Decline Curve Analysis of Shale Oil Production Using a Constrained Monte Carlo Technique

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Abstract: Shale oil production from the Bakken shale and the Eagle Ford shale was analyzed using decline curve analysis and a constrained Monte Carlo technique. The purpose of the paper is to provide a set of parameters that can be used to initialize a Monte Carlo analysis of shale oil production using a selection of decline curves. The parameters are obtained by matching shale oil production for a set of wells in the Eagle Ford shale and the Bakken shale.

Keywords: Bakken, Eagle Ford, Shale oil, decline curve analysis.

INTRODUCTION

One way to integrate uncertainty into the preparation of shale oil and gas recovery forecasts is to apply an empirical technique based on decline curve analysis and a probabilistic production forecasting workflow. A workflow for forecasting shale gas recovery based on a constrained Monte Carlo method has been used to develop a probabilistic distribution of decline curve forecasts for four major North American shale gas fields: Barnett, Fayetteville, Haynesville, and Woodford [1-3]. The work is extended here to shale oil production forecasting for the North American shale oil fields: Eagle Ford and Bakken.

We begin by reviewing some decline curve models that have been applied to production from unconventional resources. We then describe the probabilistic decline curve analysis (pDCA) method. The criteria for selecting suitable wells from the database are then described, and results from the pDCA method are presented. Ranges of model input parameters for uniform probability distributions and triangle probability distributions are presented.

DECLINE CURVE MODELS FOR UNCONVENTIONAL RESOURCES

Decline curve models used here must have finite, bounded values of Estimated Ultimate Recovery (EUR). Not all decline curve models satisfy this criterion. For example, Arps (1945) [4] presented the following empirical decline curve model for flow rate q as a function of time t and parameters a, n:

$$\frac{dq}{dt} = -aq^{n+1} \tag{1}$$

The Arps models are harmonic decline (n = 1), exponential decline (n = 0), and hyperbolic decline with values of n that are usually in the range 0 < n < 1 for conventional reservoir production. For more discussion of Arps equation and decline curve analysis, see [5-8].

The Arps harmonic decline model (n = 1) and hyperbolic decline model with n > 1 are not always suitable for modeling unconventional reservoir production because extrapolation of the decline curve can lead to unbounded values of EUR and corresponding overestimates of EUR. The method presented below is able to avoid this problem by restricting the allowed values of *n* to physically meaningful values and performing statistically significant number of calculations that lead to a set of values that best fit the data.

The Arps exponential model does not always adequately model the decline rate of unconventional reservoir production. Another model that is called the Stretched Exponential Decline Model (SEDM) was introduced by Valkó and Lee (2010) [9] into decline curve analysis as a generalization of the Arps exponential model. The SEDM is based on the idea that several decaying systems can be modeled as a single decaying system [10, 11]. If production from a reservoir is considered a collection of decaying systems (declining well production from several wells) in a single decaying system (a reservoir), then SEDM can model declining flow rate.

We use two decline curve models in this study: Stretched Exponential Decline Model (SEDM), and the Arps hyperbolic decline model (HYDM). The SEDM model has the form

$$q = q_i \exp[-(t / \tau)^n] = a \exp[-(t / b)^c]$$
(2)

with the three parameters q_i , τ , n (or a, b, c). Parameter q_i is flow rate at initial time t. The form of the SEDM

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equation simplifies to Arps exponential decline model when n = c = 1.

$$q = a(1 + bct)^{(-1/b)}$$
(3)

Table **1** summarizes the parameters for both models.

Table 1: Parameters for Decline Curve Models

Parameter	SEDM	HYDM	
DCMA	a or q _i	a or q _i	
DCMB	b or t	b	
DCMC	c or n	С	

PROBABILISTIC DECLINE CURVE ANALYSIS

The pDCA method used here is a constrained Monte Carlo technique. The workflow is illustrated in Figure **1** and described in more detail in Fanchi, *et al.* (2013) [1]. The workflow in Figure **1** is a variation of a workflow that can be applied to more complex reservoir modeling studies of green fields and brown fields [12]. The first step in the decline curve analysis study is to gather production rate versus time data for the wells of interest. The next step is to choose a decline curve model and specify unknown model input parameters using probability distributions. Decline curve model parameter values (a, b, c) are determined by sampling from the associated probability distributions. Each complete set of model input parameters is used to obtain decline curve model results. The set of input parameters and associated decline curve model results constitute a trial. The quality of each trial is determined by specifying a constraint. In this study, cumulative oil production at the end of history is specified as the constraint.

The Monde Carlo technique generates a statistically significant number of trials. Trial results are compared to available rate-time production history and userspecified criteria. If a trial satisfies user-specified criteria, it is included in the subset of acceptable trials. An acceptable trial here is any decline curve model that yields a model calculated cumulative oil production for the historical production period that is within a user specified percentage of the actual cumulative oil production. In the analysis here, model calculated cumulative oil production had to be within 2% of actual cumulative oil production at the end of history.

A probability distribution of Estimated Ultimate Recovery (EUR) values is generated for the subset of acceptable trials. The probability distribution expresses EUR values as percentiles. The EUR percentiles are related to SPE reserves definitions by P_{10} = PC90, P_{50} = PC50, and P_{90} = PC10. The reader should consult regulatory agencies such as the Securities and



Figure 1: Probabilistic DCA Workflow.

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Exchange Commission for oil and gas reporting requirements.

WELL SELECTION CRITERIA

Shale oil production rate-time data were obtained from the Drillinginfo database (Drillinginfo.com). Since decline curve analysis typically presumes single phase flow, we selected oil wells that had a relatively constant GOR over the lifetime of the production period. Wells were selected with a relatively constant GOR so that the models were being applied to data that appeared to be single phase oil flow at subsurface shale conditions. There were only a few wells in the database that satisfied this requirement. The use of wells with more GOR variability raised the possibility that production would require a more sophisticated analysis of multiphase flow.

Wells with approximately 90 months or more of history were used in the study. The duration of at least 90 months provided a well-defined decline curve for finding the model that best fit the data and estimating parameters that could be used to initialize the Monte Carlo study of other wells. Shorter production periods could have been used, but may not have provided enough data for both selecting a best-fit model and associated parameters. It is still possible that the parameter range may need to be altered to match other cases. We selected nine Bakken wells and six Eagle Ford wells based on the GOR and duration of history criteria.



Figure 2: GOR for Bakken Well BaW10.



Figure 3: Linear Regression Rate Curves for Bakken Well BaW10.

SHALE OIL PRODUCTION

The pDCA models SEDM and HYDM are used to match oil production rate versus time data for nine Bakken shale wells and six Eagle Ford shale wells using the workflow displayed in Figure **1**. The Monte Carlo analysis uses 1000 trials initially. The parameter b in the HYDM model was kept within the range constraint 0.01 < b < 0.99. Each trial in the subset of acceptable trials for a pDCA model must match cumulative oil production at the end of the historical production period within the limit specified by the user. A set of decline curve models is available for matching the shape of the decline curve throughout the decline curve model is the model that provides the best fit of the data over the decline curve history. Criteria for an

acceptable match include the choice of decline curve model and a match of cumulative oil production within user-specified limits at the end of the production period.

The quality of the match between the pDCA model and oil production rate data for a Bakken shale oil well is illustrated in Figures **2** through **4**. Similarly, the quality of the matches for an Eagle Ford shale oil well is illustrated in Figures **5** through **7**. The gas-oil ratio shows realistic variability around a relatively constant value.

Linear regression is used to fit pDCA models to actual data and displayed in the linear regression plots. The quality of the match between actual data and pDCA model parameters is displayed in the PC50 (50th percentile) plots. Minimum and maximum pDCA



Figure 4: 50th Percentile Rate Curves for Bakken Well BaW10.



Figure 5: GOR for Eagle Ford Well EFW08.



Figure 6: Linear Regression Rate Curves for Eagle Ford Well EFW08.



Figure 7: 50th Percentile Rate Curves for Eagle Ford Well EFW08.

Table 2: Bakken Shale Oil Wells

Case	Parameter	SEDM		НҮДМ	
		MIN	МАХ	MIN	MAX
PC50	а	4651	15151	1856	8683
PC50	b	2.680	21.004	0.862	0.980
PC50	С	0.3209	0.6206	0.0315	0.1092

parameter values for the PC50 trial in the subset of acceptable trials are collected for the set of wells in the Bakken shale and the Eagle Ford shale. The minimum and maximum values of pDCA parameters are tabulated in Tables **2** and **3**. The set of decline curves

that are considered matches must satisfy the requirement that the allowed parameter range represents physically meaningful parameters. For example, the hyperbolic decline curve has values of b in the range $0 \le b \le 1$ in both Tables **2** and **3**.

Table 3: Eagle Ford Shale Oil Wells

Case	Parameter	SEDM		HYDM	
		MIN	MAX	MIN	MAX
PC50	а	1603	5940	919	6276
PC50	b	1.544	9.414	0.822	0.961
PC50	с	0.3026	0.6966	0.0355	0.2799



Figure 8: HYDM Rate Curves for Eagle Ford Well EFW08.



Figure 9: SEDM Rate Curves for Eagle Ford Well EFW08.

Figures 8 and 9 show how the choice of model (HYDM or SEDM) affects the match of the shape of the curve for PC10, PC50, and PC90 cases which correspond to the 10th, 50th and 90th percentile cases. In this case, the SEDM rates in Figure 9 tend to be less than actual rates during the first 10 months and greater

than actual rates between 10 and 50 months. The cumulative production criterion is satisfied by the end of production history. By contrast, Figure 8 shows HYDM rates more closely aligned with actual rates. Both Figures 8 and 9 include forecasts of rates to 150 months and show the variability in PC10, PC50, and

PC 90 forecasts. The magnitude of the variability depends on the user-specified criteria for controlling the Monte Carlo analysis.

SUMMARY

Probabilistic decline curve analysis (pDCA) with a constrained Monte Carlo technique was used to analyze oil production rate versus time data for a sampling of wells from the Bakken shale and the Eagle Ford shale. Minimum and maximum values of pDCA parameters were determined and can be used as input parameter ranges for probability distributions. Matches of shale oil production for a selection of wells in the Eagle Ford shale and the Bakken shale provided a realistic, empirical basis for the reported parameter ranges. The selected wells were restricted to wells with a relatively constant GOR and a production history of at least 90 months. These criteria satisfy the requirement that produced oil was single phase oil at subsurface shale conditions and enough data was available to define the shape of the oil rate decline curve.

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