Predicting Oil Production Rate Using Artificial Neural Network and Decline Curve Analytical Methods

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Abstract

In oil fields where direct measurement of oil production is not feasible, it is always a challenge to accurately predict the rate of production. In such circumstances, oil production rate is estimated through Decline Curve Analytical Methods and Empirical Correlations. In some cases, there may be significant errors inherent in the application of these methods producing inaccurate results. This study focused on predicting oil production rate using Levenberg-Marquardt back propagation algorithm to train the Back Propagation Artificial Neural Network (BPANN) and Decline Curve Analytical Methods (DCAMs). The study considered 1600 data sets, with 70% for training and the remaining 30% for testing. The input parameters used are gas production rate, tubing head pressure and flowing bottom-hole pressure, with crude oil production rate serving as the output. The developed BPANN model predicts oil production rate as a function of gas rate, production time, flowing bottom-hole pressure and tubing head pressure. The accuracy of the developed BPANN model was compared with the DCAMs so as to determine the best method for predicting oil production rate. The BPANN and the DCAMs (that is Exponential, Harmonic and Hyperbolic) predicts oil production rates with mean absolute percentage errors of 3.18, 9.27, 11.55 and 14.01, respectively. Correlation coefficient of the models were 0.9966, 0.9577, 0.9391 and 0.9578 respectively. The BPANN model predicts oil production rate with higher accuracy as compared the Decline Curve Analytical Methods.

Keywords: Back Propagation Artificial Neural Network, Harmonic method, Hyperbolic method, Exponential method

1 Introduction

Petroleum is believed to originate from fossils that have been trapped for thousands of years and have transformed into hydrocarbons through various processes of change and finally trapped in the reservoir. The oil and gas industry depend on production data to determine the longevity of a producing oil/gas facility and to forecast the lucrativeness of a producing oil/gas facilities (Ibrahim, 2017). The need to predict oil production rate is imperative during planning and running of the well completion procedures (Ahmadi et al., 2013). This is necessary for economical optimisation of the subsea equipment to maximise the hydrocarbon production and to limit the production of other unwanted fluids. Failure to predict oil production rate can lead to challenges in determining the longevity of a producing oil/gas facility and predicting the profitability of producing oil/gas facilities (Ibrahim, 2017).

In an oil field where direct measurement of oil production is not feasible, it has become a challenge to most petroleum engineers and in such situations, oil production rate is estimated through decline curve analytic methods and empirical correlations. In addressing the weaknesses and limitations of the decline curve analytic methods, several researchers (Khan et al., 2020; Ghorbani *et al*., 2019; Al-Qutami *et al*., 2017; Hasanvand and Berneti, 2015; Ahmadi *et al*, 2013; Mizaei-Paiaman and Salavati, 2012) have in these recent times have resorted to the use of Artificial Neural Network (ANN) to predict oil and gas production rates. The better and accurate prediction results obtained by the ANN have shown its suitability and reliability in predicting oil production rate (Khan *et al*., 2020; Ghorbani et al., 2019; Mizaei-Paiaman and Salavati, 2012). Based on this, this paper extends the application of ANN to predict the oil production rate of an oil well in the Jubilee Field of Ghana.

1.1 Artificial Neural Network

ANN is basically a mathematically developed model that can acquire artificial intelligence. It acquires knowledge through a learning process and stores knowledge just like the human brain through assigning inter-neuron connection strengths known as weights (Al-Khalifa, 2009). The first application of ANN in petroleum engineering emerged in 1993 by Juniardi and Ershaghi (Mirzaei-Paiaman and Salavati, 2012). In the last two decades, ANN has been adapted in various aspects of petroleum engineering, like field development, reservoir modelling (Esmaili and Mohaghegh, 2016; Mohaghegh, 2011), identification of lithology and interpretation of well logs (Mohaghegh, 2000), two-phase flow through wellhead chokes (Mirzaei-Paiaman and Salavati 2012), permeability prediction (Ramgulam *et al.*, 2007), fractured reservoirs and formation damage prediction (Mohaghegh, 2000).

2 Materials, Methods Used

2.1 Materials Used

Secondary data was obtained from Well Y located in the Jubilee Field of Ghana. The data obtained include daily crude oil production rate, cumulative production, daily gas production rate, daily tubing head pressure in psig and the daily flowing bottom hole pressure in psia. One thousand six hundred data sets were used for this project with 70% of the total data was used for training and the remaining 30% for testing. Other materials used for this project include Matlab 2018b and Microsoft Excel. Table 1 shows the range of data used.

Table 1 Range of Data Used in This Study

Type of Data	Min	Max	Average
Oil rate, bbl/d	151	10,975	4,623
Gas rate, mmscf/d	0.09	13.91	5.81
Tubing Head Pressure, psig	1,603	3,059	2,488
Flowing Bottom Hole Pressure, psia	3,188	5,014	4,283
Production time, Days	1	1,573	787

2.2 Back Propagation Artificial Neural Network (BPANN)

ANN is a technology inspired by the adaptive, similar computing style of the human brain and functions through a variety of theoretical concepts and computer analogies (Arbib, 2003). Back propagation artificial neural network is a supervised feed forward neural network technique, and was employed as the learning rule in this paper. In supervised technique, the input and output data are provided and the error (difference) between the predicted output from the neural network and the actual output is calculated and used by the algorithm to adjust the weight of the neurons until the difference is within the acceptable limits, otherwise the weights will be returned (Back propagated) to be adjusted. To transfer the output of each neuron and layer from one to another, a transfer function is normally assigned to pass the signals after it has been processed inside the neuron (Al-Khalifa and Al-Marhoun, 2013). The tangent sigmoid function (tansig) was used as the transfer function in the hidden layer.

2.2.1 Data, Selection of Input and Output Parameters and Normalisation

The datasets were divided into input and output parameters. The input parameters being daily gas production rate in mmscf/d, production time in days, daily tubing head pressure in psig and the daily flowing bottom-hole pressure in psia of the datasets. The output being the daily crude oil production rate since the objective of this paper is to predict oil production rate. With respect to the use of artificial neural network, one of the factors that affects the accuracy of the predicted results is related to the calibre of datasets utilised in the modelling and selection of appropriate input and output parameters. To perform any training with respect to ANN the dataset must be normalised, that is converting the original data into a form of zeros and ones (0,1). Normalising ensures constant variability in the model. It also improves convergence speed (Opoku-Mensah, 2017). In this study, the input and output variables were normalised into the interval [-1, 1] and the mathematical expression for the normalisation is shown in Equation 1.

$$yi = y\min + \frac{(y\max - y\min)(xi - x\min)}{(x\max - x\min)} \quad (1)$$

where, yi = normalised data
xi = measured values
$x$min = minimum measured value
$x$max = maximum measured value
$y$max and ymin values are set at 1 and -1.

2.2.2 Network Training and Model Performance Evaluation

For ANN to develop a desired output, the dataset needs to be trained using particular inputs. Regarding this paper, the purpose of the training is to predict the crude oil production rate of the datasets. 70% of the total data was used for the training and the other 30% used for testing. For the network training, the Levenberg-Marquardt back propagation algorithm was used to train the BPANN. In the training process of BPANN model, the Mean Squared Error (MSE) was monitored at each training and testing stage. The correlation coefficient (R) and Mean Absolute Percentage Error (MAPE) were used to assess the performance of the models. The model with the least MAPE value and highest R was selected as the optimal model after a series of training (Opoku-Mensah, 2017).

2.3 Decline Curve Analytical Methods

The exponential, harmonic and hyperbolic methods were also used to predict oil production rate using the same 1,574 data set that were used in the model. Equations 2, 3 and 4 shows the exponential, harmonic and hyperbolic methods that were employed in this paper.

Exponential Method

$$qt = qi \times \ell \wedge (-di \times t) \tag{2}$$

Harmonic Method

$$qt = \frac{qi}{(1 + di \times t)} \tag{3}$$

Hyperbolic Method

$$qt = \frac{qi}{(1 + Di \times b \times t) \wedge \frac{1}{b}} \tag{4}$$

where, q = current production rate
qi = initial production rate
di = nominal decline rate (value of 3.1519E-05)
Di = effective decline rate (value of -0.0346)
t = cumulative time since start of production
b = a constant, b = 0 for exponential, b = 1 for harmonic, 0 < b < 1 for hyperbolic

3 Results and Discussion

After a series of training ranging from hidden neuron 1 to hidden neuron 20, hidden neuron 2 was selected as the optimum ANN model. Hidden neuron 2 because it had the highest regression and lowest MAPE value for the 1,600 data sets. The elapsed time for running the code with 2 hidden neuron is 2.08 seconds (Table 2 and Figure 1). The decline curve methods were also used to history match the production rate and a mean absolute percentage error (MAPE) and correction coefficient (R) was obtained. Table 3 shows the comparisons of the results obtained from the various models. Figures 2, 3, 4 and 5 shows actual and predicted production rate against time for exponential, harmonic hyperbolic and ANN method, respectively. These graphs show the closeness of predicted values and the actual values of the various methods employed in this paper.

Table 2 ANN Optimum Model Characteristics

ANN Model	Number of Hidden Neurons	Sample Type	MAPE	R
4 – 2 - 1	2	Training	2.45%	0.9966
		Testing	5.47%	0.9758
		Average	3.18%	0.9966

Table 3 Comparisons of Results Obtained from the Various Methods

Model	MAPE	Correlation Coefficient (R)
ANN	3.18%	0.9966
Exponential	9.27%	0.9577
Harmonic	11.55%	0.9391
Hyperbolic	14.01%	0.9578

BPANN model developed had the highest correlation coefficient and the least mean square error (0.9966 and 3.18% respectively) compared to the decline curve methods. Hence, the optimum ANN model performed better than the exponential, harmonic and hyperbolic methods with reference to the model performance evaluation, which included correlation coefficient and mean absolute percentage error (MAPE). For a model to be considered better than the other, its error statistics or model performance evaluation using the statistical indicators should be closer to zero and regression closer to one.

Hence, the back propagation artificial neural network model predicted the oil production rate with less amount of error statistically showing higher accuracy in predicting the oil production rate when compared to the exponential, harmonic and hyperbolic methods.

Based on the predicted results obtained from the ANN and the four input parameters (tubing head pressure in psig, flowing bottom-hole pressure in psia and gas rate in mmscf/d), a general predictive equation (Equation 5) was generated to predict oil production rate.

$$Qo = 766.65 - 0.32t + 738.82Qg - 0.67THP + 0.33FBHP \tag{5}$$

where Qo = Oil production rate, bbl/d

t = Production time, days

Qg = Gas rate, mmscf/d

THP = Tubing head pressure, psig

FBHP = Flowing bottom hole pressure, psia

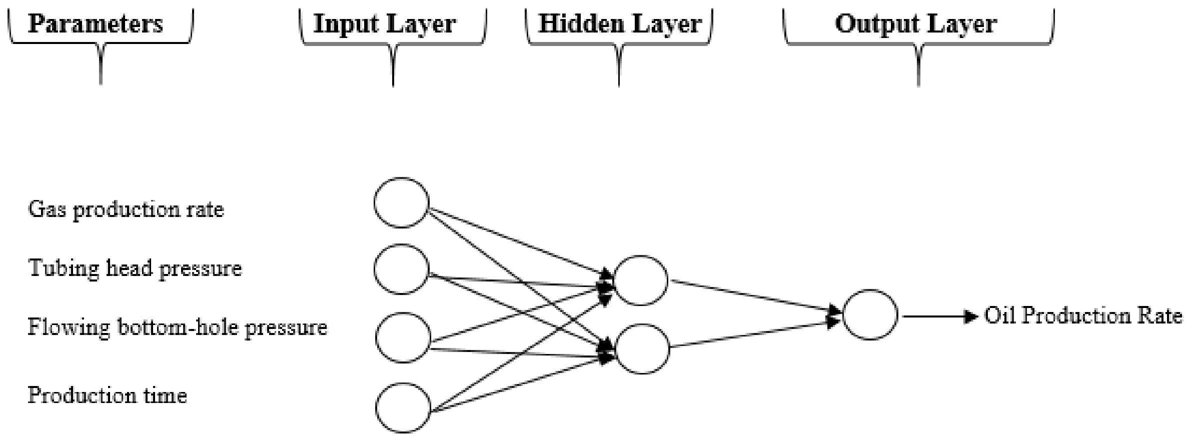

Figure 1 Structure of ANN Model Developed

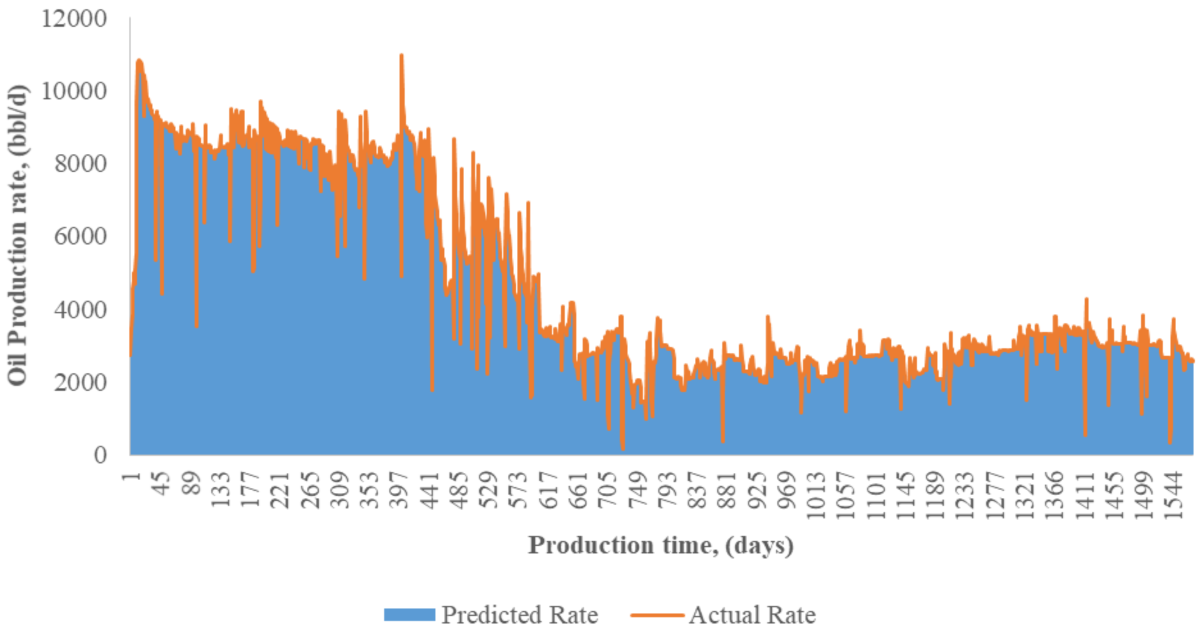

Figure 2 Actual and Predicted Oil Rate vs Time using Exponential Method

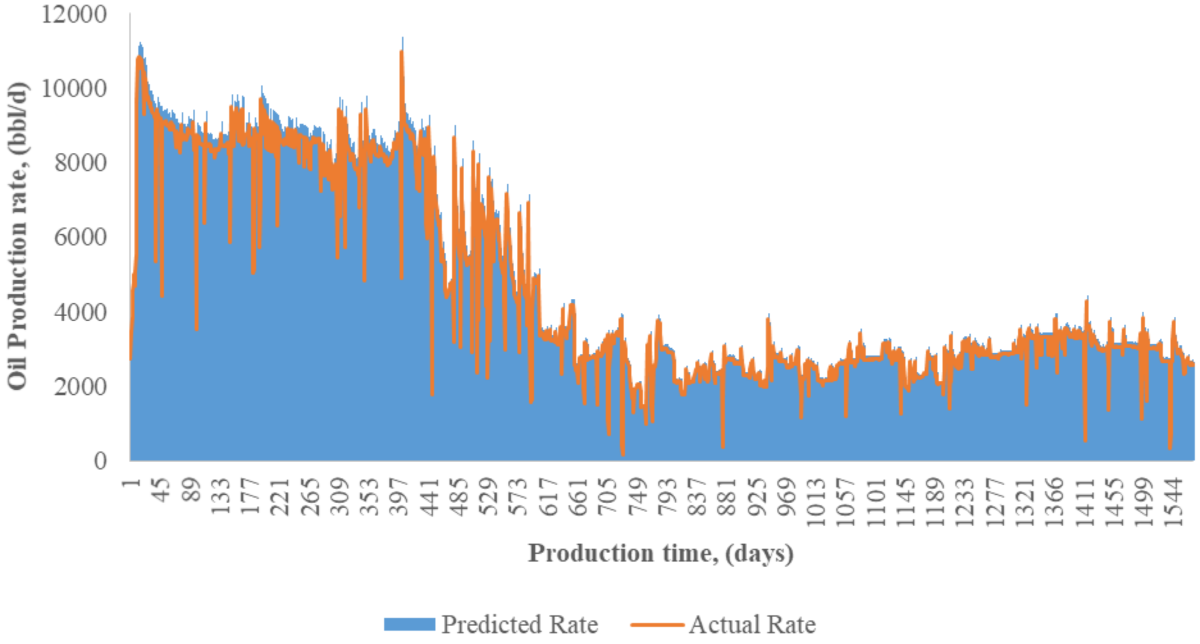

Figure 3 Actual and Predicted Oil Rate vs Time using Harmonic Method

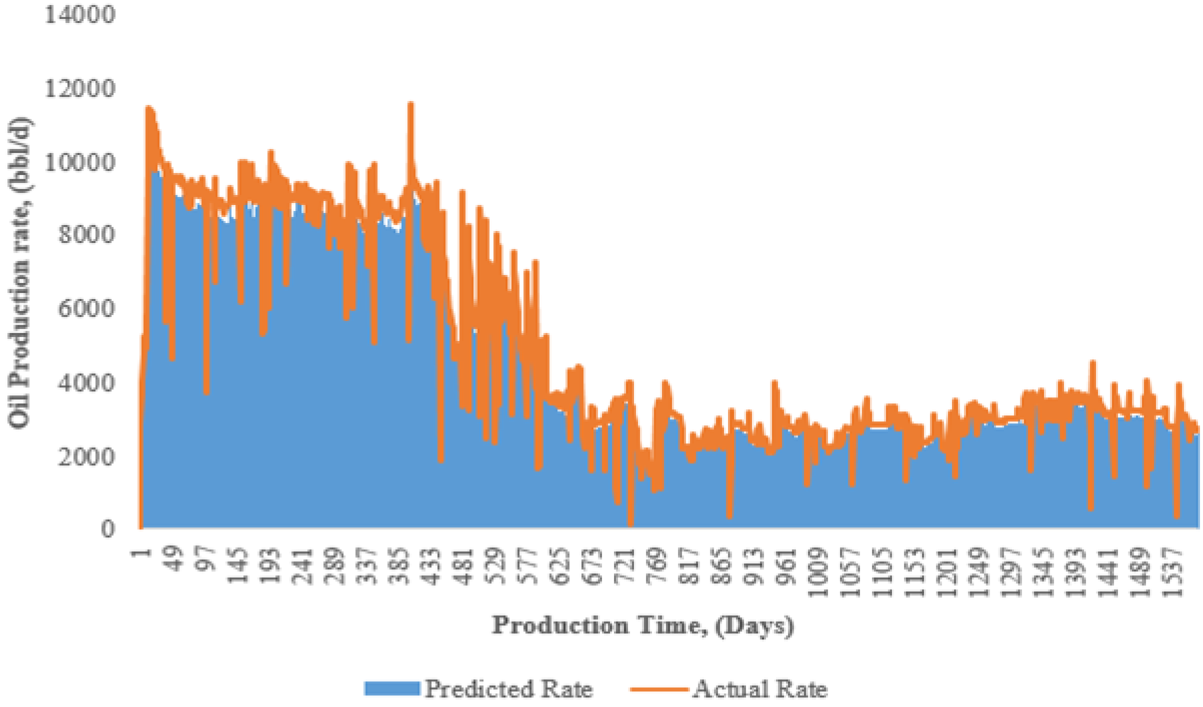

Figure 4 Actual and Prediction Production Rate vs Time using Hyperbolic Method

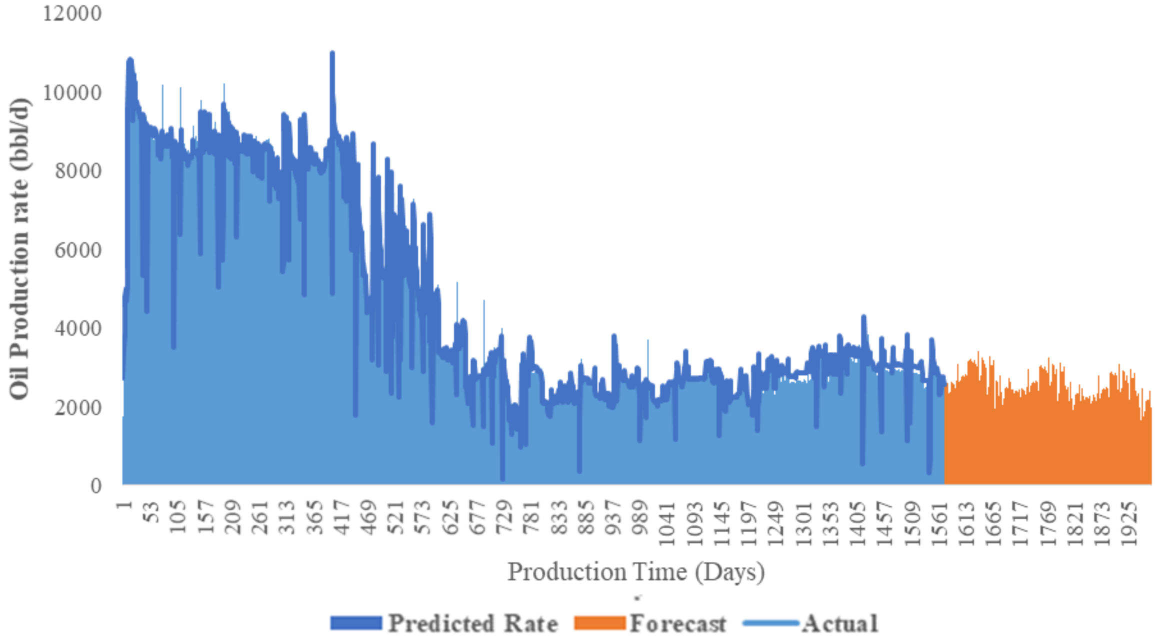

Figure 5 Actual and Prediction Production Rate vs Time Using ANN Model

4 Conclusions

Artificial neural network (ANN), exponential, harmonic and hyperbolic methods were used predict the oil production rate. From the results obtained, it can be concluded that:

a. The oil production rate was successfully predicted by an artificial neural network, exponential, harmonic and hyperbolic methods.

b. The results obtained from the ANN, exponential, harmonic and hyperbolic were obtained and comparisons of the results showed that the ANN model was a better fit in predicting oil production rate.

c. Hence the ANN can predict oil production rate with the four input parameters with 3.18% error.

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