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An analysis of stochastic discrete fracture networks on shale gas recovery

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ABSTRACT

Complex fracture networks are created by hydraulic fracturing in shale gas reservoirs. The well performance is largely affected by the geometrical properties of fracture networks. It is difficult to estimate well performance because a large number of parameters are used for characterization of a fracture network. In this study, only two parameters are screened to estimate the shale gas recovery by the method of design of experiments. Synthetic fracture networks are generated based on the stochastic theory to represent the secondary fractures in the hydraulic fracture network. Two numerical experiments are designed to correlate the fracture network properties to gas recovery estimated by a commercial software. Various fracture network parameters derived from the analyses of fracture intersection, fractal and percolation are screened to correlate the gas recovery. In terms of the internal structure of a fracture network, a dimensionless parameter called the effective fracture density is proposed to estimate shale gas recovery. It is a combination of the number of fractures, fracture length and orientation. In terms of the boundary of a fracture network, the shale gas recovery is determined by the number of intersection points between the primary fractures and secondary fractures (NIPS). The shale gas recovery predicted by the two parameters (the NIPS and the dimensionless fracture density) is accurate compared with that calculated by the commercial software, which provides us a practical method to estimate the gas recovery by eliminating the number of parameters used for fracture network properties.

1. Introduction

Shale gas resources have become increasingly important energy resources around the world in recent years (Yu and Sepehrnoori, 2014; Zou et al., 2010; Zhang et al., 2017). Shale gas reservoirs are mostly composed of nanoscale pores with a diameter ranging from 1 to 100 nm (Wu et al., 2017). A combination of horizontal wells and hydraulic fracturing has made profitable exploitation possible for these reservoirs with ultra-low matrix permeability (Xu et al., 2016). The use of large volumes of low-viscosity slickwater and the pre-existence of natural fractures increase the complexities of fracture networks created by hydraulic fracturing (Cipolla et al., 2010a). It is different from conventional reservoirs that the economic success in shale gas reservoirs is to focus on the well scale rather than the field scale (Mirzaei and Cipolla, 2012). The gas recovery of a production well largely depends on the geometries of hydraulic fracture networks (Mayerhofer et al., 2010). Therefore, it is particularly crucial to quantify the effects of fracture network properties on the prediction of gas recovery.

Gas production from shales is characterized by transient flow behavior and boundary-dominated flow is rarely observed (Duong, 2011). A production rate usually declines rapidly as it is initially dominated by fracture flow. At the later time, the decline rate becomes gradual due to the matrix-dominated transient flow. A decline analysis is extensively applied to estimate the gas recovery for shale gas wells (Kenomore et al., 2018). It is initially proposed by Arps to predict radial inflow performance of vertical wells (Arps, 1945). However, the geometries of horizontal wells in shale gas reservoirs are quite different from the previous configuration (Patzek et al., 2013). The original Arps's study indicated that the b-exponent should lie between 0 and 1.0 on a semi-log plot. In practice, we often observe values much greater than 1.0 (Ilk et al., 2008). Kanfar and Wattenbarger (2012) discussed the feasibility of different decline models in the Barnett shale gas reservoir and advised that these models have some limitations. Baihly et al. (2010, 2015) observed that there was no production improvement in the Barnett shale despite the lateral length of horizontal wells increased by approximately 50% and proppants per lateral foot increased by about 33% over five years, which asserts that the impact of reservoir quality (for example, matrix permeability) is significantly greater than that of completion quality on the productivity. The decline models are usually empirical and hardly reveal the relationship between gas recovery and

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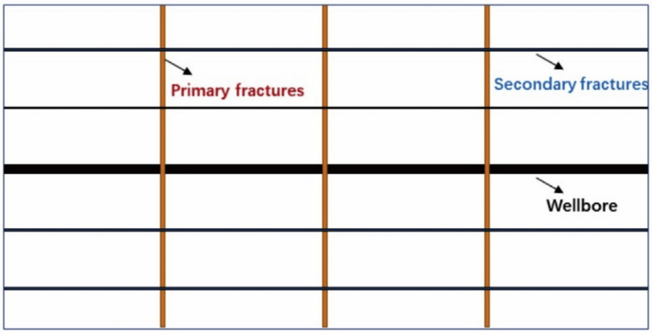

Fig. 1. The modeling of hydraulic fracture networks.

the geometries of fracture networks.

Given the complex nature of fracture networks, reservoir simulation is a preferred method to predict the gas recovery. The modeling of complex fracture networks is a prerequisite. There are two well-known approaches commonly used in the modeling of fractured reservoirs: a dual porosity/dual permeability model (Warren and Root, 1963) and a discrete fracture model (DFM). The DFM, in which fractures are represented explicitly, is better to model realistic, complex, and non-ideal fracture geometries and to account for the explicit effects of individual fractures on the overall fluid flow (Li et al., 2017). Conventional models of a single wing-like fracture are not suitable for quantifying complicated fracture networks. Fig. 1 is a common configuration used for modeling hydraulic fracture networks in naturally fractured shale gas reservoirs (Cipolla et al., 2010b; Cheng, 2012; Dehghanpour and Shirdel, 2011; Ezulike and Dehghanpour, 2014; Xu et al., 2010). This configuration consists of primary fractures and secondary fractures. The primary fractures with high conductivities, which are connected to the wellbore, are perpendicular to the horizontal wellbore. The spacing of primary fractures is controlled by the number of fracturing stages. The secondary fractures with low conductivities are assumed to be unpropped or less propped. They are placed in the perpendicular and parallel directions to the primary fractures. The secondary fractures have no direct communication with the wellbore, and gas flows from tight matrix to the primary fractures through the secondary fractures. It is obvious that the modeling of the secondary fractures in this configuration cannot capture the complex nature of fracture networks. A triple porosity model (Liu et al., 2003; Wu et al., 2004) is commonly used to model gas flow in shale reservoirs considering the number of distinct porous regions: hydraulic fractures, secondary (natural) fractures and tight matrix. Ali et al. (2013) summarized the existing models describing gas flow in shales and developed analysis equations for different flow regimes to determine the reservoirs parameters. Ezulike and Dehghanpour (2014, 2016) proposed a quadrilinear flow model considering the interaction between matrix and hydraulic fractures and investigated the effects of secondary fractures on production data using flow regime equations and specialized plots. Cipolla et al. (2011) used unstructured fracture modeling (UFM) to capture the complex geometries of natural and hydraulic fractures. Mirzaei and Cipolla (2012) developed a new reservoir modeling and simulation technique for complex fracture networks combining DFM and UFM to simulate well performance and improve stimulation design.

A clear tendency is indicated by field data and numerical simulations that large stimulated reservoir volumes (SRV) result in better well performance (Cipolla et al., 2010b; Mayerhofer et al., 2006). However, the concept of SRV does not provide any details of the fracture structure. Mayerhofer et al. (2006) conducted numerical reservoir simulations to understand the effects of fracture network properties such as network size, fracturing spacing and network conductivity on cumulative gas production using a fracture network presented in Fig. 1. Sun and Schechter (2015) employed an optimized unstructured gird to mimic complex fracture networks and performed reservoir simulations to investigate the effects of fracture aperture, spacing, length and strike on well performance based on fractal fracture networks. Yu et al. (2014) used a commercial simulator to investigate well performance with different geometries (different fracture half-length and fracture spacing) of multiple transverse hydraulic fractures. The studies discussed so far investigated the properties of fracture networks with one parameter changing at a time while keeping the other parameters fixed. Jafari and Babadagli (2009) performed a sensitivity analysis for parameters on fracture network permeability and correlated four parameters with the prediction of permeability. However, this method is not suitable for practical applications because many parameters are required to obtain.

In this paper, we will further investigate the effects of fracture network properties on the gas recovery beginning with a generation of fracture networks based on the stochastic theory. The relationship between the gas recovery and fracture network properties is analyzed by the method of design of experiments (DOE). This study aims to develop a combination of parameters describing the fracture network properties to estimate the gas recovery using simple calculations.

2. Generation of stochastic fracture networks

Despite intensive studies of fracture networks during the past years, an accurate quantification of geometrical properties of fracture networks is still a big challenge. These problems result from the difficulties even impossibility of locating, measuring and analyzing the in-situ fractures (Berkowitz, 1995). The statistical analyses of fractures at outcrops, microseismic maps, core samples and image loggings are often employed to analyze the underground fracture networks (Sun et al., 2016).

In the two-dimensional space, a fracture can be presented by a line segment using four attributes: fracture position, length, aperture and orientation. Each attribute belongs to a particular probability density function (PDF). In the developed algorithm, a uniform distribution is used to control the position and the number of fractures in a square domain, which is realized by a Matlab function $rand(N, 2)$. Here, N is the number of fractures. The $rand(N, 2)$ function can generate two-dimensional uniformly distributed random numbers. Fracture length is considered to obey the exponential distribution (Berkowitz, 1995; Long et al., 1982). The von Mises distribution is used to describe fracture orientation (Odling and Webman, 1991) and fracture aperture is considered as a constant in this study. Table 1 is the parameters for generating fracture networks.

As shown in Table 1, a fracture network can be realized using four parameters: the number of fractures N, fracture mean length μ_l, fracture orientation μ_θ and concentration parameter k_θ which is a measure of the concentration of angles. If k_θ is large, the distribution becomes very concentrated about the angle μ_θ.

Fig. 2 shows a comparison between the input parameters for generating fracture networks and the actual parameters derived from the generated fracture networks. In Fig. 2a, ten realizations of fracture networks generated using the same input parameters are averaged to derive the actual fracture length. It is observed that the input fracture length is almost identical to the derived fracture length when the value

Table 1
The parameters for generating stochastic fracture networks.

PDF	Form	Parameters
Uniform	$rand(N, 2)$	N
Exponential	$\frac{e^{-x/\mu_l}}{\mu_l}$	μ_l
Von Mises[a]	$\frac{e^{k_\theta cos(\theta-\mu_\theta)}}{2\pi \cdot I_0(k_\theta)}$	μ_θ, k_θ

[a] where $I_0(k)$ is the modified Bessel function of order 0.