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RESEARCH PAPER

Forecast of Crude Oil Production Output in An Oil Field in the Niger Delta Region of Nigeria

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ABSTRACT
Crude oil production output forecast is fundamental in the formulation of valid and suitable production policies; it is pivotal in planning and decision-making. This paper explores the use of forecasting techniques to assist the oil field manager in decision-making. In this analysis, statistical models of projected trends that involve graphical, least squares, simple moving average, and exponential smoothing methods were compared. The least-squares method was found to be most suitable to capture the recent random nature of crude oil production output in the oilfield of the Niger Delta region of Nigeria. Moreover, a multiple linear regression model was developed for predicting daily, weekly, monthly, or even yearly volumes of crude oil production output in the oilfield facility.

KEYWORDS: *Crude oil; Forecasts; Niger delta; Oilfield; Prediction error; Production output.*

1. Introduction

Virtually, all management decisions depend on forecasts [1]. Every organization invariably engages in an annual planning exercise. The heads of various functional areas such as marketing, production, materials, and finance take part in this exercise with specific objectives. An essential point of concern in all business activities is to assess the future business trend, whether it is going to be favorable or unfavorable [2]. The formulation of an appropriate and useful production policy is a critical aspect of an enterprise [3]. It involves the determination of the level of production, workforce requirements, equipment, and inventory level [4]–[6]. Every manager would like to know the exact nature of future events to plan the next course of action on time accordingly. The effectiveness of his plan depends upon the level of accuracy with which future events are known [7]–[10]. Every manager is involved in planning for the future, irrespective of the fact whether future events are exactly known or not. It is implied that the manager is involved in forecasting his/her sense of judgment, experience, and intellectual abilities [10]. This assessment helps the top management make appropriate policy decisions in advance. Planners and policymakers need to know the possible future trends about several variables, which are made possible through forecasting. Forecasting plays a vital role in most organizations, as it provides knowledge about future trends and methods for acquiring this knowledge [1], [11]–[19].

Forecasting is the process of estimating a future event by casting forward previous data. The previous data are systematically combined in a predetermined way to obtain an estimate of the future. Forecasting is an estimate of future values of specific indicators relating to a decisional/planning situation [20]. In some cases, forecast regarding a single indicator is sufficient, whereas, in some other cases, forecast regarding several indicators is necessary. The number of indicators and the degree of detail required in the forecast depend on the intended use of the forecast [21]. Prediction is a process of estimating a future event based on subjective considerations other than just past data; these subjective considerations need not be combined in a predetermined way [10], [19], [22]–[28]. Forecasting has become a continuous process and requires regular monitoring of the situation and

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continual review and updating of new data [1], [3], [10], [29], [30].

Risk and uncertainty are central to forecasting and prediction; it is generally considered to be the right practice to demonstrate the degree of difficulty attached to forecasts [31], [32].

Several researchers have delved into the forecast of oil field production output [2], [13], [33]–[35]. Oladeinde et al. [13] developed a six-variable multilinear regression model for forecasting crude oil production volume in an oilfield. However, the model was subjected to further analysis, which reduced the model to a two-variable model for predicting an oilfield production output. Research on oilfield production forecast based on least square fitting and improved neural network was carried out to predict the oilfield output [13], [36]. The paper harnessed the Scaling laws from percolation theory to predict oilfield performance. A Grey Forecasting model based on BP Neural Network for Crude Oil Production and Consumption in China was developed [17]. A multilinear regression was used for oilfield output prediction [34]. An improved multi-linear regression method was applied for forecasting the output in an oilfield [2].

This paper analyzes various forecasting techniques to produce crude oil in an oilfield in Nigeria and develops a multiple linear regression model for predicting daily, weekly, monthly, or even yearly volumes of the crude oil production output in the oilfield facility. The forecasting methods carried out in this paper are quantitative forecasting models (time series and causal or trend projection methods), which are estimates of the future based on historical data obtained from the archive of the oilfield.

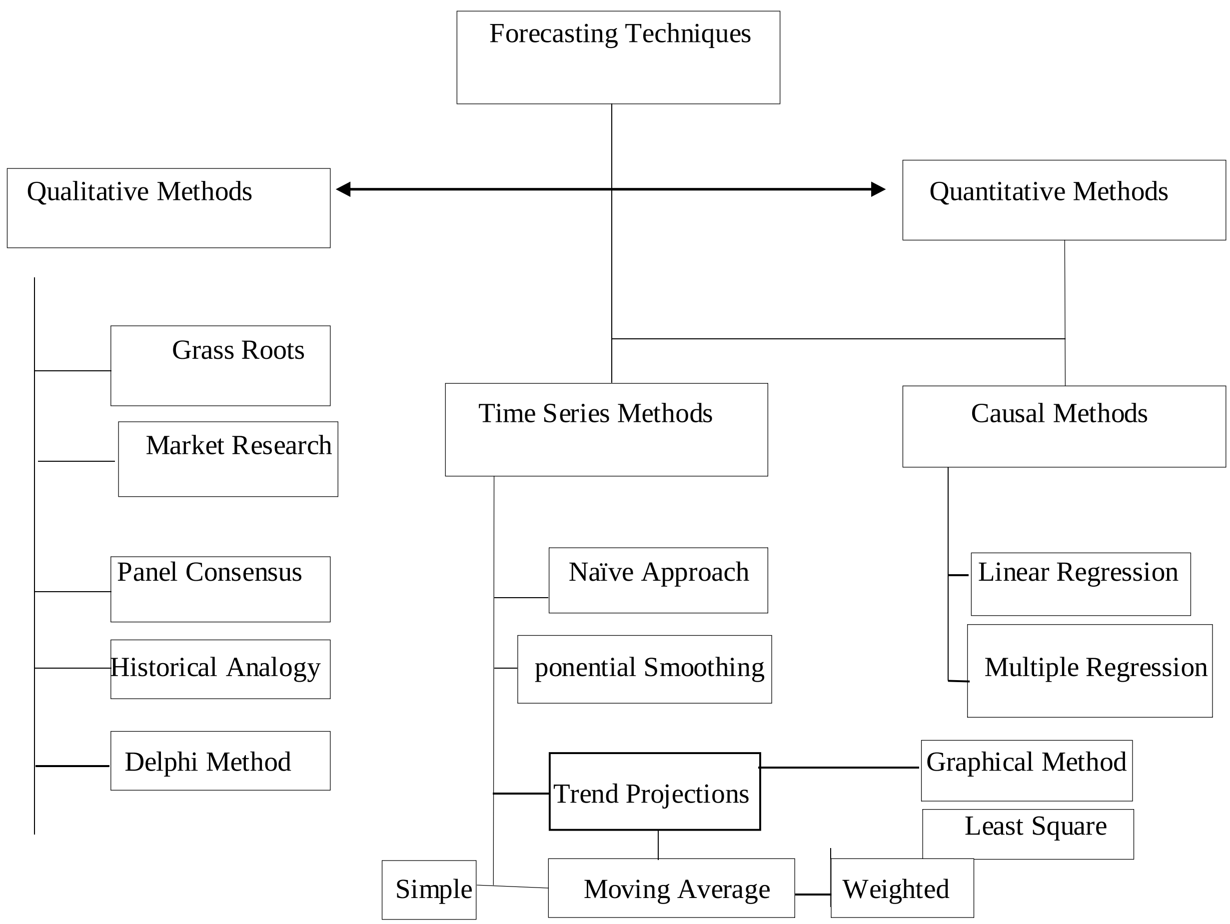

Fig. 1. Traditional forecasting methods

2. Methodology

2.1. Strategy employed

A good strategy for forecasting is the use of more than two methods and analyzing the processes critically for the best. In other to capture the best fit for predicting the volume of crude oil production output in the oilfield explored in this work, the previous trend of crude oil production output was analyzed and compared using methods of Graph, Simple Moving Averages, Least Squares, and Exponential Smoothing forecasting techniques. Finally, a multi-linear regression model was developed in the following steps:

I. Compute by the Graphical method of forecasting and its measures of prediction error.
II. Compute by the Simple Moving Averages method of forecasting and its measures of prediction error.
III. Compute by the Least-Squares method of forecasting and its measures of prediction error.
IV. Compute by the Exponential Smoothing method of forecasting and its measures of prediction error.
V. Compare the methods stated in Steps I-IV and apply their measures of prediction error.
VI. Capture the best fit method of forecasting for predicting the volume of crude oil production output.
VII. Develop a Multi-linear Regression model using past data and some subjective considerations for predicting the volume of crude oil production output suitable for daily, weekly, monthly, and yearly forecast.

2.2. Method of data collection

Past historical data obtained from the archives of the oilfield operators and the parameters needed for the various forecasting techniques were computed, compared, and analyzed with graphical plots using Microsoft Excel.

Tab. 1. The volume of Crude Oil Production Output from the oilfield from 2010 to 2016

Year	Crude Oil Production (Gross)
2010	12,035,986
2011	16,242,840
2012	17,892,169
2013	12,627,360
2014	10,898,446
2015	9,138,132
2016	7,199,010

3. Results and Discussion

3.1. Graphical method of forecasting

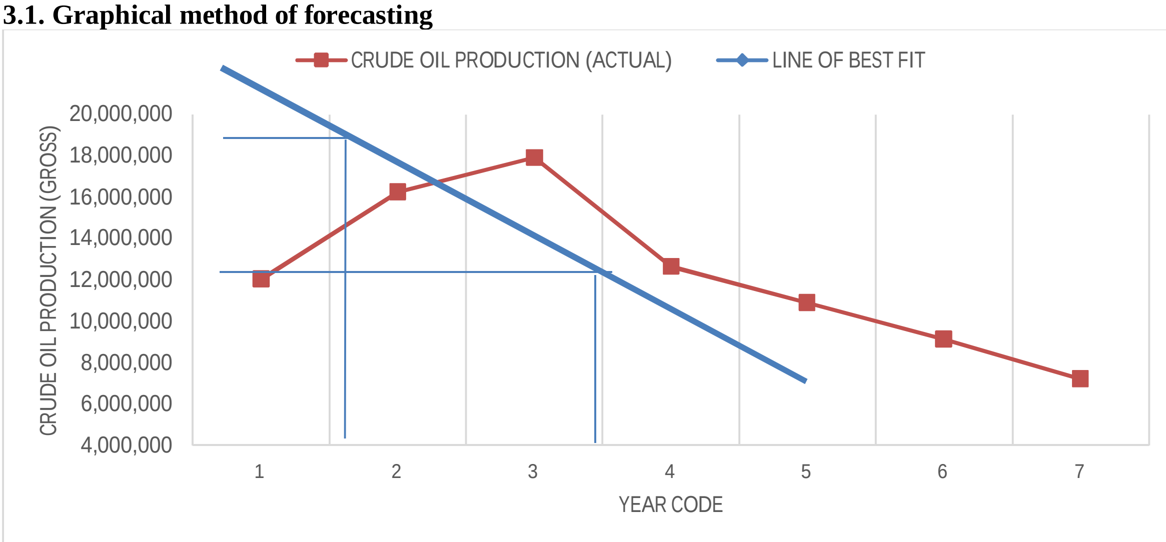

Fig. 1. The plot of the results of the graphical method of forecasting.

Tab. 2. The yearly production forecast results of graphical method of forecasting

Year	Year Code *X*	Crude Oil Production (Gross) *y*	Y	Abs Error
2010	1	12,035,986	18666666.67	6630680.67
2011	2	16,242,840	16933333.34	690493.34
2012	3	17,892,169	15200000.01	2692168.99
2013	4	12,627,360	13466666.68	839306.68
2014	5	10,898,446	11733333.35	834887.35
2015	6	9,138,132	10000000.02	861868.02

2016	7	7,199,010	8266666.69	1067656.69
2017	8	-	6533333.36	

S_{yX} = 2802413.78 ; MSE = 7853523000000; MAD = 1945294.54

Gradient, $b = -1733333.33$ & Intercept, $a = 20400000$; $Y = a + bX = 20400000 - 1733333.33X$

*where S_{yX} is the standard deviation of the values around the regression line; **MSE** is the mean squared error; **MAD** is a median absolute deviation.*

3.2. Simple moving averages method of forecasting

Tab. 3. Yearly production forecast results of simple moving averages method of forecasting

Year	Year Code	Crude Oil Production (Gross)	3-Year Simple Moving Average	Abs. Error	6-Year Simple Moving Average	Abs. Error
2010	1	12,035,986				
2011	2	16,242,840				
2012	3	17,892,169				
2013	4	12,627,360	15,390,331.67	2,762,971.67		
2014	5	10,898,446	15,587,456.33	4,689,010.33		
2015	6	9,138,132	13,805,991.67	4,667,859.67		
2016	7	7,199,010	10,887,979.33	3,688,969.33	13,139,155.50	5,940,145.50
2017	8	-	9,078,529.33		12,332,992.83	

$S_{yX_{3yr}}$ = 4031694.41 ; MSE_{3yr} = 16254560000000; MAD_{3yr} = 3952202.75

$S_{yX_{6yr}}$ = 5940145.50 ; MSE_{6yr} = 35285329000000; MAD_{6yr} = 5940145.50

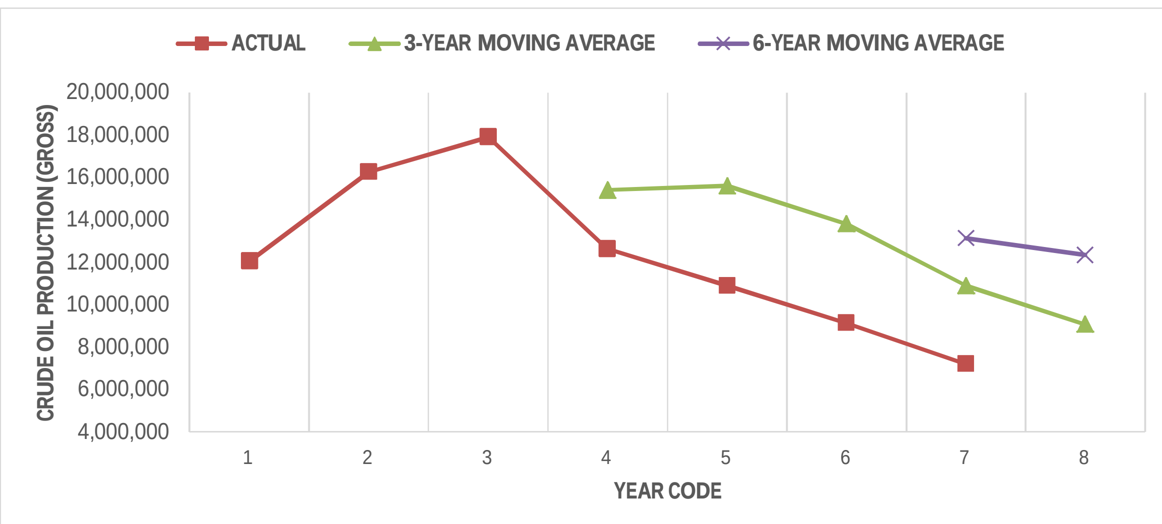

Fig. 2. The plot of the results of the simple moving averages method of forecasting.

3.3. Least squares method

The least-squares equation for linear regression is $Y = a + bX$, where Y is the dependent variable computed through the equation; y is the actual dependent variable data point; a = y-intercept; b is the Slope of the line; X is the Period.

In the least-squares method, the equations for a and b are

$$a = \bar{y} - b\bar{X} \qquad (1)$$

and

$$b = \frac{\sum Xy - n\bar{X}.\bar{y}}{\sum X^2 - n\bar{X}^2} \qquad (2)$$

where $a = Y\ intercept$, b = slope of the line, and n = the number of data points.

The standard error is given by

$$S_{yX} = \sqrt{\frac{(y_1-Y_1)^2+(y_2-Y_2)^2+\cdots+(y_n-Y_n)^2}{n}} \qquad (3)$$

Tab. 4. The yearly volume of crude oil production forecasts results of least squares method of forecasting

Year Code, X	Crude Oil Production (Gross), y	Xy	X^2	y^2 (Billions)	Y	Abs. Error
1	12,035,986	12,035,986	1	144,864.96	16,117,070.49	4,081,084.49
2	16,242,840	32,485,680	4	263,829.85	14,841,568.09	1,401,271.91
3	17,892,169	53,676,507	9	320,129.71	13,566,065.69	4,326,103.31
4	12,627,360	50,509,440	16	159,450.22	12,290,563.29	336,796.71
5	10,898,446	54,492,230	25	118,776.13	11,015,060.89	116,614.89
6	9,138,132	54,828,792	36	83,505.47	9,739,558.49	601,426.49
7	7,199,010	50,393,070	49	51,825.75	8,464,056.09	1,265,046.09
$\sum X = 28$	86,033,943	308,421,705	140			

$\bar{X} = 4$ $\bar{y} = 12290563.29$ $b = -1275502.40$; $a = I7392572.89$

$Y = 17392572.89 - 1275502.40X$

$S_{yX} = 2373155.51$; $MSE = 5631867200000$; $MAD = 1732620.56$;

Fig. 3. The plot of the results of the least squares method of forecasting.

3.4. Exponential smoothing

This study determined the exponential smoothing using the relation: $F_{t+1} = F_t + \alpha(D_t - F_t)$, where F_{t+1} is the new forecast for the next period; D_t is the latest actual production for the present period; F_t is the previously determined (old) forecast for the present period; α is the response rate, weighting factor, or smoothing constant. For the desired response, rates (weighting factors) or smooth constants are considered as 0.1 and 0.6.

Tab. 5. The yearly volume of crude oil production forecasts results of exponential smoothing forecasting method.

Year	Crude Oil Production (Gross)	Year Code	0.1	Abs. Error	0.6	Abs. Error
2010	12,035,986	1	-		-	
2011	16,242,840	2	12,035,986.00	4,206,854.00	12,035,986.00	4,206,854.00
2012	17,892,169	3	12,456,671.40	5,435,497.60	14,560,098.40	3,332,070.60
2013	12,627,360	4	13,000,221.16	372,861.16	16,559,340.76	3,931,980.76
2014	10,898,446	5	12,962,935.04	2,064,489.04	14,200,152.31	3,301,706.31

2015	9,138,132	6	12,756,486.14	3,618,354.14	12,219,128.52	3,080,996.52
2016	7,199,010	7	12,394,650.73	5,195,640.73	10,370,530.61	3,171,520.61
2017	-	8	11,875,086.66		8,467,618.24	

$S_{yX_{0.1}}$ = 3910041.94 ; $MSE_{0.1}$ = 15288428000000 ; $MAD_{0.1}$ = 3482282.78

$S_{yX_{0.6}}$ = 3528765.97 ; $MSE_{0.6}$ = 12452189000000; $MAD_{0.6}$ = 3504188.13

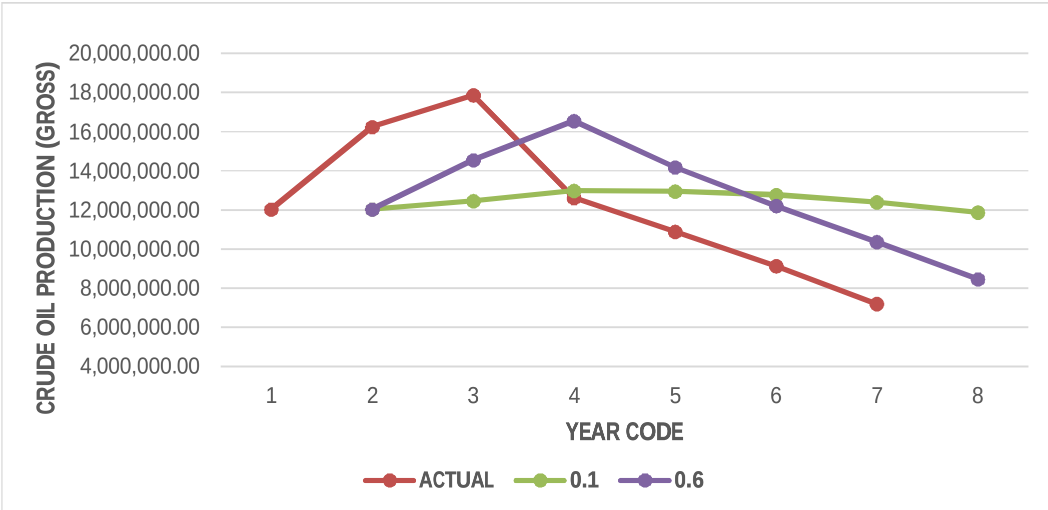

Fig. 4. The plot of the results of the exponential smoothing method of forecasting.

3.5. Comparison of the forecasting methods based on measures of prediction error

Tab. 6. Measures of prediction error for crude oil production output (Gross) in the oilfield

Error	S_{yX}	MSE	MAD
Graphical	2802413.78	7853523000000	1945294.54
3-Year Simple Moving Average	4031694.41	16254560000000	3952202.75
6-Year Simple Moving Average	5940145.50	35285329000000	5940145.50
Least Squares	2373155.51	5631867200000	1732620.56
Exponential Smoothing (0.1)	3910041.94	15288428000000	3482282.78
Exponential Smoothing (0.6)	3528765.97	12452189000000	3504188.13

A critical analysis of the results obtained by various forecasting methods as displayed in Tables 2-6 indicates that the least-squares method has the lowest forecast error, as summarized in Table 6. Therefore, the least-squares technique is the best forecasting method that depicts the recent random nature of crude oil production output in the oilfield facility.

3.6. Multiple linear regression model

The oilfield facility comprises the flow station and the gas-lift compressor station. The entire facility is designed to produce a maximum crude oil output of 70,000-bpd gross daily from a total of 40 wells, which is transported by export pumps through a network of pipelines to the primary trunk line linking the *Forcados* terminals. 70,000-bpd daily production can only be achieved when there are smooth operations. It entails that the production operations are not hindered or distorted and the equipment is in good shape and without downtime. Four unbiased compressors must run at full capacity and continuously, and four fair export pumps must be fully operational and in the right working conditions. Any anomalies or deviations will fail in attaining the set target.

When the gas-lift compression station is non-functional, the flow-station can work autonomously; however, the crude oil production output will be meager, and the maximum production output that can be achieved under this scenario is 12,000-bpd gross. This output is realized from only 8 out of the 40 wells that are flowing from natural wells/reservoir that does not require gas-lift pressure to flow.

On average, each of these natural flowing wells is capable of producing only 1500-bpd gross daily.

When being functional and fully operational, an enormous contribution from the gas-lift compressors station is clear and cannot be overemphasized. The rest of 32 weak wells are being gas-lifted at a pressure of 70 – 72 barg to produce the vast bulk of 58,000-bpd gross of crude oil output to achieve the 70,000-bpd daily gross production output. On average, each of the gas-lift wells can provide 1812.5-bpd total daily.

However, some controllable and non-controllable factors such as equipment failure, pipeline rupture, vandalism, militant activities, community interface relations, loss of containment, and leakages result in production losses and, thereby, affect the daily, monthly, and yearly crude oil production outputs at the oilfield. The daily, monthly, and yearly set targets are not achieved.

From the above scenarios and using the multiple linear regression analysis techniques of forecasting, two new models were proposed in this study to predict the daily achievable crude oil production output. These models can be summed up to predict the monthly and yearly production of crude oil output in the oilfield.

Let;

Y = Achievable total crude oil production output from the entire oilfield facility per day.

Y_N = Achievable total production output from natural flowing wells per day.

Y_G = Achievable total production output from natural flowing wells per day.

x = Number of hours of the flow-station facility shutdown per day due to the significant trunk line failure, equipment failure, militants' activities, and community interface relations

where $0 \leq x \leq 24$

x_n = Number of pipelines of the natural flowing wells that are vandalized, ruptured, experiencing leakages, and are non-functional, not in operation, or not inflow, where $0 \leq x_n \leq 8$

x_g = Number of pipelines of the gas-lifted well-strings that are vandalized, ruptured, experiencing leakages, and are non-functional, not in operation, or not inflow, where $0 \leq x_g \leq 32$

Assuming a perfect system, the following can be achieved:

$$Y_N = 1500 \times x_n = 1500 \times 8 = 12{,}000\ bpd \quad (where\ \ x_n = 8) \tag{4}$$

$$Y_G = 1812.5 \times x_g = 1812.5 \times 32 = 58{,}000\ bpd\ (where\ \ x_g = 32)$$

$Production\ per\ hour\ for\ the\ natural\ flowing\ wells$

$$= \frac{Y_N}{24} = \frac{12{,}000 bopd}{24} = 500 boph$$

$Production\ per\ hour\ for\ the\ gas-lifted\ wells$

$$= \frac{Y_G}{24} = \frac{58{,}000 bopd}{24} = 2416.67 boph \tag{5}$$

For an imperfect system craving for perfection, Equations (2) – (5) were combined to model two equations using the multiple regression techniques.

$$Y_N = 12{,}000 - 500x - 1500x_n \tag{6}$$
$$Y_G = 58{,}000 - 2416.67x - 1812.5x_g \tag{7}$$

Note that

$$Y = Y_N + Y_G \tag{8}$$

Once the flow-station is up and running, the natural flowing wells must be on stream except if there is an issue resulting in the non-functionality of any well(s). Therefore, among the numerous scenarios that can take place in the facility, the following are the basic established scenarios that are obtainable from the proposed multiple linear regression model:

1. Without the compressors and only natural wells flowing, the total crude oil production output for 24 hours will be $Y = Y_N = 12{,}000\ bpd$.
2. With one unbiased compressor up and running with an output pressure of 70 barg, eight weak wells will be gas-lifted and, with the eight natural well-strings all flowing for 24 hours, the total crude oil production output will be as follows:
   $Y = Y_N + Y_G = 12{,}000 + [58{,}000 - 2416.67 \times 0 - 1812.5(32 - 8)]$
   $Y = 12{,}000 + [58{,}000 - 0 - 1812.5 \times 24]$
   $Y = 12{,}000 + [58{,}000 - 43500] = 12{,}000 + 14{,}500 = 26{,}500\ bpd$
3. With two unbiased compressors up and running with an output pressure of 70 barg, 16 weak wells will be gas-lifted and, with the eight natural wells all flowing for 24 hours, the total crude oil production output will be as follows:

   $Y = Y_N + Y_G = 12{,}000 + [58{,}000 - 2416.67 \times 0 - 1812.5(32 - 16)]$
   $Y = 12{,}000 + [58{,}000 - 0 - 1812.5 \times 16]$
   $Y = 12{,}000 + [58{,}000 - 29{,}000] = 12{,}000 + 29{,}000 = 41{,}000\ bpd$
   (3)
4. With three unbiased compressors up and running with an output pressure of 70 barg, 24 weak wells will be gas-lifted
   (4)

and, with the eight natural wells all flowing for 24 hours, the total crude oil production output will be as follows:

$Y = Y_N + Y_G = 12{,}000 + [58{,}000 - 2416.67 \times 0 - 1812.5(32 - 24)]$
$Y = 12{,}000 + [58{,}000 - 0 - 1812.5 \times 8]$
$Y = 12{,}000 + [58{,}000 - 14{,}500] = 12{,}000 + 43{,}500 = 55{,}500\ bpd$

5. With four unbiased compressors up and running with an output pressure of 70 barg, the 32 weak wells will be gas-lifted and, with the eight natural wells all flowing for 24 hours, the total crude oil production output will be as follows:

$Y = Y_N + Y_G = 12{,}000 + [58{,}000 - 2416.67 \times 0 - 1812.5(32 - 32)]$
$Y = 12{,}000 + [58{,}000 - 0 - 1812.5 \times 0]$
$Y = 12{,}000 + [58{,}000 - 0] = 12{,}000 + 58{,}000 = 70{,}000\ bpd$

3.7. Test for model adequacy with a scenario

On the 1st of October 2012. Six wells were non-functional and not in operation. Out of the six, three natural wells were out of use due to pipeline rupture and leakages. The rest of the three were weak wells that were vandalized. Six compressors maintained an output pressure gauge of 70 barg, and four export pumps ran on full stream. Four Waukesha and two Clark compressors were operational and running. One Clark compressor unit is capable of gas-lifting eight weak wells. The gas-lift pressure output capacity of one Clark compressor unit is twice the gas-lift pressure output capacity of one Waukesha compressor unit. The oilfield equipment was fairly in good condition, and the entire facility ran for 24 hours without interruption; then, a production output gross of 60,105 bpd was achieved.

3.8. Prediction with the developed model

Since three natural wells were out of use and the facility ran for 24 hours, we get:

$Y_N = 12{,}000 - 500x - 1500x_n = 12{,}000 - 500 \times 0 - 1500 \times 3$
$= 12{,}000 - 4500 = 7{,}500\ bpd$

Since three weak wells were shut-in and the facility was operational for 24 hours, we get:

$Y_G = 58{,}000 - 2416.67x - 1812.5x_g = 58{,}000 - 2416.67 \times 0 - 1812.5 \times 3$
$= 58{,}000 - 5437.5 = 52562.5\ bpd$

Total daily production predicted is as follows:

$Y = Y_N + Y_G = 7{,}500\ bpd + 52562.5\ bpd = 60{,}062\ bpd$

Prediction Error = Actual Value – Forecast Value = 60,105 – 60,062 = 43 bpd.

4. Conclusion and Recommendation

Virtually all forecasts show some degree of errors to a large extent depending on the forecast technique used. Therefore, one has to be careful in the collection of data and in the choice and monitoring of the prediction model used to minimize errors. Statistical models work on the principle that future events are an extension of past events.

By comparing the measures of prediction errors of standard deviation, mean square error, and mean absolute deviation error, it was evident that the Least Squares method achieved better results than the Graphical, Simple Moving Averages, and Exponential Smoothing models because the former holds the minimum prediction error, as shown in Table 6.

However, the forecast obtained through any of the models should not be used blindly. It should be evaluated from a logical point of view against some related variables or phenomena to ascertain if the figures obtained are feasible and should be subjected to further modifications.

The Multiple Linear Regression Model developed is highly reliable. Future work on this model should consider and incorporate the rate of good depletion and the required quantity of gas sent to each well.

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