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Production Forecasting Using Arps Decline Curve Model with The Effect of Artificial Lift Installation

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ABSTRACT - There are many methods for predicting production performance of oil wells, using the simplest method by looking at the declining trend of production, such as decline curve analysis (DCA), Material Balance, and reservoir simulations. Each of these methods has its advantages and disadvantages. The DCA method, the Arps method, is often used in production forecast analysis to predict production performance and estimate remaining reserves. However, limitation of this method is that if the production system changes, the trend of decline will also change. At the same time, the application in the field of taking the trend of decreasing production does not pay attention to changes in the production system. This study aims to see that changes in the well production system will affect the downward trend of well production, estimated ultimate recovery (EUR) value, and well lifetime. To see the effect of these changes, the initial data tested used the results of reservoir simulations and field data. From the evaluation results, it is found that if the production system changes during the production time, for example, from changing natural flow using artificial lifting assistance, the trend taken from the production profile will follow the behaviour of the reservoir if the trend is taken in the last system from the production profile, not from the start of production. If the downward trend is taken without regard to the changing system, then the prediction results will not be appropriate.

Keywords: production forecasting, least-square method, arps' model, estimated ultimate recovery

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INTRODUCTION

When reservoir pressure decreases, production of oil wells tends to decrease as well. To maintain production levels despite lower reservoir pressure, an artificial lift is added as a solution. Installation of an artificial lift has no impact on reservoir conditions. In this study, we analysed the impact of artificial lifts on production performance and lifespan of the wells. decline curve analysis (DCA) is a simple and easy-to-use method widely used to predict future production flow rates and oil reserves. This method requires availability of production data which then looks for the downward trend with empirical equations. Using the trend, we can predict future production. DCA has the advantage that it does not depend on size and shape of the reservoir or the driving mechanism Holstein., (2007). The Arps empirical model is a famous example of this method, designed specifically for conventional wells. Manually adjusting the curve for flow rate versus time data can be subjective, as it depends on the observer. In research conducted in the "R" field, the Kais formation, trial-and-error method and chi-square test showed results that are more representative than the loss ratio proposed by Arps' to identify the type of decline in production Arief Rahman., (2019). An alternative method is to utilize curve fitting to identify the type of decline. Although various quantitative best-fit criteria are available, the least square principle Spivey., (1986) is the most widely utilized. After obtaining the decline parameter and trendline, one can use them to estimate the ultimate recovery (EUR) until reaching the economic limit. It is important to note that Arps's method is sensitive to changes in operating conditions, such as variations in flowing bottom-hole pressure. According to Palash Panja., (2022), when making predictions, we assume that the primary recovery or operating conditions will stay the same. However, if the recovery process changes, we should not use past decline curve parameters for analysis.

Even though changes in treatment or operating conditions may occur in the field, the decline curve parameter is often still considered the same leading to inaccurate predictions. This study aims to analyze the impact of installing an artificial lift on the decline rate, as well as how alterations in operating conditions can influence production forecasting and estimated ultimate recovery (EUR). These factors should be considered. In this study, two types of datasets are utilized. The first was created through simulations for validation purposes, while the second was obtained from real-life field data for implementation. The historical production data used in the study only contains flow rate data for specific time intervals, mostly on daily basis.

METHODOLOGY

This study utilizes two types of data: synthetic and real datasets. The initial artificial dataset comes from the second SPE Comparative Solution Project Weinstein, Chappelear & Nolen., (1986). This dataset contains production rate information obtained through simulations conducted with commercial software. The project features a radial reservoir model with 150 geometrically spaced grid blocks. This simulation is centered on a specific oil well that started operating on January 1st, 1994, with a bottom hole pressure of 3200 psi. During production, the pressure will decrease to 3000 psi. Bottom hole pressure conditions are utilized as an operating constraint, while a surface oil rate of less than 5

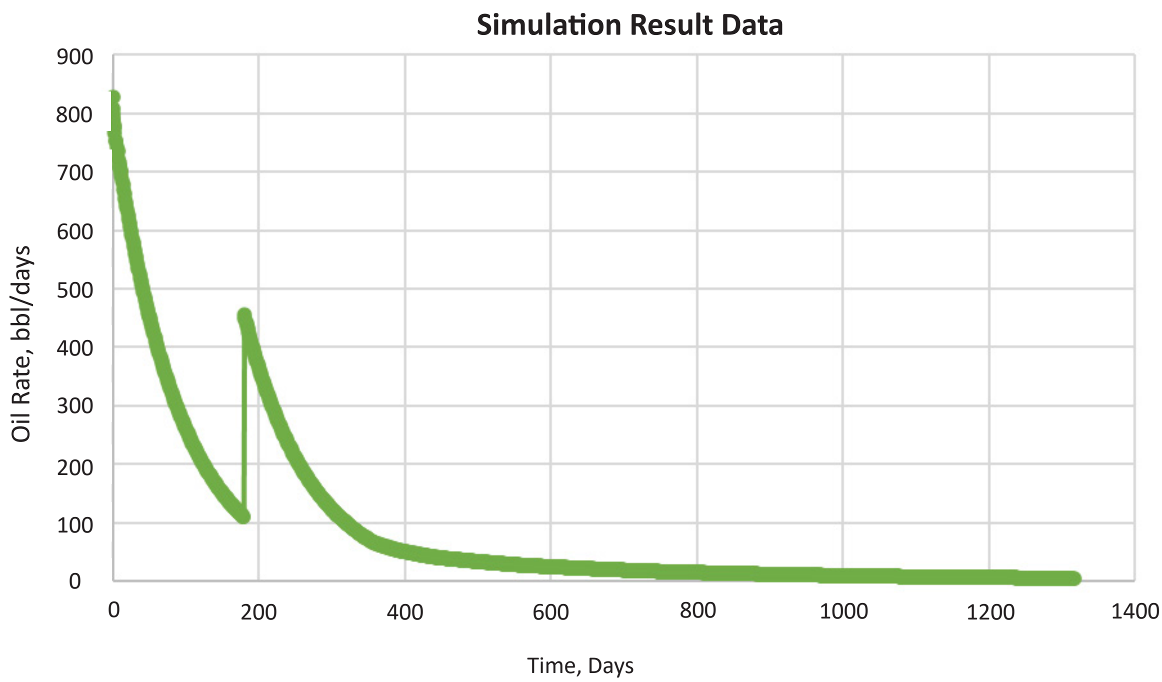

Figure 1
Production profile of first dataset (synthetic data) generated by reservoir simulastion

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bbl/day is monitored to shut down the well. Figure 1 shows the raw daily production rate data obtained from simulation results. With minimal fluctuation in the production profile, this dataset is used as an ideal case of the production profile that may occur.

This study uses the data from paper, "second comparative solution project: A Three-Phase Coning Study." Journal of Petroleum Technology Weinstein, Chappelear & Nolen., (1986). Our objective is to simulate a single well under natural flow conditions. To achieve this, we have adjusted the following parameters:

- Reservoir's radial extent or radius, which was initially 2050ft, is changed to 820.21ft (~250m).
- Radius of each block in the I direction is adjusted to match the reservoir radius, but the previous radius ratio is retained.
- Permeability in the I and J directions, which initially had different values for each layer, was changed to 100mD to create a homogeneous reservoir.
- Permeability in the K direction, which initially had different values for each layer, is changed to 10 mD.
- Modified values for water-oil relative permeability are shown in Table 1.
- Modified values for water-oil relative permeability are shown in Table 2.

The data used for the reservoir analysis came from Gulf Research and Development Co. The Gulf black-oil coning model utilizes a standard point-centered spatial differencing method and takes into account the capillary end effect in the boundary conditions of wells. This effect assumes that the pressure of oil is consistent from the reservoir to the wellbore, and water is not produced until the saturation of water reaches the zero point of the imbibition capillary-pressure curve. Gas is only produced when the gas saturation reaches a critical level. In the absence of imbibition curve data, the zero point of the imbibition curve is assumed to occur when Weinstein, et al., (1986). With a focus on producing smooth production data where oil production is the primary fluid, the model is simplified without gas coning. The previously detailed steps for changes in relative permeability and capillary pressure are implemented. The purpose of using simulation data is to observe how Arps' model can fit the data even with the installation of an artificial lift and the absence of outlier data. Since the data is obtained from modeling results, the EUR value can be determined for each pressure condition change. The simulation consists of two cases, as follows:

- Case I: Cumulative production objective for the second group is still determined by subtracting the first group's EUR from its cumulative production.
- Case II: Cumulative production objective for the second group is determined by subtracting the

Table 1
Water-oil relative permeability data used in modeling

S_w (Fraction)	K_{rw} (Fraction)	K_{row} (Fraction)	P_{cow} (Fraction)
0.22	0	1.0	7.0
0.25	0.03	0.7	0
0.40	0.15	0.125	0
0.50	0.24	0.0649	0
0.60	0.33	0.0048	0
0.80	0.65	0	0
0.90	0.83	0	0
1.0	1.0	0	0

Table 2
Liquid-gas relative peremeability data used in modeling

S_l (Fraction)	K_{rg} (Fraction)	K_{rog} (Fraction)	P_{cog} (Fraction)
0.22	1.0	0	3.9
0.30	0.8125	0	3.5
0.40	0.5	0	3.0
0.50	0.42	0	2.5
0.60	0.34	0	2.0
0.70	0.24	0.02	1.5
0.80	0.1	0.1	1.0
0.90	0.022	0.33	0.5
0.96	0	0.6	0.2
1.0	0	1.0	0

Table 3
Arps' model for decline curve analysis (Arps, 1945)

Parameter	Exponential Decline	Hyperbolic Decline	Harmonic Decline
	If b=0	If 0<b<1	If b=1
Rate-time	$q = q_i e^{(-D_i \Delta t)}$	$q = \frac{q_i}{(1+bD_i t)^{1/b}}$	$q = \frac{q_i}{(1+bD_i t)}$
Rate-Cumulative	$Q = \frac{q_i - q}{D_i}$	$Q = \frac{q_t^b}{D_i(1-b)}\left(q_i^{(1-b)} - q^{(1-b)}\right)$	$Q = \frac{q_i}{D_i}\ln\left(\frac{q_i}{q}\right)$
EUR	$Q_f = Q_t + \left[\frac{q_i - q_f}{D_i}\right]$	$Q_f = Q_i + \left[\frac{q_i^b}{D_i(1-b)}\left(q_i^{(1-b)} - q_f^{(1-b)}\right)\right]$	$Q_f = Q_{i+}\left[\frac{q_i}{D_i}\ln\left(\frac{q_i}{q_f}\right)\right]$

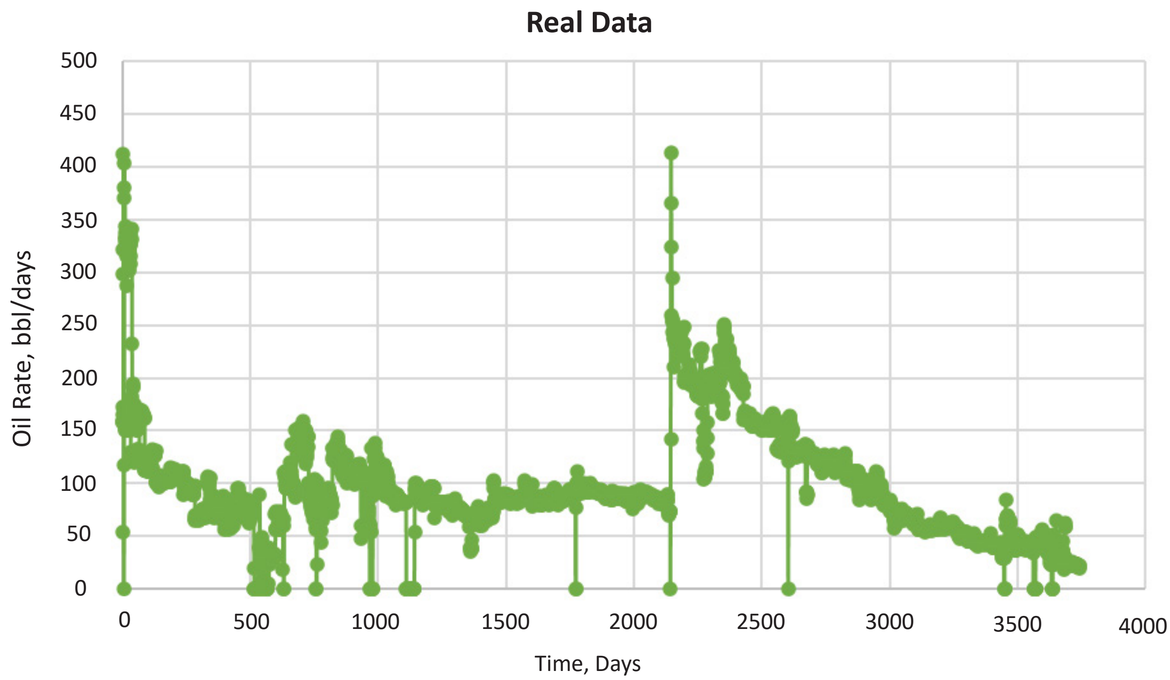

Figure 2
Production profile of real data

EUR in the last pressure condition change from the cumulative production of the first group.

The Arps' decline curve model is utilized and represented in mathematical form, as shown in Table 3.

As a form of translating the Arps model into actual field data, the data used must show a significant increase in productivity in the middle of production, which we call a "spike". The spike is believed to be caused by the installation of an artificial lift. Analyze post-peak production periods and predict decline rates. Data is from well TM-20 in the "X" field. Data is obtained in the form of flow data produced for approximately ten years. Flow forecasting is performed until a feed flow of 20 bbl/day is reached. The raw daily productivity data used in this study is shown on Figure 2. The workflow developed in this study adopts studies with a machine learning approach used in hydraulic fractured well that includes the production predicting phase. The workflow is divided into three major stages, namely data preparation, production, and water cut production, with a machine learning approach and model application Hamzah, et al., (2021). Overall workflow has been modified according to the study shown on Figure 3. The steps of this study also consist of three major stages, data screening, data processing, and data forecasting. The first stage is data screening, which represents data preparation in a reference paper. In this stage, data will be screened, conditioned, and defined. Data screening will begin with identifying where the significant increase in production is located after showing a declining trend. This point of increment will be called a spike. The spike This will divide the data into two groups. The first group of data, that is, the historical data before the peak, is used to obtain the analysis parameters of the decay curve as the limit when fitting the second set of data. The data of the second group will be used as reference data regardless of whether the forecast parameters are suitable for this group..

The second stage is curve fitting that, which is similar to the stages where the approach using machine learning is carried out. In this study, the least square concept is carried out at the data processing and data forecasting stages. The least-square concept is one of the methods applied in linear regression. Linear regression is a supervised machine learning model in which the model finds the best fit linear line between the independent and dependent variables Kamal Hamzah., (2021). The curve fitting of the first set of data is done using the least squares concept, where the residual values must have the smallest value that can be produced. Residuals are calculated from the absolute difference between calculated and actual data Spivey., (1986). Calculations are performed using the Microsoft Excel Solver add-in. In order to achieve the minimum residual value, the parameters (b and D) of the decay curve are optimized, and the parameters b and $0 < D$ become variable variables with a value range of 0-1. Although the value of b could be greater than one and is misused to match transient data. Ram G. Agarwal., (1999). Since it is assumed the data is not in a transient phase, the upper limit is set to the value of 1.

After obtaining all the parameters, the EUR calculation is carried out using the Arps decline curve, the use of the equation is based on the obtained b-values. EUR is calculated using t-values obtained by extrapolating the rate-time relationship to marginal rates or abandonment rates. The workflow of the curve fitting phase is shown in Figure 4.

In this stage, the decline curve parameters, including the parameters b and a for the second group of data, will be forecasted by performing curve fitting similar to the previous data. However, the difference lies in the objective function used in the solver. The objective function is no longer the minimum residual value between the observed data and the predicted

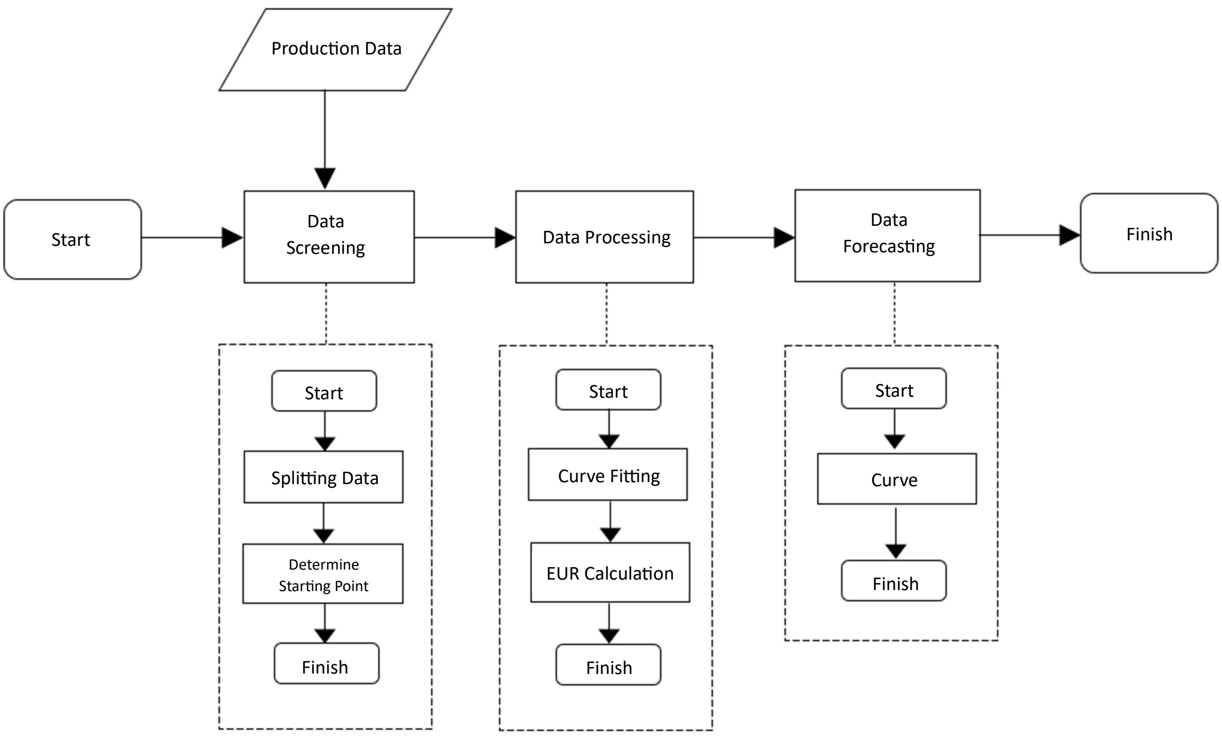

Figure 3
Workflow for production forecast of well after artificial lift installation

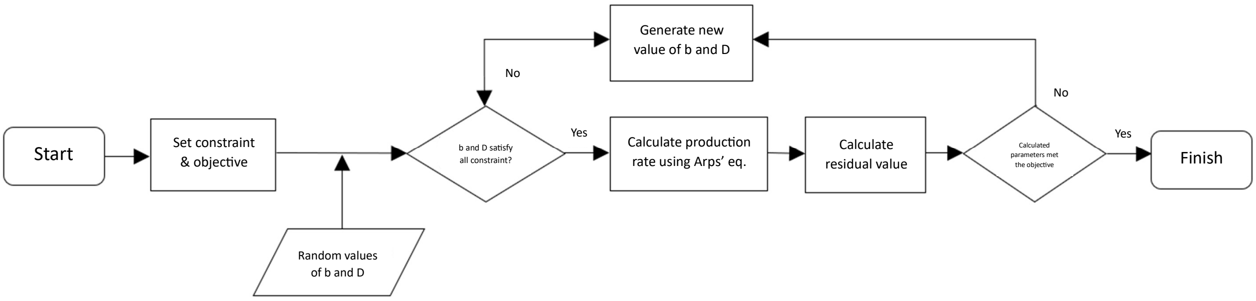

Figure 4
Flowchart of curve fitting stage

data, but the cumulative production (Np) that is set to a specific value. Additionally, the estimation of the remaining life of the well will be determined at this stage. The prediction of the flow rate will be compared against the actual data to evaluate the goodness of fit.

RESULT AND DISCUSSION

This study uses simulation data to verify the accuracy of decline curve analysis and to eliminate the impact of outliers that are commonly found in field data. The aim is to achieve smoother data from the simulator in order to minimize the error between the predicted and actual data. The type of artificial lift used in this study is not specified, and the installation conditions were simulated by reducing the bottom hole pressure from 3200 psi to 3000 psi. By using an artificial lift, the drawdown is increased, which in turn reduces the backpressure or bottom hole pressure, resulting in additional pressure that can lift formation fluids to the surface. As shown on Figure 5, in Case 1, the calculated data matches well with the original data, with an error of only 1.57% in the cumulative production. If the predicted data generated in the second group also fit perfectly with the actual data, it indicates that the decline curve model is accurate. However, this is not the case for the second group, which has an error of 75.82%. Note that the available data used to study the production decline profile covers only 179 days, resulting in a steep decline profile due to the absence of pressure support in the undersaturated conditions. However, a bottom drive type aquifer in the reservoir model can help maintain pressure and prevent steep production rates Richard O. Baker., (2015).

Although water production and saturation in the perforation layer are still low, it is likely that water has not yet reached the oil zone. Therefore, the decline profile lasting only about 4 months cannot be used as a reference for making predictions since it cannot describe the potential effect of water drive later in the mid-late production. A long-term production profile is necessary to accurately extrapolate the EUR value from the trendline. Alternatively, determining the EUR value at the last production condition, which is the condition in the second case, can also be considered.. Figure 6 depicts how the data fit to the simulation data in Case 2. In the absence of outlier data, either the first or second group of Arps' models fit the actual data perfectly. The error in comparing cumulative production from calculation and actual data for the first and second groups is 1.57% and 0.03%, respectively.

The accuracy of the resulting predictions is significantly different with the same reservoir conditions as in the first case. The use of the EUR value in the last change condition as the forecasting objective resulted in a significant reduction in error. The error values of EUR calculated against the actual EUR are 0.82%. This error occurs when the EUR value is different, the production forecasting results will also be different, this is because the EUR value affects the prediction of the production profile. Therefore, this production forecasting method will be very good if the EUR value is determined not only by using DCA but by using other methods such as reciprocal or Fetcovich as a comparison. In absence of a sufficiently long-term production profile, the EUR value for the last change condition becomes a parameter that must be known when modeling production decline using the Arps' decline model.

The linear relationship between cumulative oil produced and pressure does not exist in most actual conditions. Pressures are usually not proportional to the amount of remaining oil, but they appear to decrease at a gradual and slow rate as the amount

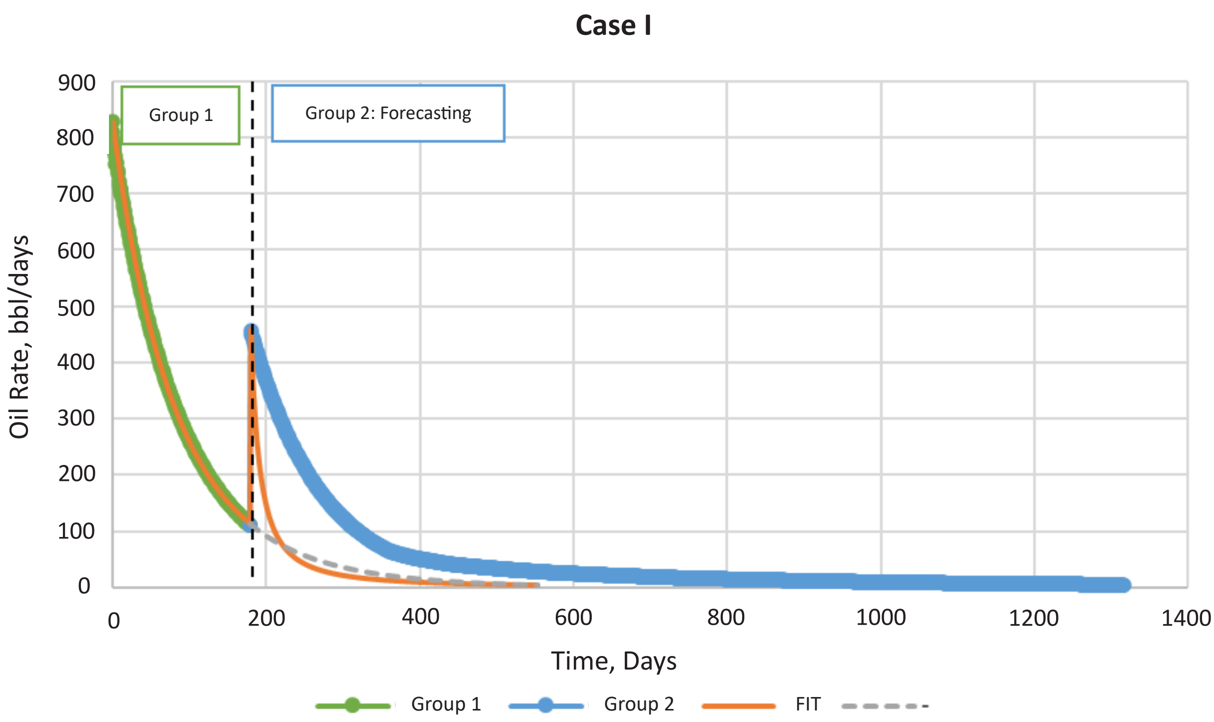

Figure 5
Fitted calculated production rate of first dataset (synthetic data) for case I

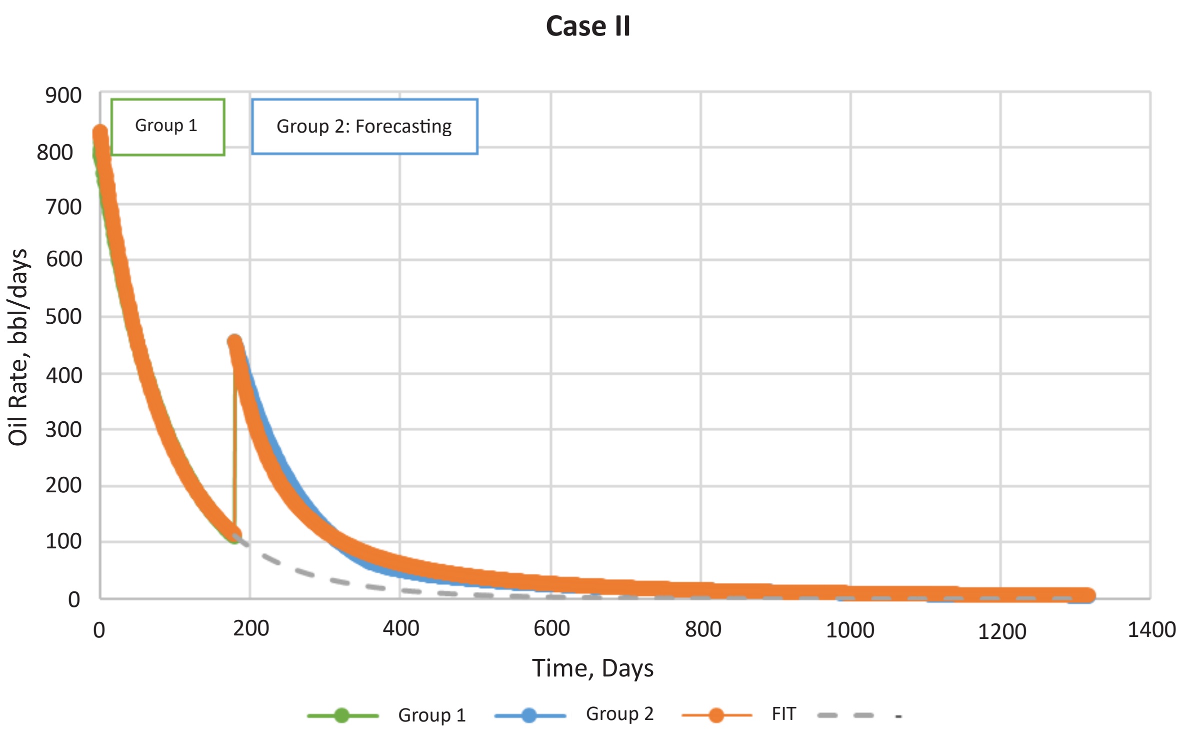

Figure 6
Fitted calculated production rate of second dataset (actual data) for Case II

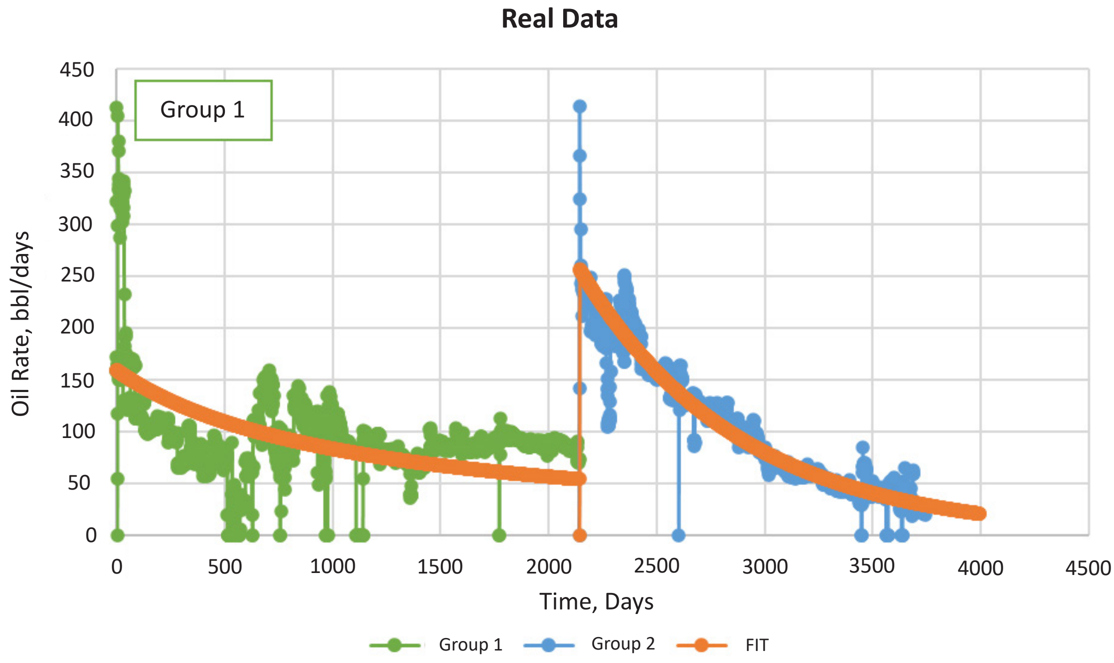

Figure 7
Calculated production rate of real field data case compared to actual data

of remaining oil decreases Arps., (1945). As shown in the tail of the production profile on Figure 6, this condition results in a slower decline in the production rate at the end of the well's life, which is still successfully modeled by Arps' decline model. Nonetheless, the well's remaining life was predicted using this method, with an error of 8.82%. Table 2 shows the decline curve parameters for each data group in well TM-020. Figure 7 depicts how the Arps' model for production rate in TM-020 fit the actual data. Flow rate forecasting begins with an increase in flow rate on day 2143, which is assumed to be the day an artificial lift is installed.

These data will be used as the starting point for the second group of data. The overall trend of the predicted flow rate is consistent with actual data, with a 1.43% error, while absolute difference between the calculated and actual data is used to calculate the error. Table 4 shows the prediction of the remaining life with the well's error. The calculated production rate visually matched the actual data for the first group. However, as illustrated on Figure 7, calculated production began by underestimating the actual data and ended up overestimating it. The first group experienced several insignificant increases in production rates, resulting in one group experiencing several decline trends. Actual data contains a large amount of data that is worth 0 bbl/day and is assumed to be down time. With the characteristics of the data as mentioned above, it is difficult to remove or change the data because the well's history is not available. Aside from the initial data with a significant decline, the entire data set was still used, resulting in a 1.43% error in predicted cumulative production. Meanwhile, predictions of the well's remaining life have been made using this method, with an error of 17.5%. Overall, the calculated production rate corresponded to the actual data. With production data spanning approximately 5 years, this method can fit known data and predict future production performance using the Arps' decline model, even after a significant increase, which is assumed to be the result of the installation of artificial lifts. Looking at the data characteristics that have many trends, particularly in the first group of data, this affects the prediction stage for the second group and results in an error of 6.03%. Because of the numerous trends, filtering data by selecting the most representative data on the first group of data can also aid in error reduction. Data with smooth conditions after filtering can be compared to data from the simulation case to see the effect on error reduction. Only production data is currently available; it is recommended that historical well events, such as what treatments have been performed, be checked to sort out the data.

Table 4
Arps' decline curve parameters for each case

Type of Data		Decline Curve Parameters					
		Group 1			Group 2		
		qi (bbl/day)	*D*	b	qi (bbl/day)	*D*	b
Field Data		159	0.0009	1	256	0.0014	0.0010
Simulation result Data	Case I	828.53	0.0124	0.1097	456.54	0.0874	0.7043
	Case II	828.53	0.0124	0.1097	456.54	0.0166	0.5601

Table 5
Cumulative production calculation error compared to actual data for each case

Type of Data		Cumulative Production (Mbbl)			Remaining Cumulative Production (Mbbl)			EUR (Mbbl)		
		Actual	Arps'	Error (%)	Actual	Arps'	Error (%)	Actual	Arps'	Error (%)
Field Data		187.77	190.47	1.43	163.13	172.97	6.03	352.70	363.43	3.04
Simulation result Data	Case I	61.28	62.62	1.57	53.81	13.01	75.82	115.10	75.64	34.61
	Case II	61.28	62.62	1.57	53.81	53.80	0.03	115.10	116.04	0.82

Table 6
Prediction of remaining well time for each case

Type of Data		Actual Well Lifetime (Days)	Calculated Well Lifetime (Days)	Error (%)
Field Data		1591	1869	17.5
Simulation result Data	Case I	1137	374	67.10
	Case II	1137	1237	8.82

CONCLUSION

The proposed method may estimate a production decrease profile using the Arps' decline model even after the installation of an artificial lift that modifies operating conditions. The proposed method is deemed reliable enough to forecast production performance with an error of 3.04% in the case of real field data and 0.82 % in the case of smooth synthetic data from simulation in terms of EUR. Length of known production data must have a long production period, such as a data case field with a duration of 5 years, in order to investigate its decline and generate reliable decline profile projections. It is known that the scatter nature of the data affects the accuracy of the prediction findings; a comparison may be made between the original data case and the simulation data case 2 to illustrate this point. For field data, the error rate in estimating the remaining well lifetime is 17.5%, for simulation data scenario I it is 67.1%, and for simulation data case II it is 8.82%. The remaining well life is predicted from the extrapolation of the flow rate to the economic limit, where the area of the curve will reflect the EUR value. This is in line with the results of the eur prediction where a small error will produce an accurate remaining lifetime prediction of well.

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GLOSSARY OF TERMS

Symbol	Definition	Unit
b	Curvature exponent	dimensionless
D	Decline rate	/day
q_i	Initial production rate	bbl/day
q_t	Production rate at t time	bbl/day
Q	Cumulative production at certain time	bbl
Q_f	Cumulative production at final condition	bbl
t	Time since start of production	day
S_w	Water saturation	Fraction
K_{rw}	Water relative permeability	Fraction
K_{row}	Oil-water relative permeability	Fraction
P_{cow}	Oil-water capillary pressure	psi
S_l	Liquid saturation	Fraction
K_{rg}	Gas relative permeability	Fraction
K_{rog}	Oil-gas relative permeability	Fraction
P_{cog}	Oil-gas capillary pressure	Psi

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