisting models

In this plot, the solid blue trend line dictates the annular frictional pressure loss obtained from the field data, the bright yellow colored trend line dictates the generated model annular frictional losses predictions with the ash and Orange trend line indicating the API-13D and the Herschel Buckley's model predictions respectively. Obviously, the annular frictional loss model generated produced a better fit to the field data than the API -13D and Herschel Buckley's. Furthermore, the model shows the least variability in it's predictions, ranking it the most accurate amidst the three models.

## IV. Conclusion

As proven by the results of this project, the stepwise linear regression model, SLRM is potent in estimating and forecasting nonlinear trends, with an accuracy of 95% in it prediction of the annular friction losses, with a maximum standard error as low as 5% , it clearly performs better than the API-13D and the Herschel Buckley models in frictional loss prediction, which implies it has the potential to achieve the aim of ensuring constant BHP as adequate SBP can be supplied in real time using the model's prediction.Furthermore, the methods employed in this model can be used in any geography however adequate correction factors may be included based on the region using data from the region.Finally, the SLRM is generally suitable for modelling nonlinear trends and curve fitting.

**Nomenclature**

| | |
|---|---|
| API | American Petroleum Institute |
| AFL | Annular Frictional Losses |
| BHP | Bottom Hole Pressure |

| | |
|---|---|
| CBHP | Constant Bottom Hole Pressure |
| DFE | Drill Floor Elevation |
| ECD | Equivalent Circulating Density |
| HB | Herschel Buckley |
| KB | Kelly Bushing |
| MPD | Managed Pressure Drilling |
| PMCD | Pressurized Mud Cap Drilling |
| SBP | Surface Back Pressure |
| SLRM | Stepwise Linear Regression Model |
| SPP | Stand Pipe Pressure |

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