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Hydrocarbon reservoirs characterization by co-interpretation of pressure and flow rate data of the multi-rate well testing

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ABSTRACT

Pressure transient behavior is among the most important information for characterizing a reservoir, forecasting its future performance, and designing an appropriate recovery scheme. Although a continuous real-time monitoring of reservoir bottom-hole pressure has become a routine task in intelligent wells, complete extraction of the potential information from these valuable sources of data may not be achieved by using traditional interpretation methods. Deconvolution transforms the pressure transient data related to the wells with variable production rates into an equivalent constant rate pressure data with duration equal to the whole duration of the multi-rate test i.e., unit step response. This technique can reveal high valuable information over a distance from the wellbore which may be several orders of magnitude greater than the radius of investigation of individual flow periods. In the present study, a robust and practical deconvolution methodology is developed for extracting the unit step response (USR) from synthetic, noisy and incomplete pressure transient histories pertaining to multi-rate data. Our proposed scheme calculates the USR from those multi-rate well testing data which may contain high levels of noises in both the flow rate and pressure data. A coupled wavelet transform/superposition theorem is the basis of the proposed method. The algorithm has shown an excellent performance for revealing reservoir/boundary models and their associated parameters.

1. Introduction

Descripting dynamic behaviors of underneath formations containing crude oil, gas and water is of great importance in the petroleum engineering. Success of a hydrocarbon reservoir simulation for evaluating its current and future behavior depends heavily on the accuracy of the reservoir characteristic parameters. There are several possible ways to obtain some valuable information about the reservoir characteristics: seismic data (Arora and Tomar, 2010), well log data (Dashtian et al., 2011), well drilling data (Shahverdi et al., 2011), and transient pressure testing (Braester and Zeitoun, 1993; Vaferi et al., 2011, 2012, 2015).

Although a consistent and complete characterization of a hydrocarbon reservoir can only be realized through collecting and analyzing all of these different sources of data, the method with dynamic nature can represent dynamic behavior of a hydrocarbon reservoir more accurately. Well testing operations which are basically conducted by creating a pair of flow disturbances in the wellbore and monitoring their associated pressure response at the bottom of the wellbore is a well-known and widely used dynamic technique for hydrocarbon reservoirs (Vaferi et al., 2011, 2015). Alteration of production conditions creates sequences of pressure transient signals that can sense a large portion of a reservoir structure progressively (Vaferi et al., 2012). The reservoir properties are usually estimated by appropriate well-test methods which try to match the observed pressure responses on some ideal reservoir models. Since propagation of the pressure signal through the reservoir structure can represent the average reservoir conditions rather than its local heterogeneities in properties, these types of signals are the most effective sources of information for estimating and predicting the dynamic behavior of the hydrocarbon reservoirs. In fact, well testing analysis enables us to establish the reservoir/boundaries models as well as their associated parameters through an inverse solution and history matching (Vaferi et al., 2011, 2015).

Allain and Horne (1990) employed a combined artificial intelligence technique with a rule-based pattern recognition scheme to identify the key characteristics of some de-noised pressure derivative (PD) plots. Athichanagorn and Horne (1995) focused on the reservoir models detection using a coupled scheme based on sequential predictive probability method and a multi-layer perceptron neural network (MLPNN). Their MLPNN model was trained to detect the key features of the PD graphs of some

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Nomenclature

B_o	oil formation factor
c	compressibility
E_i	exponential integral function
F_{cd}	dimensionless fracture conductivity
$g(t)$	impulse response
h_L	formation thickness
$h(t)$	unit step response
h_p	perforated interval
h_{top}	distance from top of layer to top of perforations
k	permeability
k_z	vertical permeability
$m(t)$	independent random variable of Eq. (24)
N	number of recorded pressure data
p	pressure
p_0	initial pressure
q	flow rate
q^o	time derivative of the flow rate
r	radius
r_b	boundary radius
S	skin factor
S_f	fracture face skin
$s(t)$	noisy signal
$\bar{s}(t)$	de-noised signal
t	time
t_p	production time
W	orthogonal $N \times N$ matrix
w_s	wellbore storage
X_f	fracture half length
Z	vector of the wavelet coefficients
z_i	wavelet coefficients

Subscripts

f	fracture
m	matrix
t	total
w	wellbore

Abbreviations

BU	build-up
CPR	constant production rate
DD	drawdown
EMD	empirical mode decomposition
MLPNN	multi-layer perceptron neural networks
PD	pressure derivative
PDE	partial differential equation
STB	standard tank barrel
USR	unit step response
WT	wavelet transform

Greek symbols

∂	partial differentiation
α	diffusivity coefficient
Δ	difference
ϕ	porosity
λ	interporosity flow coefficient
μ	viscosity
σ	noise variance
ω	storativity ratio

candidate reservoir models. The initial guess for the sequential predictive probability method were obtained from the trained MLPNN approach. May and Dagli (1998) provided a hybrid system for analyzing the well testing data. The authors highlighted the low running time and possibility of using both symbolic and numeric data as two key features of their developed hybrid method.

Vaferi et al. (2011) designed an optimal MLPNN approach for identification of various oil reservoir models with different boundaries, and applied it to both synthetic and real field well-testing data. They approved the performance of their proposed approach against noisy data by applying it to several noisy well testing data.

The above-mentioned research studies have only been concentrated on the constant rate well testing operation, and no multi-rate test data have been considered in these studies (Allain and Horne, 1990; Athichanagorn and Horne, 1995; May and Dagli, 1998; Vaferi et al., 2011). In these studies only those constant rate tests have been analyzed which their radius of investigation reach the reservoir boundary. Since the PD can only be calculated from a constant rate test, the constant rate duration in these studies are up to 400 days (Allain and Horne, 1990; Athichanagorn and Horne, 1995; May and Dagli, 1998; Vaferi et al., 2011). The pressure derivative analysis over constant rate periods (traditional method) have several drawbacks such as it only covers a limited volume of reservoir, reveals restricted reservoir information, and sometimes provides an uncertain diagnosis for reservoir model (Du, 2007).

van Everdingen and Hurst (1949) were the first researchers who employed the superposition theorem (Duhamel principle) to drive a dimensionless wellbore pressure drop solution for a continuously varying production rate. Hutchison and Sikora (1959), Coats et al. (1964), Jargon and van Poollen (1965), Stewart et al. (1983), Kucuk and Ayestaran (1985), Thompson and Reynolds (1986), Ahn and Horne (2008), von Schroeter et al. (2004), and Levitan et al. (2006) are other research groups who have investigated some other applications of the Duhamel principle in the field of petroleum engineering.

Stewart et al. (1983) introduced the flow rate data as a piecewise linear function into the convolution process for radial flow in homogeneous reservoirs. However this approach did not yield much advantage since the success of representation of flow rate signals by stepwise functions depends on data quality (Stewart et al., 1983).

Kucuk and Ayestaran (1985) used an exponential and polynomial function for approximation of flow rate and pressure signal of multi-rate well testing data, respectively. Solution of the deconvolution integral in the Laplace domain shows serious problems in handling of noisy data, and provides unstable results in these situations (Kucuk and Ayestaran, 1985).

Thompson and Reynolds (1986) employed the piecewise linear function to approximate both flow and pressure data, and carried out the calculation of the deconvolution integral in the time domain. Although this real-time deconvolution algorithm presents a general solution for multi-rate well testing analysis, but its calculations is very complex, time consuming, and involves a complicated recurrence relation with severe numerical difficulties (Thompson and Reynolds, 1986).

Ahn and Horne (2008) solved a deconvolution problem using convex optimization approaches in the presence of noises in both pressure and flow rate data. This method shows severe problem for handling an incomplete buildup transient especially when the