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¹ Production Decline Prediction of Shale Gas using Hybrid Models

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5 Abstract

⁶ Hybrid models have frequently been used for shale gas production decline prediction by

7 manipulating the unique strength of each of the known decline models. The use of a

⁸ combination of models provides a more precise predicting model for forecasting time series

9 data as compared to an individual model. In this study, the forecasting performance of decline

¹⁰ curve hybrid models and ANN-ARIMA hybrid models are evaluated and compared with

¹¹ Arps?, Duong?s, the Power Law Exponential Decline, Autoregressive Integrated Moving

¹² Average (ARIMA) and Artificial Neutral Network (ANN) models, respectively. The variable

 $_{13}$ used to assess the models was the respective flow rate, q(t) monitored over a period of time

¹⁴ (T). The results have shown that the single model approach can outperform hybrid models.

¹⁵ The average deviation of the two best models indicates a central tendency of the production

¹⁶ data around the mean. Subsequently, the spread in the data between the actual and predicted

values is found to be less. It can thus be concluded that the ARIMA and ANN models have

¹⁸ the best forecasting accuracy for production decline in shale gas compared to the other models.

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.

Author ?: e-mail: 690765@students.wits.ac.za a) Production Decline Models

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

¹⁹

Index terms— shale gas decline forecasting, arps? decline model, duong?s decline model, PLE decline model;
 ARIMA, ANN and hybrid models

Production Decline Prediction of Shale Gas using Hybrid Models Introduction ate-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].

The Arps decline model is inaccurate within the transient flow regime (TFR) and the Duong model is inaccurate 35 within the boundary dominated flow (BDF). Although the Power Law Exponential (PLE) model incorporates 36 both these flow regimes and was specifically developed for SGRs, the model has its own shortcomings. Hence, 37 38 the scope to develop a new decline model or a new method to predict more accurately the recovery of SGRs. 39 Accordingly, the approach would be to combine the above-mentioned methods i.e. to evaluate the hybrid decline 40 curve models. As the PLE and Duong's models model the transient flow well and because the Arps model 41 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 42 they are commonly known, will be investigated. 43

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].

49 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

52 prediction of production decline in shale gas.

⁵³ 1 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

59 and ANN method.

According to Faruk [8], hybrid methods have a higher degree of accuracy than neural networks. ARIMA is 60 able to recognise time-series patterns well except non-linear data patterns. On the other hand, neural networks 61 only handle non-linear data. Therefore, hybrid models combine the advantages of ARIMA with respect to linear 62 modelling and neural networks in terms of nonlinear edge modelling [9]. Ayub and Jafri (2020) [10] in their 63 paper highlighted that the combined model has improved forecasting accuracy as compared to when the models 64 are used individually. Notwithstanding this, in some circumstances the single model approach can outperform 65 hybrid models [8]. Babu et al. (2014) [5] explored ARIMA and ANN as a new hybrid model for better prediction 66 of time series. Their results preferred the use of the hybrid model compared to the individual ARIMA and ANN 67 68 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

rs several times until a satisfactory model is finally selected and can then be used for prediction purposes [12]. In an
 ARIMA model, the future 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

77 model, which is capable of predicting fairly extensive functions with a high degree of accuracy. No assumptions 78 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 ??aryani et al. [3]. 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].

88 2 II.

⁸⁹ 3 Methodology

90 4 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.

⁹⁶ 5 b) Production Behaviour

97 6 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 boundarydominated 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].?? = ?? ?? (1+???? ?? ??) 1 ?? (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. [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]:??(??) = ?? ???(??, ??) + ?? ?(2)

Where t (a,m) is the time constant in 1/s, and q ? is the iii. Power Law Exponential Decline Model (PLE) 115 Ilk et al. [25] presented the PLE, which is an extension of the exponential Arps formula for the decline degree in 116 shale reservoirs. This model was developed precisely for SGR and approximates the rate of decline with a power 117 law decline. The PLE model matches production data in both the transient and boundarydominated regions 118 without being hypersensitive to remaining reserve estimates [26]. Seshadri and Mattar [27] presented that the 119 120 PLE model can model transient radial and linear flows, while Kanfar and Wattenbarger [28] proved that the 121 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 122 changes throughout the initial 10 years of the well, the PLE model will yield a very optimistic recovery. The 123 model characterizes the "loss ratio" (which is assumed to be constant from Arp) [30]. The production rate is 124 derived as follows:?? ???? /???? = ??? (3) ?? = ?? ? + ?? ?? ?? ?(1??? ?)(4) 125

Production Decline Prediction of Shale Gas using Hybrid Models Where ????/???? is the slope, D ? is the decline rate over a long-term period, and ?? ? is the time exponent. By substituting the above equations, the production rate is obtained: 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:??(??) = ?? ?? ?????? ?????? ?????? ?????? (5)???? = [???? ??][1 + ???? ??]??? 1(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.

¹³⁴ 7 vi. The Arps-Power Law Exponential Hybrid Model

¹⁴⁴ 8 ? Relatively small BIC b. The Integrated Process

The integrated process is the archetype of nonstationary 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).

Generally, each observation consists of a random component i.e. a random shock, ? and a linear combination of the previous observations. ? 1 in the equation is the self-regression coefficient.

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.

Where qt is the flow rate in STB/day or Mscf/day, t is the time in days, D? the decline rate over along-term period and D i the initial decline constant, which are both measured in days -1 and ?? ?is the time exponent. q m is the flow rate at slope m in m 3 /s.

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

¹⁶³ 9 ix. Artificial Neutral Network (ANN) Model

169 ? ??? + ?? ?? (13) where ? ?? (j = 1,2,3, ..., q) and ?? ?? (i = 1,2,3, ..., p; j = 1,2,3, ..., q) are the 170 parameters of the model (often called the weights), p is the number of input points (input nodes), and q is the 171 number of hidden nodes. The activation function used in the hidden layer is the logistic sigmoid function and 172 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 ?? ?? = δ ??" δ ??"(?? ???1 + ?? ???2 , ? , ?? ?????) (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:?? ? ?? = ?? ? ?? + ???? . (16)

N t is obtained from the predicted values of the ANN model while ?? ? ?? is the forecasted value from ARIMA based on the residual values.

181 **10 III.**

182 11 Results and Discussion

Kappa Citrine and JMP software were used for the simulation of the models. The experimental results obtained
 are explained below. in Figure 1 gave the best model.

185 12 x. ANN-ARIMAHybrid Model

Zhang investigated the concept of the hybrid ANN-ARIMA model to obtain precise results as compared to using 186 both models separately [12]. Numerous techniques, which explored the hybrid approach have been used for 187 many years to take advantage of the unique strengths of each of the various types of models. The objective of 188 merging the models is due to the notion that a single model is able to define all the specifics of time series [32]. 189 Mathematically, timeseries data can be expressed as a combination of linear and non-linear components [15]: 190 (14) Where Y t shows the time-series data, L t indicates the linear components, and the non-linear components 191 are represented by N t . 192 = ?? ?? + ?? ?? . Y t a) Results for the Arps Model Kappa Citrine software was initially used for 193

where c is the asymptote, a the growth rate while b is the inflection point. The actual and forecasted flow rate 198 values are shown graphically in Figure 2. The results for the model appear in some instances to over-and in other 199 instances to underestimate the data. The results concur with literature, which suggests that the weakness of the 200 Arps model is overestimation of results. [32] in their study highlighted that although the Arps model is simple 201 and fast, it often fails to accurately fit the decline curve of unconventional reservoirs. They further explained 202 that the model often tends to overestimate the EUR for shale gas wells because it assumes that a BDF regime is 203 evident. Paryani et al. (2018) [3] concurred with these findings, explaining that the drainage area is not constant 204 because the pressure pulse continues to spread from the fracture to other areasof the reservoir volume. Under 205 these conditions, the bvalue predicted by the Arps model for the actual production data will be greater than 1 as 206

 $_{207}$ in this case b =1.10. This in turn leads to inaccurate estimates of reserves.

²⁰⁸ 13 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:?? = ???? + ?? (18)

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

3. ??013) [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

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.

²¹⁷ 14 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:?? = ?? + ???? (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. 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].

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

forecasting. The parameter q i used was 361.2 which was noted earlier in Duong's model. The forecasting equation is given as:?? = ?? + ???? ???? (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. 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.

²³⁶ 16 e) Result for the Arps-Duong Hybrid Model

A plot of ???? ?? vs.t was used in the model forecasting. The forecasting equation is given as:?? = ??(1 ? ?? ?????) (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. 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 boundarydominated 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,

²⁴⁶ for the Austin Chalk wells, whereby the Duong model gave the highest weighted residual of production rate.

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

248 A plot of

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. 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.

²⁵⁶ 18 g) The Duong-PLE Hybrid Model

A plot of ???? ???? vs. t was used in the model forecasting. The forecasting equation is given as:?? = ??(1 ? ?????????????) (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 ??.

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

263 the results when combining the models.

²⁶⁴ 19 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 to having the lowest MSE of 4.82, a low BIC of 8.23 and highest adjusted R 2 of 0,979. The best model is reflected as follows:?? ?? = ?? 2 ?? ???2 + ?? 1 ?? ???1 + ?? 2 ?? ???2 + ?? (24)

The actual and forecasted values can be seen in Figure ??. The predicted results from the model appear to follow a close trend to the actual values. ??aymond (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

273 discussed so far.

²⁷⁴ 20 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. 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.

²⁸² 21 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:?? ?? = ?? ?? ?? ?? (25)

Y t is time series while N t is the nonlinear component. ARIMA is used to reproduce e t to generate the 285 forecast series of q t. The actual and forecasted values can be seen in Figure 11. The predicted results from 286 the model appear to be overestimated compared to the actual values. This result appears to contradict what 287 has been indicated through the literature. According to Faruk (2010) [40], hybrid methods have a higher degree 288 of accuracy than neural networks. Cybenko (1989) [38] indicated in his work that hybrid models combine the 289 advantages of ARIMA with respect to linear modelling and neural networks in terms of non-linear edge modelling. 290 However, Taskaya-Temizel and Ahmad (2005) [41] made reference in their work that in some circumstances, the 291 single model approach can outperform hybrid models. This has been observed during this study. 292

²⁹³ 22 k) Model Accuracy Evaluation

In order to assess the accuracy of the models, three sets of different production data were used to perform the 294 evaluation. In the first step, the ANN is used to predict qt and residual et is produced and provided to the 295 ARIMA to predict the error. In the second step, the predicted qt by ANN is summed with the error produced 296 by the ARIMA model to give the final predicted values. The equation is as follows: The results from graphs a, b 297 and c indicate that the ARIMA and ANN models appear to predict the production data very close to the actual 298 values in all three production data; however, this is not the same trend observed for the Arps-PLE hybrid model. 299 The model appears in one instance to underestimate the data and in the other two instances to overestimate the 300 data. Hence, the results prove that with the Arps-PLE hybrid model there is no consistency or accuracy in the 301 302 prediction of results in the three different production data when compared to the ARIMA and ANN models.

303 23 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. ? 309 The DCA hybrid models also did not give the best outcome, which it was assumed they would, in comparison to 310 the individual DCA models. However, the Arps-PLE hybrid model gave the closest predicted results compared 311 to the other DCA hybrid models and the individual models. ? Both the ARIMA and ANN models gave the best 312 predicted results compared to all the models evaluated in this study. However, when both models were combined 313 into the ANN-ARIMA hybrid model the strengths of both models referenced in literature did not provide accurate 314 predictive data. The result was an overestimation in the production flow rate. ? Overall, the models which gave 315 predicted values closest to the actuals in order of rank were the ARIMA, ANN and the Arps-PLE hybrid model. 316 ? In the model accuracy evaluation, the Arps-PLE hybrid model did not provide a consistent prediction. The 317 model under-and overestimated the production data compared to the ARIMA and ANN models. 318

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.



Figure 1:

1

Production Behaviour	Assumptions		ConditionParameters			
Boundary Dominated Flow (BDF)	Dec	eline	pai	cameter,	0 < b	$\mathbf{b}=1.10\;\mathbf{D}\;\mathbf{i}$
	b, beh	defines aviour	the	decline	<1	= 0.12
ii. Duong's Decline Curve Model						
Doung						

Figure 2: Table 1 :

$\mathbf{2}$

[Note: of the Duongs model behaviour, assumptions, condition and parameters decline rate by infinite time, D? which is defined as a]

Figure 3: Table 2 :

3

[Note: Where qt is the flow rate in STB/day or Mscf/day, t is the time in days, D? the decline rate over a long-term]

Figure 4: Table 3 :

6

Production Behaviour	Assumptions	Condi	tRarameters
BDF and TFR	Approximates	0 >	n = 0.182
	the rate of	b	D i =
	decline with a	>1	0.194 b =
	logistic decline		1.10
vii. The Duong-Power Law Exponential Hybrid Mo	dels		
The fourth proposed model incorporates the			
Duong and PLE models. These models both consid	er		
TFR. The equation is given as:			

Figure 5: Table 6 :

7

Production Behaviour		Assumptio	ons Condi	tion	Parameters
	Approximates the rate of	decline	n = 0.	.182	
BDF and TFR	with a mechanistic growth		0 > b	>1	D i =
					0.194
		decline	q m =	7.12	
viii. Autoregressive (ARIMA) Model	integrated	Moving	Average		

Figure 6: Table 7 :

8

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

Figure 7: Table 8 :

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