Journal of Petroleum Science and Engineering 167 (2018) 418–425

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

A new pattern recognition model for gas kick diagnosis in deepwater drilling

Xiaohui Sun, Baojiang Sun*, Shuai Zhang, Zhiyuan Wang, Yonghai Gao, Hao Li

School of Petroleum Engineering, China University of Petroleum (East China), Qingdao, 266580, China

ARTICLE INFO

Keywords:
Pattern recognition
Drilling
Kick
Fault diagnosis
Probability

ABSTRACT

Early kick detection is important to reduce the possibility of well blowouts, which have serious safety and financial implications in deepwater drilling. In this paper, a novel pattern recognition model for kick diagnosis is proposed. In the model, trend detection is used to make good decisions based upon noisy drilling data. The integrated model comprises two parts: (i) a dynamic wellbore flow model, which extracts the kick mode via multiphase flow simulation; and (ii) improved piecewise approximation and similarity measure algorithms. The proposed model successfully diagnoses gas kick faults in real time when it is applied in a field well. It offers significant sensitivity improvements while reducing the false alarm rate caused by ambiguous data, as both kick and non-kick events are accurately extracted and rapidly identified. This model is a new attempt to combat the problem of early kick detection via pattern recognition.

1. Introduction

Gas kicks are one of the most serious drilling accidents, and occur when the formation fluid enters the wellbore under high formation pressure. If the kick is not detected in the early stage, a slight initial kick will rapidly develop and transform into a well blowout, which can pose a significant threat to worker safety, the marine environment, and the economic viability of drilling projects (Skogdalen and Vinnem, 2012). As oil and gas exploration expands into deepwater regions (Pinder, 2001), the problem of kick detection becomes increasingly important because of the complicated drilling conditions, including the uncertain formation pressure (Falcao, 2002), narrow mud weight window (Rocha et al., 2003), and large water depth. Therefore, an effective approach for kick diagnosis is needed to ensure the safety and economy of deepwater drilling.

At present, great efforts have been made in the development of kick monitoring devices and model-based estimation techniques (Fu et al., 2015; Jacobs, 2015; Li et al., 2017; Ojinnaka and Beaman, 2018; Vajargah and Oort, 2015); however, the early kick detection remains a challenging problem. In general, the major kick detection methods can be divided into two groups: thresholding methods (Weishaupt et al., 1991; Benveniste and Basseville, 1984) and predictive methods (Swanson, 1997). In the early systems, kicks were usually detected by thresholding, whereby an alarm was generated when the flow parameters exceeded pre-set values. The problem with thresholding is the high false-alarm rate caused by the noise inherent in the measurements. An improved windowed threshold technique can increase the noise tolerance, but this method detects abrupt changes in data and is not suitable for the gradual variations of flow parameters during a kick. Furthermore, the choice of optimal parameters varies significantly according to the drilling conditions (Weishaupt et al., 1991). In predictive systems, accurate simulations of wellbore dynamics must be performed in real time. Kicks are detected when there is a certain difference between the measured and predicted values (Swanson, 1997). Moreover, kick detection models based on neural networks (Yin et al., 2014; Deregeh et al., 2013) construct different layers of warning networks through sufficient network training and testing.

Under complicated drilling scenarios, existing systems have several limitations which make it difficult to meet the stringent requirements of early kick detection in deepwater drilling. In particular:

(1) The performance of a thresholding method depends on how the well is set up. In deepwater drilling, flow parameters measured by crude sensors (such as pump strokes and flow paddle) under various wind, current, and wave conditions can include high noise levels. The resulting threshold values may be too high, leading to late detection, or too low, leading to a high false-alarm rate.
(2) To identify kicks through the difference between predicted and measured results, model simulations in a predictive system require accurate calibration to ensure optimal performance. Calibration can be quite difficult because of uncertainties in both the input data and model parameters, which significantly influences the accuracy of the wellbore flow model (Udegbunam, 2014).
(3) To justify their economic viability, there are fewer wells in

* Corresponding author. School of Petroleum Engineering, China University of Petroleum (East China), 66 Changjiang West Road, Huangdao, Qingdao, 266580, China.
E-mail address: sunbj1128@126.com (B. Sun).

https://doi.org/10.1016/j.petrol.2018.04.035
Received 21 November 2017; Received in revised form 31 March 2018; Accepted 14 April 2018
Available online 16 April 2018
0920-4105/

deepwater regions compared to their onshore counterparts. Therefore, historical data of kick events are insufficient for the threshold setting, network training, and prior probability statistics.

Therefore, it is necessary to develop a new kick diagnosis method for deepwater drilling. In this study, a pattern recognition model for gas kick diagnosis is proposed. This paper proceeds as follows. First, we describe the model development process, in which a dynamic wellbore flow model is built to extract the typical modes of kick events and pattern recognition algorithms are proposed. Next, the proposed model is applied to the detection of gas kicks in a field well using flow parameter measurements. Subsequently, the model performance is analyzed through comparison to a typical thresholding method, and good noise tolerance is verified. Finally, the conclusions to this study are summarized.

2. Model development

Considering the process of kick development, the time series of flow data usually show a gradual variation during a kick. It is expected that pattern recognition using trend detection will enable early fault diagnosis (Diallo et al., 2005; Rengaswamy and Venkatasubramanian, 1995). Furthermore, the false-alarm rate can be reduced by distinguishing between kick and non-kick events. The structure of the proposed model is shown in Fig. 1.

2.1. Kick modes extraction via wellbore dynamics simulations

Gas kicks during drilling operations are a transient coupled process of multiphase flow in the wellbore and gas percolation in the reservoirs. As the gas in the wellbore migrates and expands, the bottomhole pressure will decrease dynamically, leading to an increase in the mass transfer rate between the wellbore and reservoir.

After a gas kick occurs, the measured flow data will undergo a significant change, as shown in Fig. 2. The obvious signatures of kick events are as follows: (i) The additional gas in the annulus increases the outflow rate (Q_{out}); (ii) the pit gain (tank volume) increases; (iii) the bottomhole pressure (p_{wf}) and stand-pipe pressure (p_{in}) decrease gradually because of the loss of hydrostatic pressure in the annulus; and (iv) the rate of penetration (ROP) increases abruptly, because permeable formations usually have good drillability.

2.1.1. Dynamic wellbore flow model

(1) Conservation equations

During gas kick development, the flow parameters of gas and liquid (e.g., phase distributions, velocities and pressure) can be obtained by solving the continuity equations and momentum conservation equation.

$$\frac{\partial}{\partial t}(A\alpha_g\rho_g) + \frac{\partial}{\partial s}(A\alpha_g\rho_g v_g) = -m_{gl} + q \tag{1}$$

$$\frac{\partial}{\partial t}(A\alpha_l\rho_l) + \frac{\partial}{\partial s}(A\alpha_l\rho_l v_l) = m_{gl} \tag{2}$$

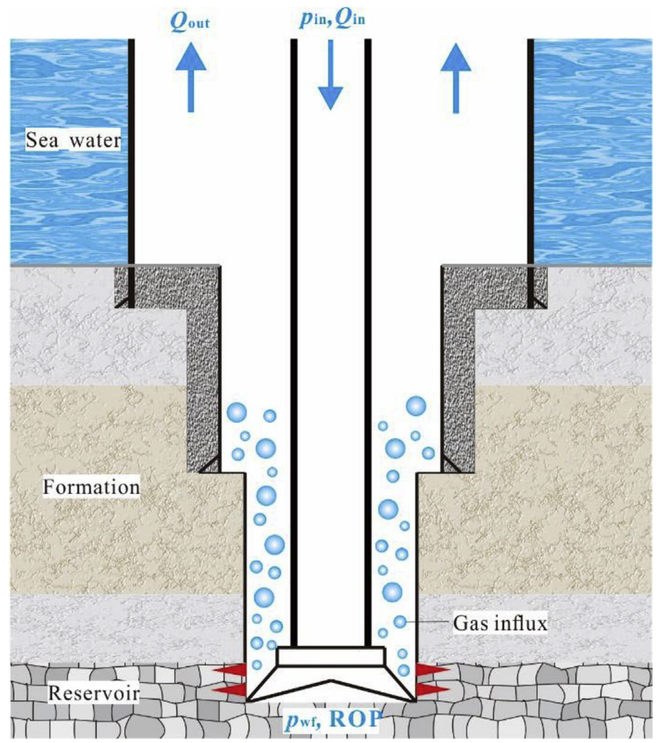

Fig. 2. Schematic of a drilled gas kick during deepwater drilling. (Q_{in}: inflow rate; Q_{out}: outflow rate; p_{in}: stand-pipe pressure; p_{wf}: bottomhole pressure.)

$$\frac{\partial}{\partial t}(A\alpha_g\rho_g v_g + A\alpha_l\rho_l v_l) + \frac{\partial}{\partial s}(A\alpha_g\rho_g v_g^2 + A\alpha_l\rho_l v_l^2) + \frac{\partial}{\partial s}(Ap) = -\left(A\frac{\mathrm{d}p}{\mathrm{d}s}\right)_F - Ag\cos\theta(\alpha_g\rho_g + \alpha_l\rho_l) \tag{3}$$

where A is the cross-sectional area of the annulus, m^2; α_g is the void fraction of gas, m^3/m^3; α_l is the void fraction of liquid, m^3/m^3; m_{gl} is the gas dissolution rate, kg/(m·s); q is the gas influx rate, kg/(m·s); p is the fluid pressure, Pa; and θ is the deviation angle, rad.

(2) Drift relation

Due to the gas buoyancy and inhomogeneity of phase distribution, there exits slippage between gas and liquid phases, which has an important influence on the profiles of gas void fraction and fluid pressure along the wellbore. The relation between velocities of gas and liquid phases can be described using the drift model:

$$v_g = C_0(\alpha_g v_g + \alpha_l v_l) + v_{sg} \tag{4}$$

where C_0 is the distribution coefficient, dimensionless; and v_{sg} is the drift velocity, m/s. Both the two parameters are functions of fluid properties and flow behaviours.

$$(C_0,\ v_{sg}) = f(d_c,\ \rho_g,\ \rho_l,\ \mu_l,\ \alpha_g,\ v_g,\ v_l,\ \sigma) \tag{5}$$

Based on multiphase flow experiments, several slip relations have been developed. However, they were usually suitable for a specific flow pattern (Bhagwat and Ghajar, 2014) or a limited scope of flow rate (Shi

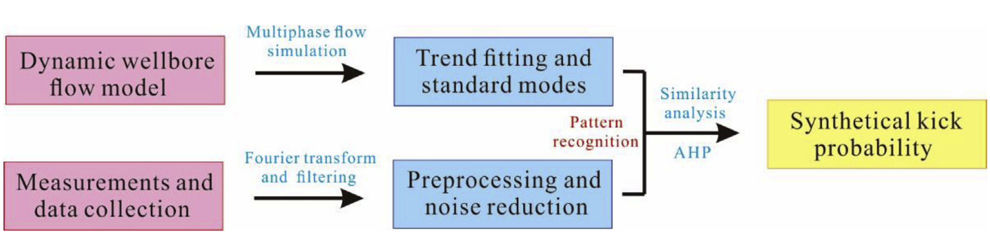

Fig. 1. Structure of the proposed model. (AHP: Analytical hierarchy process method.)