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Production Decline Prediction of Shale Gas using Hybrid Models

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P. Manda [α] & D.B. Nkazi [σ]

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I. Introduction

Rate-time decline curve extrapolation is one of the oldest and most commonly used tools by a petroleum engineer. Results obtained for a well are subject to a wide range of alternate interpretations, mostly as a function of the experience and objectives of the evaluator. Recent efforts in the area of decline curve analysis (DCA) have been directed towards a purely computerised statistical approach, its basic objective being to arrive at a unique "unbiased" interpretation [1]. In the past few decades, several DCA models have been proposed and benchmarked with commercial reservoir simulators or shale gas production data before being applied to more shale gas reservoirs (SGRs) [2].

Numerous studies have highlighted the importance of DCA models, however, there are limitations with these models. Analysis conducted using these techniques for the prediction and estimation of reservoirs in shale well production have highlighted shortcomings in the models [3]. These shortcomings include underestimation, finite and overestimation of the estimated ultimate recovery (EUR) of reserves. Taking these facts into consideration, the scope exists for developing improved models which address these shortcomings.

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a) *Production Decline Models*

The Arps decline model is inaccurate within the transient flow regime (TFR) and the Duong model is inaccurate within the boundary dominated flow (BDF). Although the Power Law Exponential (PLE) model incorporates both these flow regimes and was specifically developed for SGRs, the model has its own shortcomings. Hence, the scope to develop a new decline model or a new method to predict more accurately the recovery of SGRs. Accordingly, the approach would be to combine the above-mentioned methods i.e. to evaluate the hybrid decline curve models. As the PLE and Duong's models model the transient flow well and because the Arps model is widely used for BDF, the new approach combines the methods to achieve the objectives and eliminate the shortcomings of the stand-alone models. In this paper, the combination of different models, or hybrid models as they are commonly known, will be investigated.

Hybrid models have frequently been used for prediction by manipulating the unique strength of each of the models [4]. The use of a combination of models provides a more precise predicting model for forecasting time series data as compared to an individual model [5]. The results from studies have indicated that hybrid models have higher prediction accuracy for one-step and multi-step forward forecasts and various hybrid models have been used for obtaining accurate prediction [5; 6].

The evaluation of the forecasting performance of decline curve hybrid models and ARIMA-ANN hybrid models is essential, and these models should be compared with Arps', Duong's, the Power Law Exponential Decline, Autoregressive Integrated Moving Average (ARIMA) and Artificial Neutral Network (ANN) models for accurate prediction of production decline in shale gas.

b) *Hybrid Models and ANN-ARIMA Hybrid Models*

In the literature, hybrid methods are considered to yield better results [7].The accuracy of time series forecasting is challenging for scientists [7]. Time series data often comprise linear as well as non-linear components [8]. In some cases, linear-based approaches might be more suitable than non-linear approaches due to the data characteristics. The use of hybrid models, which combine DCA models, is a new approach and there is minimal literature covering this aspect. However, as mentioned, the known approach to the hybrid method is a combination of the ARIMA and ANN method.

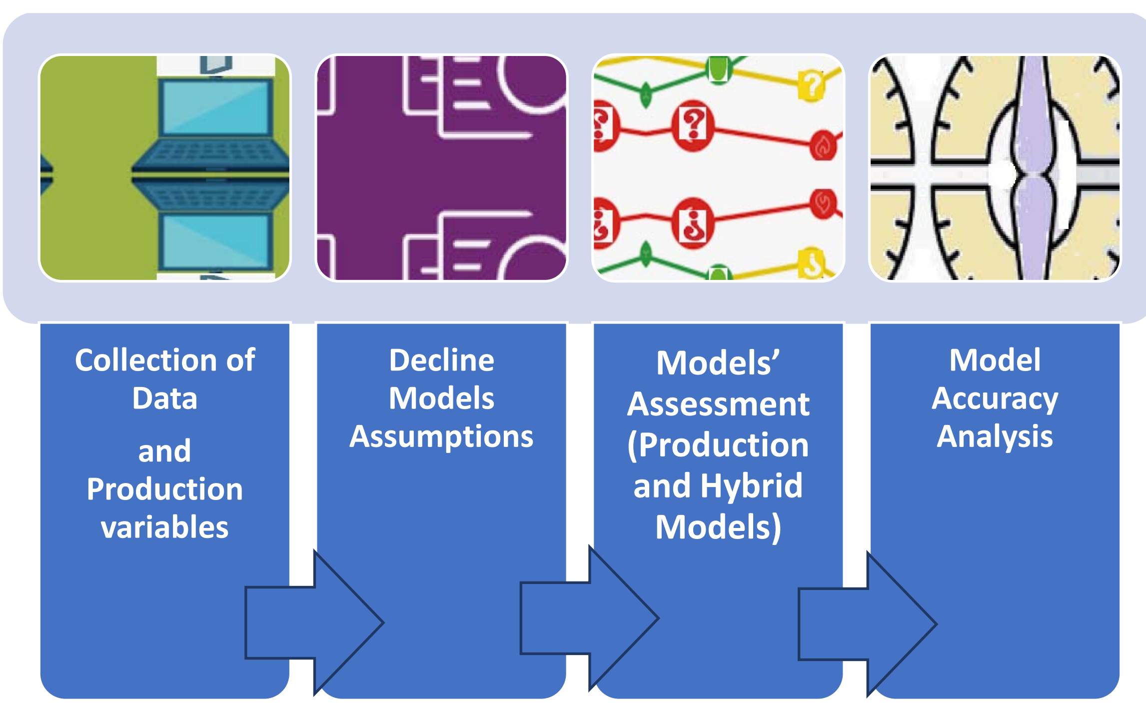
According to Faruk [8], hybrid methods have a higher degree of accuracy than neural networks. ARIMA is able to recognise time-series patterns well except non-linear data patterns. On the other hand, neural networks only handle non-linear data. Therefore, hybrid models combine the advantages of ARIMA with respect to linear modelling and neural networks in terms of non-linear edge modelling [9]. Ayub and Jafri (2020) [10] in their paper highlighted that the combined model has improved forecasting accuracy as compared to when the models are used individually. Notwithstanding this, in some circumstances the single model approach can outperform hybrid models [8]. Babu et al. (2014) [5] explored ARIMA and ANN as a new hybrid model for better prediction of time series. Their results preferred the use of the hybrid model compared to the individual ARIMA and ANN models.

The ARIMA processes follow a stochastic behaviour used to analyse time series [11] and is mostly used to predict demand. The application of the ARIMA methodology for the study of time series analysis was developed by Box and Jenkins [11]. The Box–Jenkins methodology includes three iterative steps of model identification, parameter estimation and diagnostic checking [12]. This three-step model building process is typically repeated several times until a satisfactory model is finally selected and can then be used for prediction purposes [12]. In an ARIMA model, the future value of a variable is assumed to be a linear function of several past observations and random errors [11]. During the past decades, researchers have been focusing more on linear models due to their simplicity in comprehension and application [13]. A disadvantage of the classical ARIMA methodology is that it requires a large number of observations to determine the best fit model for a data series [13].

The ANN model, on the other hand, has found increasing consideration in forecasting theory, leading to successful applications in various forecasting domains including economics, business, financial and many more [14]. One advantage of neural networks compared to other non-linear models is their universal model, which is capable of predicting fairly extensive functions with a high degree of accuracy. No assumptions are required for neural networks, thus neural networks conform to the characteristics of the data [15]. However, there are disadvantages associated with this model such as constructing the forecasting model, the selection of the network architecture and the data pre-processing techniques which apply to the time series data [16; 17].

This investigation uses different hybrid models in forecasting production decline and evaluating the hybrid models for improved forecasting accuracy of time series by using the unique strengths of the models. The experimental results used are based on the study of shale gas production data obtained from a previous study done by Paryani et al. [3].

II. Methodology



a) Collection of Data

The variable used in this investigation is flowrate, q(t) in STB/day, monitored over a period of time (T) in days. The estimated data was extracted from the research conducted by Paryani et al. (2018), who obtained the data from the Cannon Well located in Karnes County evaluated over a two-year period. Kappa Citrine and JMP software are used for simulation of the DCA, hybrid DCA, ARIMA, ANN and ANN-ARIMA hybrid models respectively.

b) Production Behaviour

i. *Arps' Decline Curve Model*

Arps' decline curve analysis is the most commonly used method of estimating ultimate recoverable reserves and future performance [18]. Paryani et al. [3] attribute this to reliable history match (even with b > 1) and its simplicity. The model process is based on the following vital assumptions: that past operating conditions will remain unaffected; that a well is produced at or near capacity; and that the well's drainage remains constant and is produced at a constant bottom-hole pressure [19]. Notably, the Arps model is only applicable in pseudo-steady flows when the flow regime transfers from linear flows to boundary-dominated flows (BDF) [20]. This indicates that the Arps equations are not applicable to the production forecasting of the entire decline process of horizontal wells in low-permeability reservoirs [21]. The most commonly employed hyperbolic form of Arps' decline equation [1] is used for shale reservoirs. The hyperbolic decline equation is suitable to use due to the "best fit" that it provides for the long transient linear-flow regime observed in shale gas wells with b values greater than unity [22].

$$q = \frac{q_i}{(1+bD_i t)^{\frac{1}{b}}} \tag{1}$$

Where q is the flow rate in STB/day or Mscf/day, q_i is the initial flow rate in STB/day or Mscf/day, D_i is the initial decline constant, which is measured in days-1, and b is the decline exponent.

Table 1: Summary of the Arps model behaviour, assumptions, condition and parameters

Production Behaviour	Assumptions	Condition	Parameters
Boundary Dominated Flow (BDF)	Decline parameter, b, defines the decline behaviour	$0 < b < 1$	$b = 1.10$ $D_i = 0.12$

ii. *Duong's Decline Curve Model*

Doung [23] presented an unconventional rate decline method to evaluate the performance of shale gas wells that does not depend on the fracture types. The model assumes linear or near-linear flow, as indicated by a log–log plot of rate over cumulative production versus time, which yielded a straight-line tendency [24]. The rate is calculated in the model using the following equation [2]:

$$q(t) = q_i t(a,m) + q_\infty \tag{2}$$

Where t (a,m) is the time constant in 1/s, and q_∞ is the production rate at infinite time in m^3/s.

Table 2: Summary of the Duongs model behaviour, assumptions, condition and parameters

Production Behaviour	Assumptions	Condition	Parameters
Transient Flow Regime (TFR)	Very low permeability and long periods of transient flow	$b > 1$	$q_i = 361.24$ $a = 1.07$ $m = 1.10$

iii. *Power Law Exponential Decline Model (PLE)*

Ilk et al. [25] presented the PLE, which is an extension of the exponential Arps formula for the decline degree in shale reservoirs. This model was developed precisely for SGR and approximates the rate of decline with a power law decline. The PLE model matches production data in both the transient and boundary-dominated regions without being hypersensitive to remaining reserve estimates [26]. Seshadri and Mattar[27] presented that the PLE model can model transient radial and linear flows, while Kanfar and Wattenbarger[28] proved that the model is reliable for linear flow, bilinear flow followed by linear flow, and linear flow followed by BDF, or bilinear flow followed by linear flow and finished with BDF flow. Vanorsdale[29] deduced that when the flow regime changes throughout the initial 10 years of the well, the PLE model will yield a very optimistic recovery. The model characterizes the decline rate by infinite time, $D\infty$ which is defined as a "loss ratio" (which is assumed to be constant from Arp) [30]. The production rate is derived as follows:

$$\frac{q}{dq/dt} = -b \tag{3}$$

$$b = D_{\infty} + D_i t^{-(1-\hat{n})} \tag{4}$$

Where dq/dt is the slope, D_∞ is the decline rate over a long-term period, and $\hat{n}$ is the time exponent. By substituting the above equations, the production rate is obtained:

$$q(t) = \hat{q}_i e^{[-D_\infty t - \hat{D}_i t^{\hat{n}}]} \tag{5}$$

Table 3: Summary of the PLE model behaviour, assumptions, condition and parameters

Production Behaviour	Assumptions	Condition	Parameters
BDF and TFR	Approximates the rate of decline with a power law decline	b changes with time	n = 0.182 D_i = 0.268

iv. *The Arps'-Duong's-Power Law Models Hybrid Model*

The first proposed method incorporates the three DCA models, namely Arps', Duong's and PLE models. The Arps model only considers BDF while Duong's and PLE models consider TFR. The PLE model also considers BDF and has been specifically developed for SGRs. Hence, by combining the three models the limitations from each is presumed to be minimised or eliminated.The equation is given as:

$$\frac{qt}{qi} = t\,(-D_\infty - D_i\hat{n}) - In\frac{b+1}{b} \tag{6}$$

where q_t is the flow rate in STB/day or Mscf/day, *qi* is the initial flow rate in STB/day or Mscf/day, t is the time in days, $D\infty$ the decline rate over along-term period, while D_i is the initial decline constant, which are both measured in days $^{-1}$, $\hat{n}$ is the time exponent and *b* is the decline exponent.

Table 4: Summary of the Arps-Duong-Power Law hybrid model behaviour, assumptions, condition and parameters

Production Behaviour	Assumptions	Condition	Parameters
BDF and TFR	Approximates the rate of decline with anexponential decline	0 > b >1	n = 0.182 D_i = 0.194 b = 1.10

v. *The Arps-Duong Hybrid Model*

The second proposed model incorporates the two developed DCA models. Arps' model only considers BDF while Duong's considers TFR, hence both these flow regimes will be taken into account when combining these two models. The equation is given as:

$$qt = [\tfrac{qt}{t}][1 + bD_i]^{-\frac{1}{b}} \tag{7}$$

Where *qt* is the flow rate in STB/day or Mscf/day, *t* is the time in days, D_i is the initial decline constant, which is measured in days $^{-1}$and *b* is the decline exponent.

Table 5: Summary of the Arps-Duong hybrid model behaviour, assumptions, condition and parameters

Production Behaviour	Assumptions	Condition	Parameters
BDF and TFR	Approximates the rate of decline with a mechanistic growth decline	0 > b >1	D_i = 0.194 b = 1.10

vi. *The Arps-Power Law Exponential Hybrid Model*

The third proposed model incorporates the Arps and PLE models. These models consider BDF and TFR flows. Since the PLE model was developed specifically for SGRs, it would be advantageous to evaluate these two models combined due to both being simple equations to use. The equation is given as:

$$t[-D_\infty - D_i\hat{n}] = \frac{-\frac{1}{b}}{qt} In(1 + bD_i) \tag{8}$$

Where *qt* is the flow rate in STB/day or Mscf/day, t is the time in days, $D\infty$ the decline rate over a long-term period and D_i the initial decline constant, which are both measured in days^{-1}, $\hat{n}$ is the time exponent and *b* is the decline exponent.

Table 6: Summary of the Arps-Power Law Exponential hybrid model behaviour, assumptions, condition and parameters

Production Behaviour	Assumptions	Condition	Parameters
BDF and TFR	Approximates the rate of decline with a logistic decline	0 > b >1	n = 0.182 D_i = 0.194 b = 1.10

vii. *The Duong-Power Law Exponential Hybrid Models*

The fourth proposed model incorporates the Duong and PLE models. These models both consider TFR. The equation is given as:

$$\frac{In\ qt}{qm} = t\left[-D_{\infty} - D_i\hat{n}\right] \quad (9)$$

Where *qt* is the flow rate in STB/day or Mscf/day, t is the time in days, $D\infty$ the decline rate over along-term period and D_i the initial decline constant, which are both measured in days^{-1} and $\hat{n}$is the time exponent. q_m is the flow rate at slope m in m^3/s.

Table 7: Summary of the Duong-Power Law Exponential hybrid model behaviour, assumptions, condition and parameters

Production Behaviour	Assumptions	Condition	Parameters
BDF and TFR	Approximates the rate of decline with a mechanistic growth decline	0 > b >1	n = 0.182 D_i = 0.194 q_m= 7.12

viii. *Autoregressive integrated Moving Average (ARIMA) Model*

As mentioned earlier in the paper, the ARIMA processes follow a stochastic behaviour used to analyse time series [11] and are mostly used to predict production demand. The model is labelled as an ARIMA model (p, d, q), where: -

1. p is the number of autoregressive terms;
2. d is the number of differences; and
3. q is the number of moving averages.

According to Ayub and Jafri (2020) [10], the best ARIMA model is determined according to criteria as follows:

- Relatively small BIC
- Maximum adjusted R^2

a. The Autoregressive Process

This process assumes that Y_t is a linear function of the preceding values and is given by equation (5).

$$Y_t = \propto_1 Y_{t-1} + \varepsilon_t \quad (10)$$

Generally, each observation consists of a random component i.e. a random shock, ε and a linear combination of the previous observations. $\propto_1$ in the equation is the self-regression coefficient.

b. The Integrated Process

The integrated process is the archetype of non-stationary series. A differentiation of order 1 assumes that the difference between two successive values of Y is constant. An integrated process is defined by equation (6).

$$Y_t = Y_{t-1} + \varepsilon_t \quad (11)$$

where the random perturbation ε_t is a white noise.

c. The Moving Average Process

The moving average process is a linear combination of the current disturbance with one or more previous perturbations. The moving average order indicates the number of previous periods embedded in the current value. Thus, a moving average is defined by equation (7).

$$Y_t = \varepsilon_t - \theta_1\varepsilon_{t-1} \quad (12)$$

In order to evaluate the best fit for the ARIMA model, a number of scenarios were evaluated and the ARIMA scenario (2,1,2) was selected to give the best forecast values, due to having the lowest MSE of 4.82, a low BIC of 8,23 and highest adjusted R^2 of 0,979. Table 2 indicates the best results for the ARIMA model, which are highlighted in bold.

Table 8: Statistical results for the different p,d,q for the ARIMA model

ARIMA	BIC	MSE	Adjusted R^2
(0,0,0)	8,63	46.91	0.000
(1,1,1)	6,19	5.86	0.974
(1,2,1)	9.42	5.84	0.958
(1,3,1)	6,69	6.35	0.899
(2,1,1)	8,25	5.08	0.974
(2,1,2)	**8,23**	**4.82**	**0.979**

ix. *Artificial Neutral Network (ANN) Model*

The model consists of three interconnected layers: the input layer, the hidden layer, and the output layer. The basic unit of any ANN is the neuron or node (processor). Each node is able to sum many inputs x1, x2,..., x3 whether these inputs are from a database or from other nodes, with each input modified by an adjustable connection weight [14]. The relationship that occurs in the output and input layers follows equation (8).

$$Y_t = \propto_0 + \sum_{j-1}^{q} \propto_j g\left(\beta_0 j + \sum_{I=1}^{p} \beta_i j Y_t - i\right) + \varepsilon_t \qquad (13)$$

where $\propto_j$ (j = 1,2,3, ..., q) and $\beta_i j$ (i= 1,2,3, ..., p; j = 1,2,3, ..., q) are the parameters of the model (often called the weights), p is the number of input points (input nodes), and q is the number of hidden nodes. The activation function used in the hidden layer is the logistic sigmoid function and the linear function is the output layer.

To choose the best algorithm for the model, the number of hidden nodes and layers are changed. The accuracy can also be increased by increasing the number of nodes and layers [31]. In the case of this study, a univariate input layer and four nodes as shown in Figure 1 gave the best model.

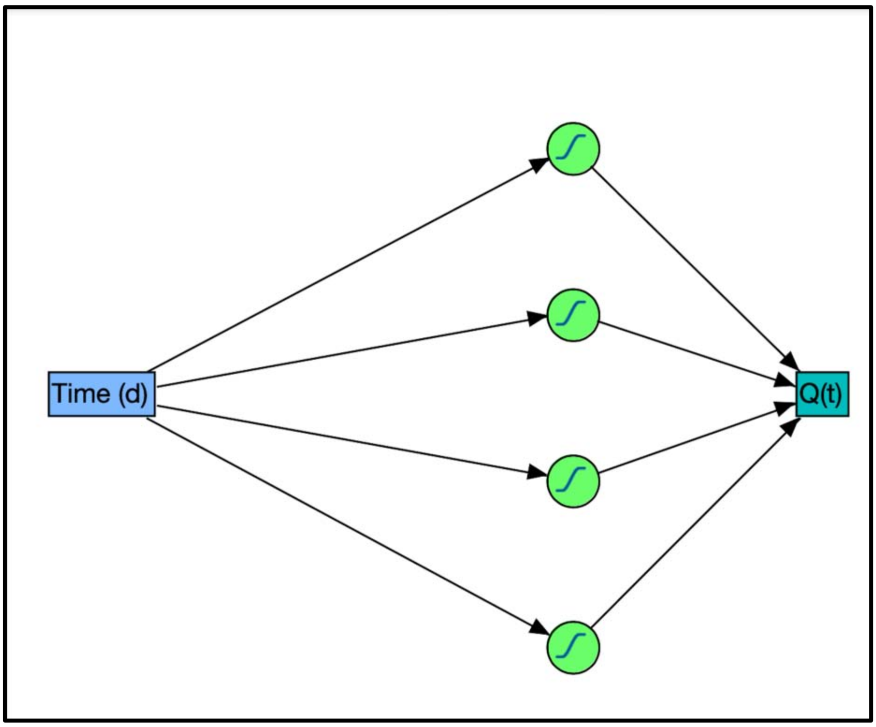


Figure 1: Univariate Artificial Neutral Network obtained from JMP

x. *ANN-ARIMAHybrid Model*

Zhang investigated the concept of the hybrid ANN-ARIMA model to obtain precise results as compared to using both models separately [12]. Numerous techniques, which explored the hybrid approach have been used for many years to take advantage of the unique strengths of each of the various types of models. The objective of merging the models is due to the notion that a single model is able to define all the specifics of time series [32]. Mathematically, time-series data can be expressed as a combination of linear and non-linear components [15]:

$$Y_t = L_t + N_t. \qquad (14)$$

Where Y_t shows the time-series data, L_t indicates the linear components, and the non-linear components are represented by N_t.

Mathematically, the neural network model for residual of n input nodes can be expressed as follows:

$$e_t = f(e_{t-1} + e_{t-2}, \dots, e_{t-n}) \qquad (15)$$

Where f is a non-linear function that is specified by the neural network. With regard to the results of the prediction error of N_t, the combination forecast using the hybrid method can be expressed as:

$$\hat{y}_t = \hat{L}_t + \hat{N}_t. \qquad (16)$$

N_t is obtained from the predicted values of the ANN model while $\hat{L}_t$ is the forecasted value from ARIMA based on the residual values.

III. Results and Discussion

Kappa Citrine and JMP software were used for the simulation of the models. The experimental results obtained are explained below.

a) Results for the Arps Model

Kappa Citrine software was initially used for determining the parameters for the Arps model. The b and D_i values were found to be 1.10 and 0.12 respectively. Subsequently, JMP software was used to construct the prediction model. The second step was to graph a semi-log plot (log q vs. t) to determine the model forecasting equation and parameters. The forecasting equation is given as follows:

$$y = \frac{c}{1+e^{(-ax^2-b)}} \quad (17)$$

where c is the asymptote, a the growth rate while b is the inflection point. The actual and forecasted flow rate values are shown graphically in Figure 2.

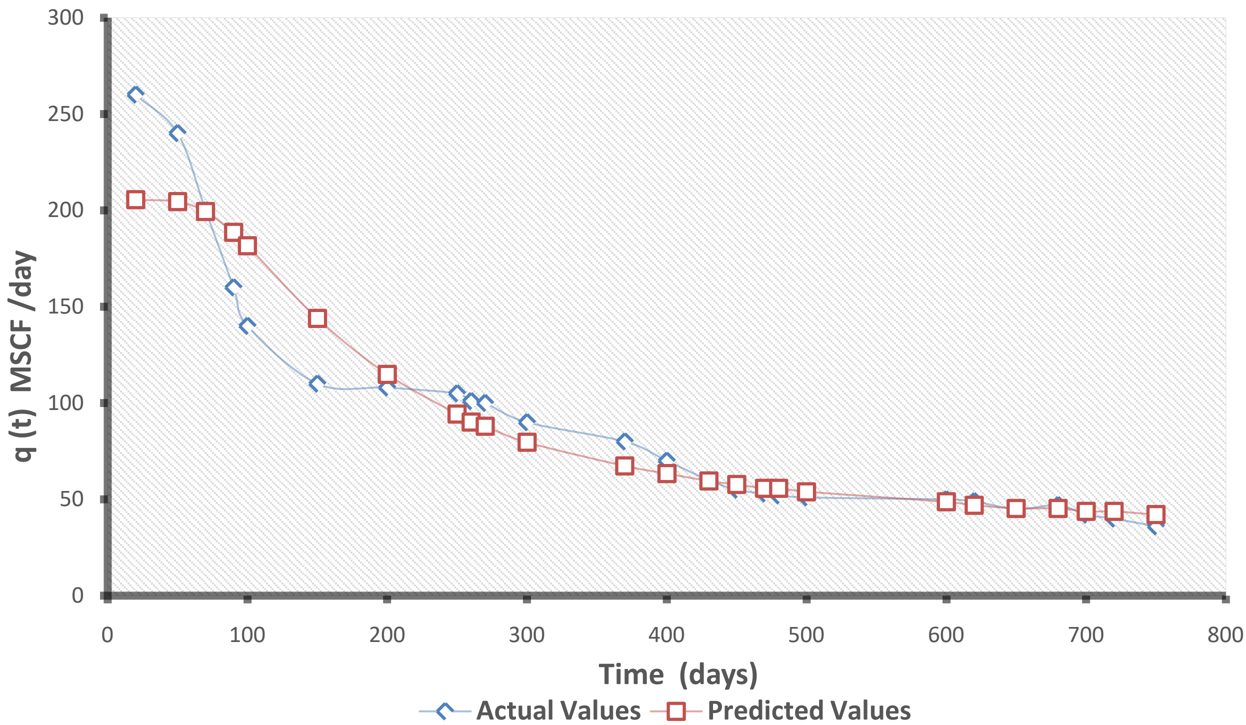


Figure 2: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the Arps model

The results for the model appear in some instances to over- and in other instances to underestimate the data. The results concur with literature, which suggests that the weakness of the Arps model is overestimation of results. Tan et al. (2018) [32] in their study highlighted that although the Arps model is simple and fast, it often fails to accurately fit the decline curve of unconventional reservoirs. They further explained that the model often tends to overestimate the EUR for shale gas wells because it assumes that a BDF regime is evident. Paryani et al. (2018) [3] concurred with these findings, explaining that the drainage area is not constant because the pressure pulse continues to spread from the fracture to other areasof the reservoir volume. Under these conditions, the bvaluepredicted by the Arps model for the actual production data will be greater than 1 as in this case b =1.10. This in turn leads to inaccurate estimates of reserves.

b) Results for the Duong Model

The parameters for the Duong model were q_i = 361.2, a = 1.07 and m = 1.10 respectively. In this instance a log–log linear plot (log *q* vs. log *t*) was used. The forecasting equation is given as:

$$y = bx + c \quad (18)$$

where b is the slope and c is the intercept. The actual and forecasted flow rate values can be seen in Figure 3.

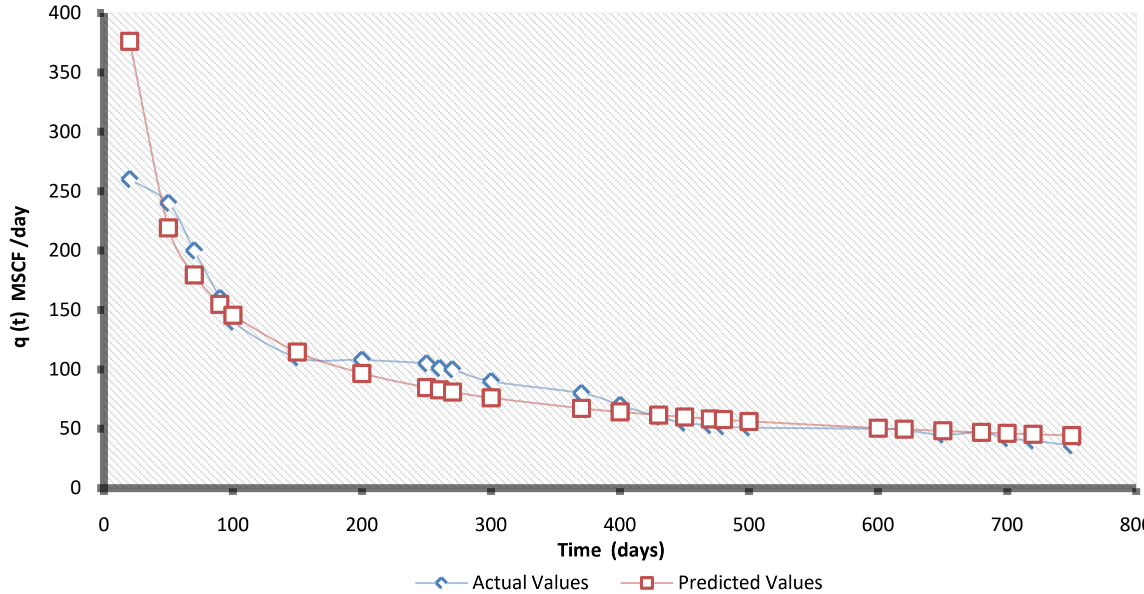


Figure 3: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using Duong's model

The results for the Duong model indicate an overall underestimate of the data. Meyet et al. (2013) [33] mentioned in their work that the Duong model tends to provide the most conservative results. This could also be attributed to the fact that the Duong model tends to be more accurate for linear flows and bilinear–linear flows[28]. Paryani et al. (2018) [3] in their work found that the well fitted with 51% of the historical production data, and that the Duong model fits better with longer and less noisy historical production data.

c) Results for the Power Law Exponential (PLE) Model

The parameters used in the model for n and D_i are 0.182 and 0.268 respectively. A log–log plot (log *q* vs. log *t*) was used in the model forecasting. The forecasting equation is given as:

$$y = a + be^{cx} \tag{19}$$

where a is the asymptote, b is the scale and c is the growth rate.The actual and forecasted values can be seen in Figure 4.

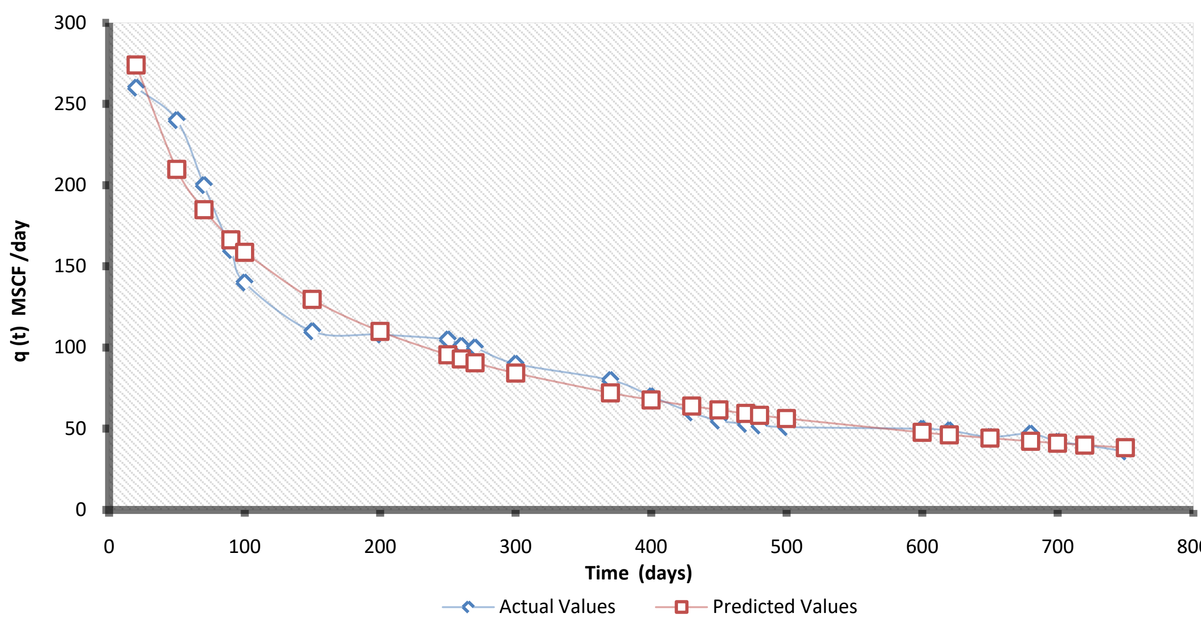


Figure 4: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the PLE model

The results for the PLE model appear to underestimate the data although the PLE considers BDF and TFR, which is an advantage of the model. Furthermore, the model was specifically developed for SGRs, hence it was assumed that the results would be better. This is comparative to the findings by Paryani et al. (2018) [3], as based on their results the PLE consistently gave the lowest forecasts for all the models. It is therefore the most conservative method for production forecasting and reserves estimation. Seshadri and Mattar (2010) [27] concluded that for tight gas wells, the PLE model is complex and non-intuitive. The power law model can result in a non-unique solution due to four degrees of freedom resulting from the four unknown parameters[34].

d) Result for the Arps-Duong-PLE Hybrid Model

A plot of $\frac{qt}{qi}$ vs. t was used in the model forecasting. The parameter q_i used was 361.2 which was noted earlier in Duong's model. The forecasting equation is given as:

$$y = a + be^{cx} \tag{20}$$

where a is the asymptote, b is the scale and c is the growth rate. The actual and forecasted values are graphically represented in Figure 5.

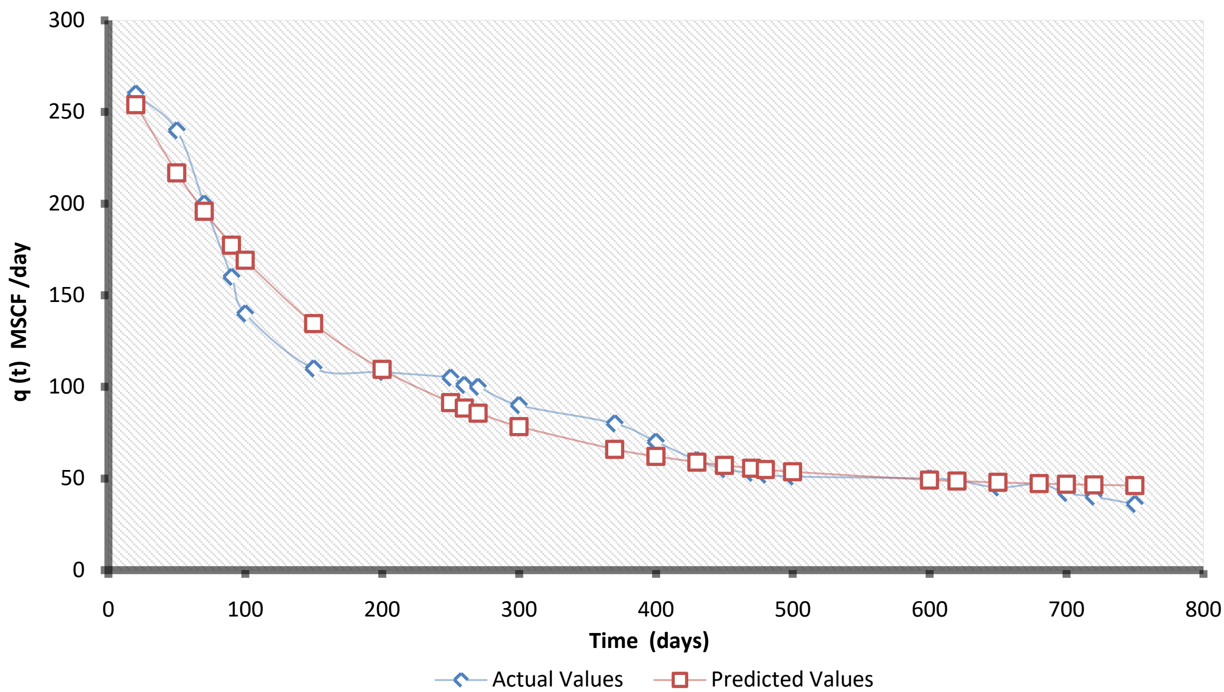


Figure 5: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the Arps-Duong-PLE hybrid model

Based on the results, the model appears to over- and underestimate the data. However, the gap between the actual and predicted results is minimised. This could be attributed to both BDF and TFR being considered. In addition, the conservative approach of Duong's and the PLE models along with the inaccurate fitting of the Arps decline curve of unconventional reservoirs could be a contributing factor.

e) Result for the Arps-Duong Hybrid Model

A plot of $\frac{qt}{t}$ vs.t was used in the model forecasting. The forecasting equation is given as:

$$y = a(1 - e^{-cx}) \tag{21}$$

where a is the asymptote, b is the scale and c is the growth rate. The actual and forecasted values can be seen in Figure 6.

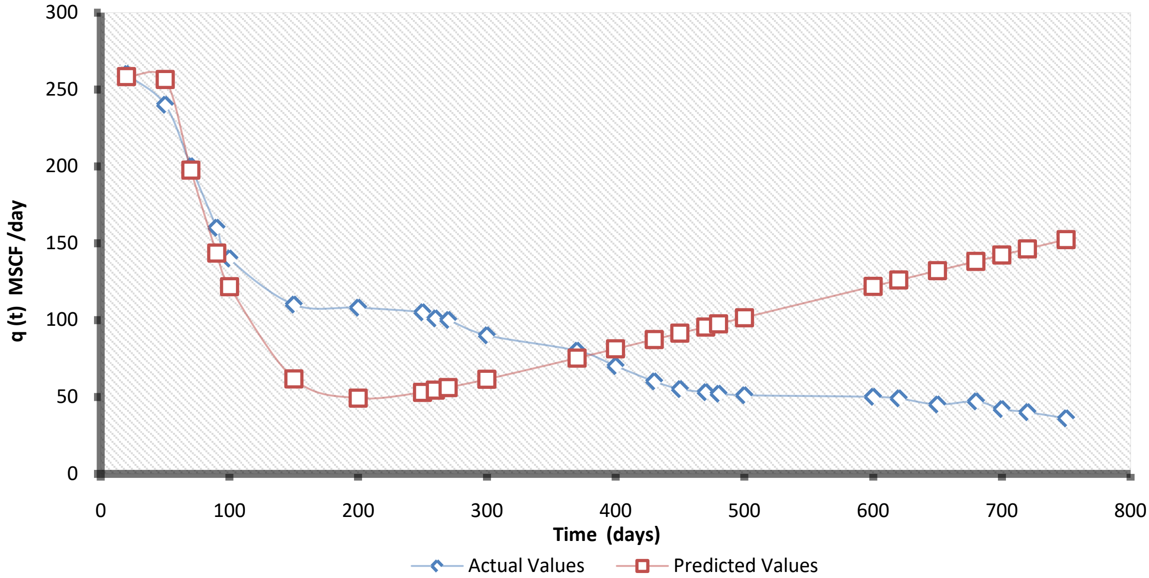


Figure 6: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the Arps-Duong hybrid model

The predicted results for the model appear to be severely overestimated from the actual results in the latter stage of production. This would be the result of combining the drawbacks of the two models, which causes the elevated results observed. In line with this, firstly, most shale gas wells rarely reach the boundary-dominated flow regime, hence the Arps model cannot be applied directly to SGRs without significant modifications [32].Secondly, in the findings of Paryani et al. (2018) [3], extremely high reserves estimates were occasionally observed with the Duong model. The results of Hu et al. (2018) [35] concurred with these results, for the Austin Chalk wells, whereby the Duong model gave the highest weighted residual of production rate.

f) Result for the Arps-Power Law Exponential Hybrid Model

A plot of $\frac{\frac{1}{b}}{qt}$ vs.*t* was used in the model forecasting. The forecasting equation is given as:

$$y = \frac{c}{1+e^{(-ax-b)}} \tag{22}$$

where c is the asymptote, b is the inflection point and a is the growth rate.The actual and forecasted values can be seen in Figure 7.

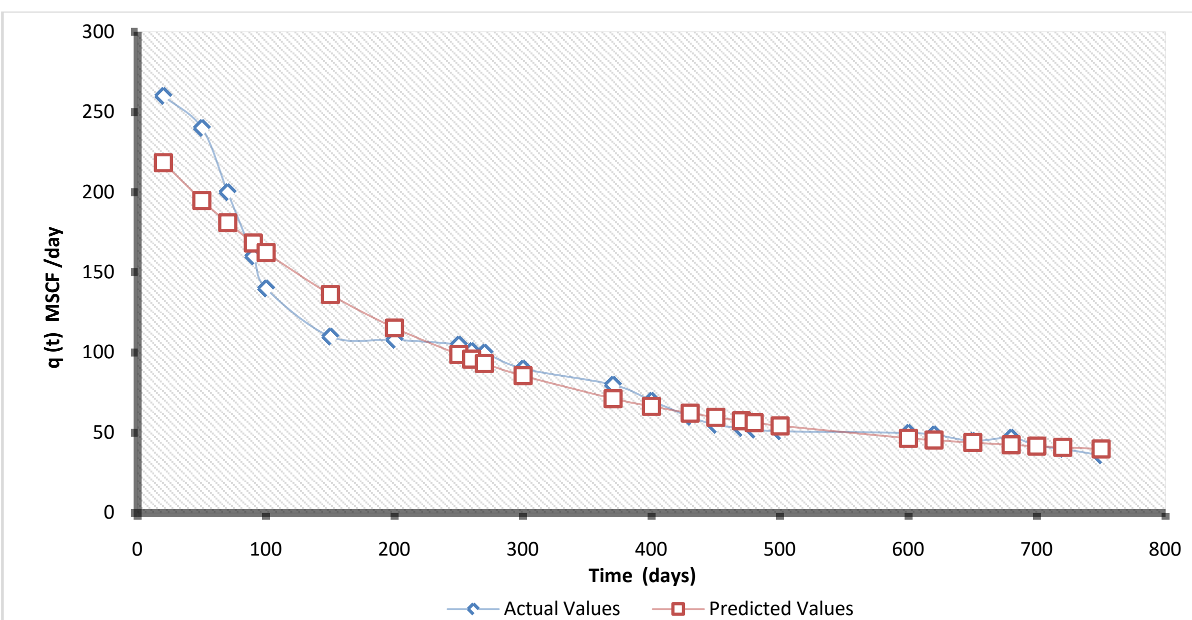


Figure 7: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the Arps-PLE hybrid model

The results from the model initially appear to over- and underestimate the data prediction; however, the results tend to move closer to the actual values over time. This would be attributed to the reliability in the Arps model and the fact that the PLE model was developed precisely for SGR. Moreover, both flow regimes are considered and since most shale gas wells rarely reach the boundary-dominated flow regime, the results appear to move closer to the actuals when reaching the TFR. Hence, by combining the models the overestimation of the predicted results is minimised over time.

g) The Duong-PLE Hybrid Model

A plot of $\frac{In\ qt}{qm}$ vs. t was used in the model forecasting. The forecasting equation is given as:

$$y = a(1 - be^{-cx}) \qquad (23)$$

where a is the asymptote, b is the scale and c is the growth rate. The actual and forecasted values can be seen in Figure 8.

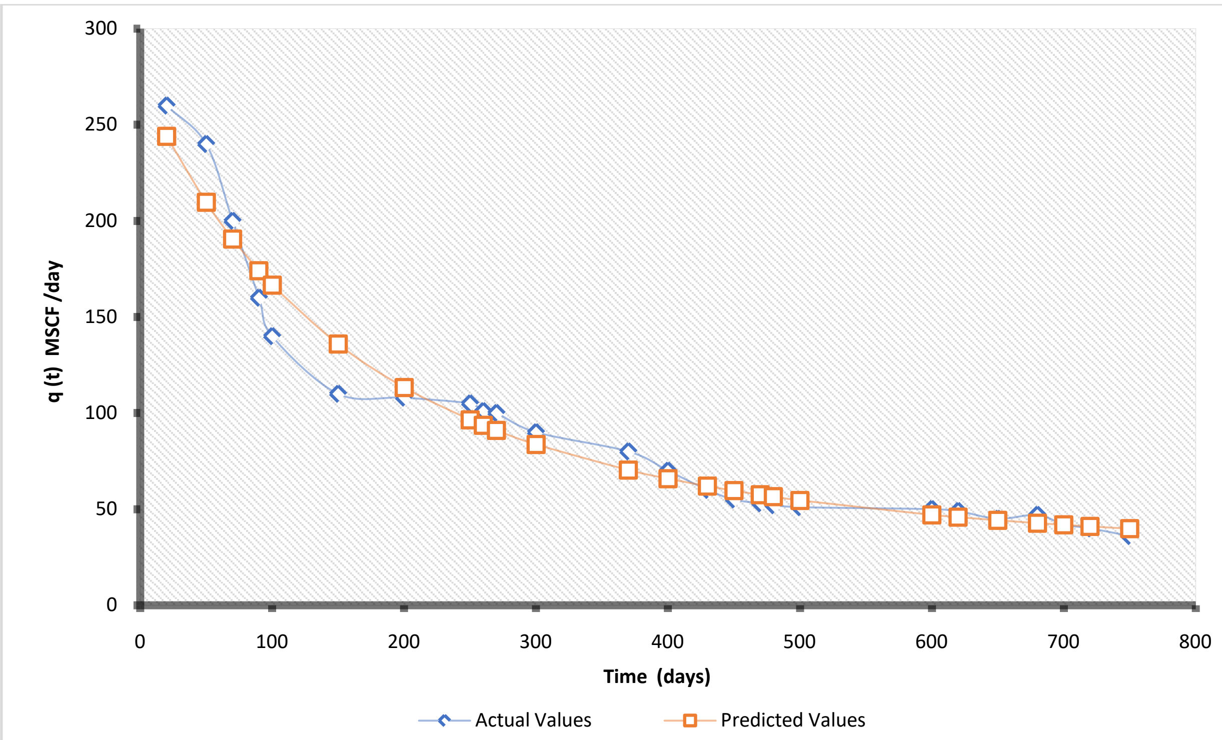


Figure 8: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the Duong-PLE hybrid model

The trend of the results indicate an over- and underestimation. As mentioned by Vanorsdale [36], the PLE and Doung's model will yield an optimistic recovery when the flow regime changes. This trend is clearly evident in the results when combining the models.

h) Result for the ARIMA Model

As mentioned earlier under the Research Methodology section, the best fit for the ARIMA model was a (2,1,2), which gave the best forecast values due tohaving the lowest MSE of 4.82, a low BIC of 8.23 and highest adjusted R^2 of 0,979. The best modelis reflected as follows:

$$Y_t = \theta_2 Y_{t-2} + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \varepsilon_t \qquad (24)$$

The actual and forecasted values can be seen in Figure 9.

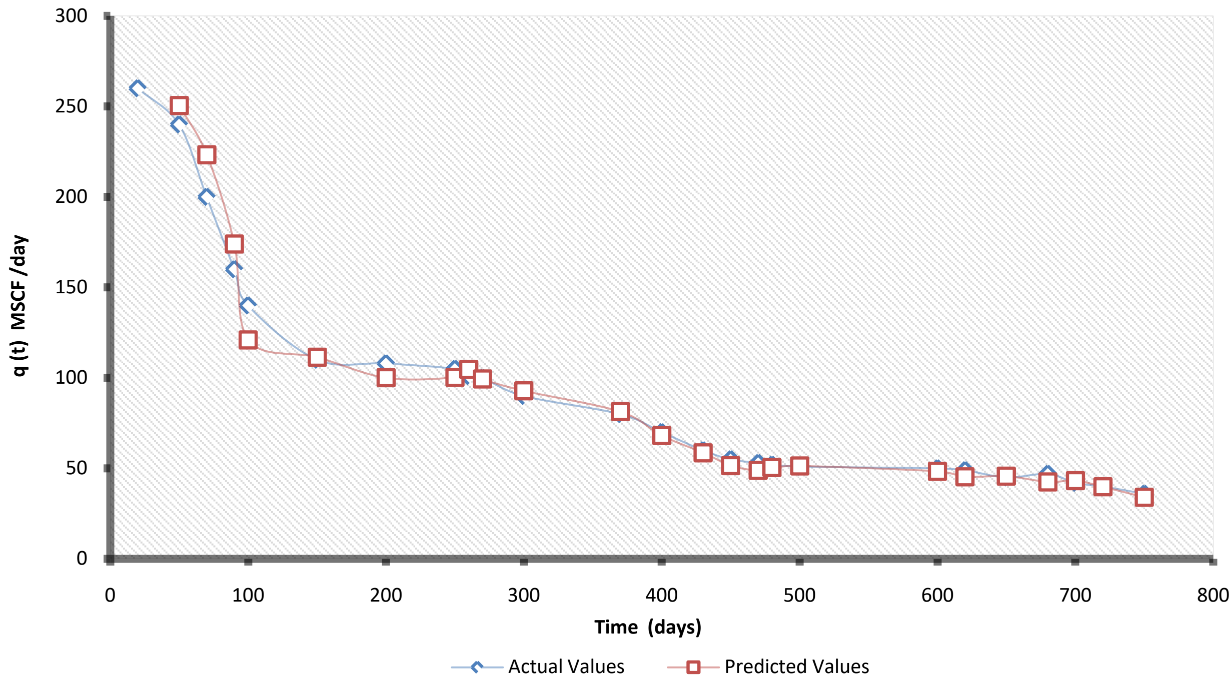


Figure 9: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the ARIMA model

The predicted results from the model appear to follow a close trend to the actual values. Raymond (2007) [37] suggested that ARIMA models have proved to be excellent short-term forecasting models for a wide variety of time series because short-term factors are expected to change slowly. This can explain the reason as to why the ARIMA fared well compared to the other models discussed so far.

i) Results for the ANN Model

In the case of this study, a univariate input layer and four nodes gave the best model fit i.e. (1-4-1) for the production flow rate over a period of time. The actual and forecasted values are graphically represented in Figure 10.

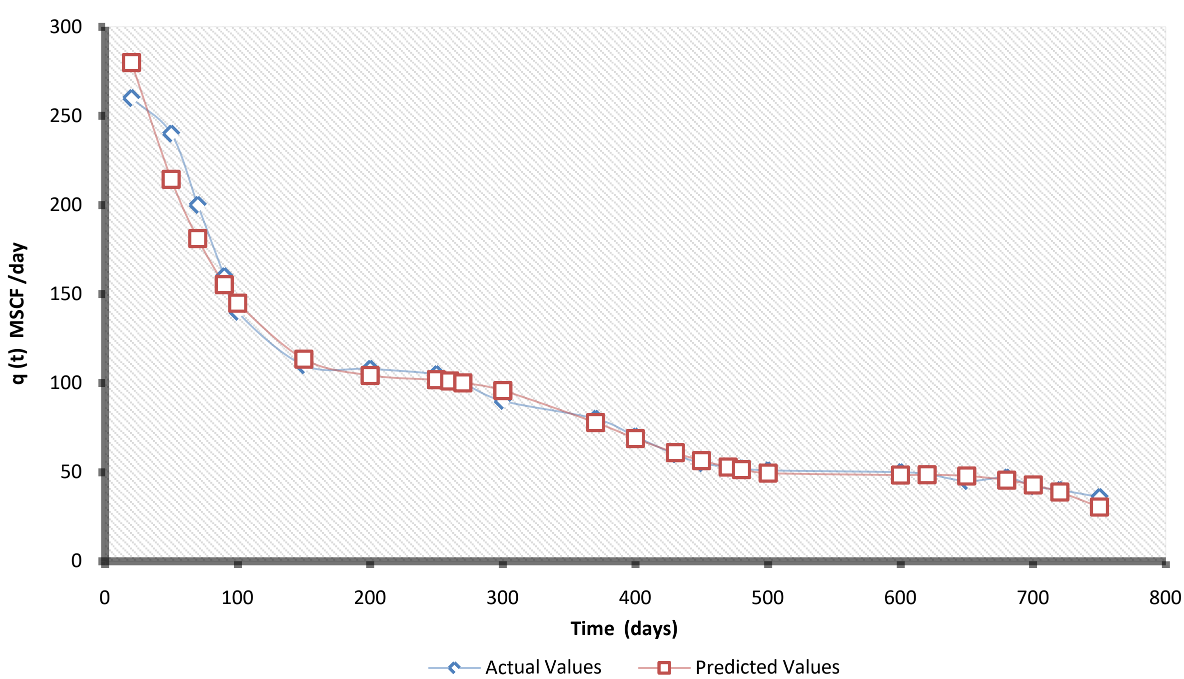


Figure 10: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the ANN model

The predicted results from the model appear to follow a very close trend to the actual values. Zhang (2003) [12] indicated that neural networks are useful for modelling and predicting the properties of time series data. Cybenko (1989) [38] described neural networks as having a universal non-linear function and a relatively good degree of forecasting accuracy. In addition, according to Hill et al. (1996) [39], neural network forecasting provides better results than traditional forecasting methods over monthly as well as quarterly periods.

j) Results for the ANN-ARIMA Hybrid Model

The steps employed by Ayub and Jafri (2020) [10] were used to construct the ARIMA-ANN hybrid model. This entailed a two-step process, which involved the following:

In the first step, the ANN is used to predict qt and residual et is produced and provided to the ARIMA to predict the error. In the second step, the predicted qt by ANN is summed with the error produced by the ARIMA model to give the final predicted values. The equation is as follows:

$$e_t = Y_t - N_t \tag{25}$$

Y_t is time series while N_t is the nonlinear component. ARIMA is used to reproduce e_t to generate the forecast series of q_t.The actual and forecasted values can be seen in Figure 11.

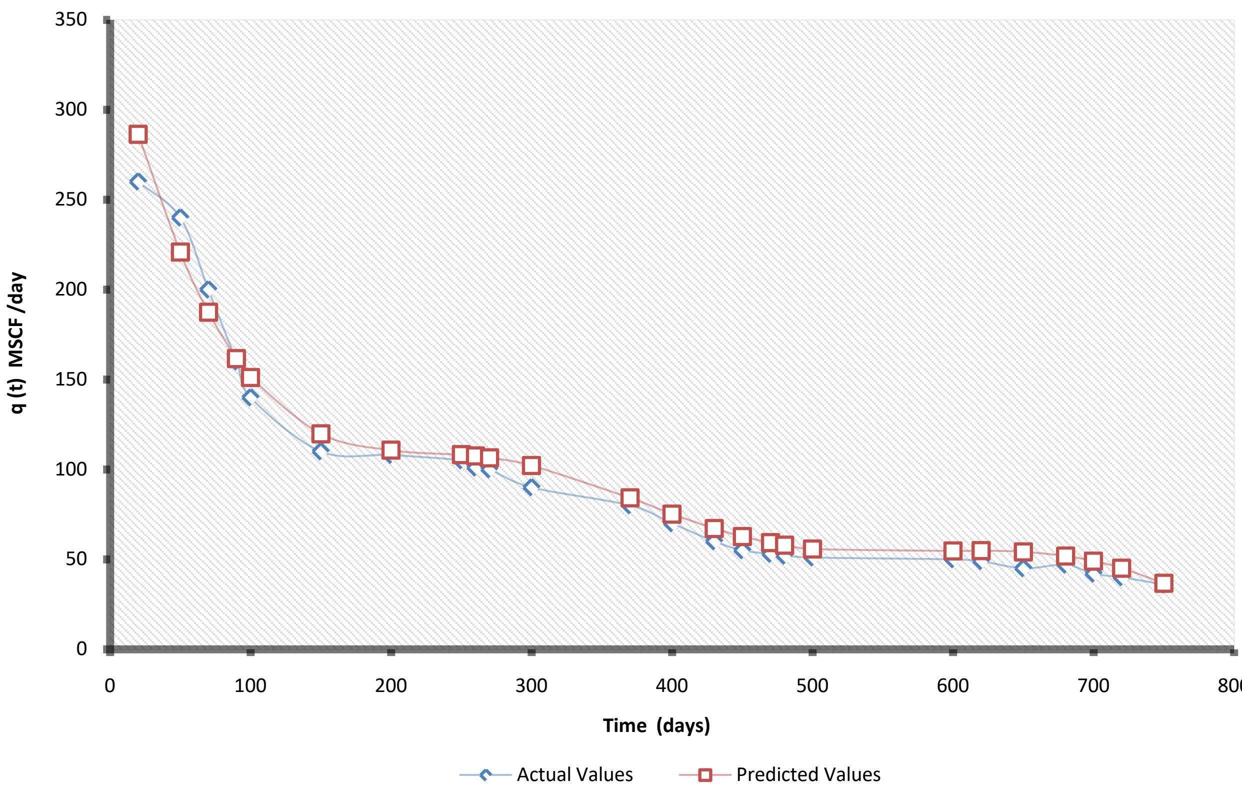
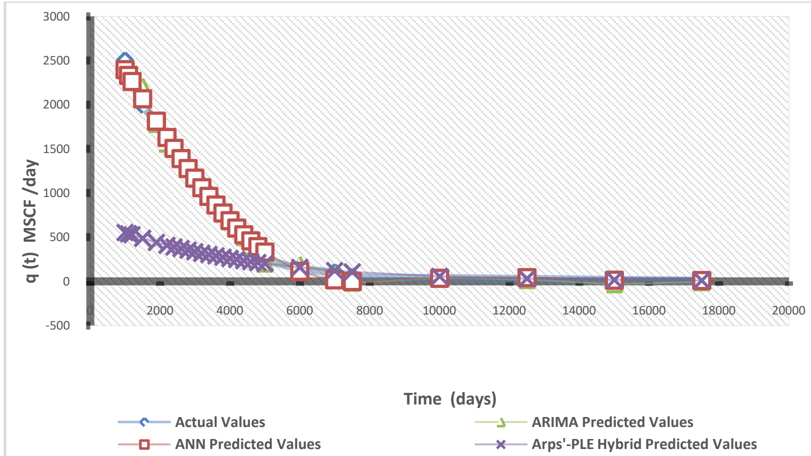


Figure 11: Graphical representation of actual flow rate vs. forecasted flow rate for shale gas production using the hybrid model

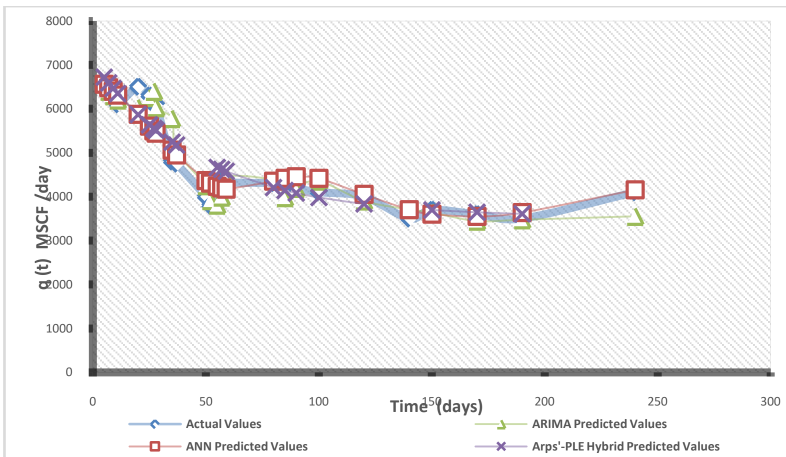
The predicted results from the model appear to be overestimated compared to the actual values. This result appears to contradict what has been indicated through the literature. According to Faruk (2010) [40], hybrid methods have a higher degree of accuracy than neural networks. Cybenko (1989) [38] indicated in his work that hybrid models combine the advantages of ARIMA with respect to linear modelling and neural networks in terms of non-linear edge modelling. However, Taskaya-Temizel and Ahmad (2005) [41] made reference in their work that in some circumstances, the single model approach can outperform hybrid models. This has been observed during this study.

k) Model Accuracy Evaluation

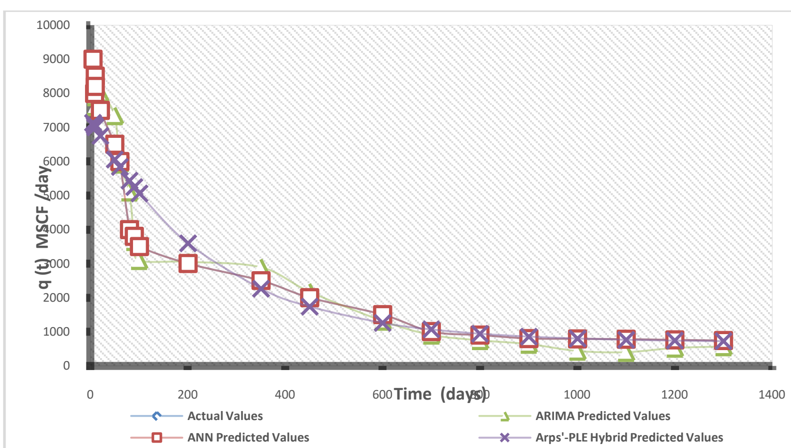
In order to assess the accuracy of the models, three sets of different production data were used to perform the evaluation. The estimated data was extracted from the work of Adekoya et al. (2009), Brantson et al. (2019) and Tan et al. (2018) [32;42;43]. Figure 12 illustrates the actual data vs. the predicted data for the ARIMA, ANN and Arps-PLE hybrid models.



(a)



(b)



(c)

Figure 12: Estimated production data to determine accuracy of the different hybrid models (a), (b) and (c) ARIMA vs. ANN vs. Arps-PLE hybrid model [32;42;43]

The results from graphs a, b and c indicate that the ARIMA and ANN models appear to predict the production data very close to the actual values in all three production data; however, this is not the same trend observed for the Arps-PLE hybrid model. The model appears in one instance to underestimate the data and in the other two instances to overestimate the data. Hence, the results prove that with the Arps-PLE hybrid model there is no consistency or accuracy in the prediction of results in the three different production data when compared to the ARIMA and ANN models.

IV. Conclusions

The objective of this study was to evaluate the forecasting performance of decline curve hybrid models and ANN-ARIMA hybrid models with Arps', Duong's, PLE decline models, ARIMA and ANN models respectively. The experimental results were obtained using the different prediction models i.e. Arps', Duong's, PLE, Arps-Duong-PLE hybrid, Arps-Duong hybrid, Arps-PLE hybrid, Duong-PLE hybrid, ARIMA, ANN and, lastly, the hybrid ANN-ARIMA model. The following can be concluded from the study:

- The current DCA models, Arps', Duong's and PLE models appear to over- and underestimate the data.
- The DCA hybrid models also did not give the best outcome, which it was assumed they would, in comparison to the individual DCA models. However, the Arps-PLE hybrid model gave the closest predicted results compared to the other DCA hybrid models and the individual models.
- Both the ARIMA and ANN models gave the best predicted results compared to all the models evaluated in this study. However, when both models were combined into the ANN-ARIMA hybrid model the strengths of both models referenced in literature did not provide accurate predictive data. The result was an overestimation in the production flow rate.
- Overall, the models which gave predicted values closest to the actuals in order of rank were the ARIMA, ANN and the Arps-PLE hybrid model.
- In the model accuracy evaluation, the Arps-PLE hybrid model did not provide a consistent prediction. The model under- and overestimated the production data compared to the ARIMA and ANN models.

In conclusion, this study contradicted the findings from literature which indicated that hybrid models have a higher degree of accuracy. However, the study concurred with Taskaya-Temizel and Ahmad (2005) [41], whereby in certain circumstances the single model approach can outperform the hybrid models. Future investigation should therefore validate the ARIMA and ANN models for SGR decline forecasting using the factors R^2, MSE and MAPE.

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