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Early Detection of Drillstring Washout Based on Hydraulics Model and Pattern Recognition Method

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ABSTRACT

Drillstring washout early detection is important to prevent drillstring twist-off and well blowout. In this paper, a new diagnosis method of washout failure is proposed based on a dynamic hydraulic model during a drillstring washout and pattern recognition method. The novel hydraulics model gives a detailed variation description of standpipe pressure, which can improve the washout prediction accuracy. The proposed method applied in a field well successfully recognized the drillstring washout accident at an early stage and the predicted results show a high noise-tolerant level.

KEY WORDS: Drillstring washout; Pattern recognition; Probability; Drilling; Hydraulics model; Fault diagnosis.

INTRODUCTION

During the drilling process, harsh formation conditions and deep drilling depth are inevitable, making drillpipe failure occur frequently (Abdollahi, 2003; Albdiry, 2016). As a common type of drillpipe failure, drillstring washout is a hole or crack on drillpipe, allowing drilling mud in the drillstring flow into the annulus directly and reduce drilling efficiency (Liu, 2016). Usually, the washout holes in the drillstring develop rapidly and eventually evolve into a twist-off. Once a twist-off occurs, necessary fishing job will significantly extend the non-productive time and increasing drilling costs (Bert, 2009; Godhavn, 2010). In order to ensure economy and efficiency, an effective method for drillstring washout early diagnosis is necessary during drilling operation.

Compared with gas kick, loss and many other downhole incidents, drillstring washout has little effect on the flow rate out of the well (Owings, 1982). Therefore, it is difficult to detect a washout by monitoring pit gain variation or the difference between pump rate and flow rate out of the well. At present, many methods have been proposed to diagnose drillstring washout during drilling process, which can be divided into two categories: parameter monitoring method and model-based prediction method. In some drilling systems, washouts would be detected by threshold monitoring technique (Skalle, 2013). By installing measuring devices, washout detecting system will rise an alarm if the parameters exceeded the pre-set threshold. The problem with this method is that high noise level in the measurement usually induces high false-alarm rate. Reasonable threshold varies dramatically depending on drilling operations and measuring facilities, making it difficult to choose sensible thresholds of monitoring parameters. Furthermore, specific detecting equipment needs to be added to the system before drilling operation. In another method, model-based prediction method, a single-phase flow model under normal conditions is used to estimate the flow state of drilling fluid in the wellbore (Willersrud, 2015). A drillstring washout incident can be identified based on the difference between the estimates and measurements. Considering the error of the predicted results and measured data, the diagnosis results of model-based prediction method is not ideal during the initial stage of washout development with the small changes of parameters. To reduce the false-alarm rate, a washout incident can be detected when the deviation is large enough, which has adverse effects on early detection. Recently, the Bayesian network is applied to monitor washout incidents in real time. After sufficient training with historical data, a Bayesian network is established to model the correlation between drilling parameters and failures (Ambrus and Ashok, 2018). However, the predicted results are influenced significantly by the representation of the measured historical data.

As a result, it is necessary to develop an early detection method for drillstring washout early detection with a high noise-tolerant level. In this paper, an early diagnosis method of washout based on pattern recognition is proposed. A dynamic wellbore single phase flow model is developed to simulate the variation trends of drilling parameters after a washout occurred. On this basis, a pattern recognition algorithm is employed, which can estimate the probability of a drillstring washout failure. Then, the proposed method is applied to detect a washout incident of a field well with measured data. The performance of proposed method and traditional detection method is analyzed, and the results show that the proposed method has a higher noise-tolerant level. The method proposed in this paper can help to accomplish the early detection of drillstring washout on drilling site with high accuracy.

MODEL DEVELOPMENT

Pattern recognition model based on the variation trend of the drilling parameters has been successfully used in the early kick detection (Ritchie, 2008). Similar to gas kick incidents, the time series of drilling parameters will show a specific development feature after a drillstring washout failure occurred. The dynamic wellbore flow model was developed in order to get the variation trend of drilling parameters during washout failure. Then, the pattern recognition model based on the extracted modes was used to detect drillstring washout.

Dynamic wellbore flow model with a washout

The drillstring washout provides a new path for drilling fluid to flow from the drill pipe to the annulus, leading to changes in the wellbore flow regime (Teslyuk, 2009). Driven by the pressure difference between the inside of the drill pipe and the annulus, drilling fluid is shunted at the washout hole and part of it flows directly into the annulus through the washout hole. Correspondingly, the drilling fluid flow rate at the bottom of the well decreases due to the influence of shunting effect. Drilling fluid flow regularity with a drillstring washout is shown in Fig. 1.

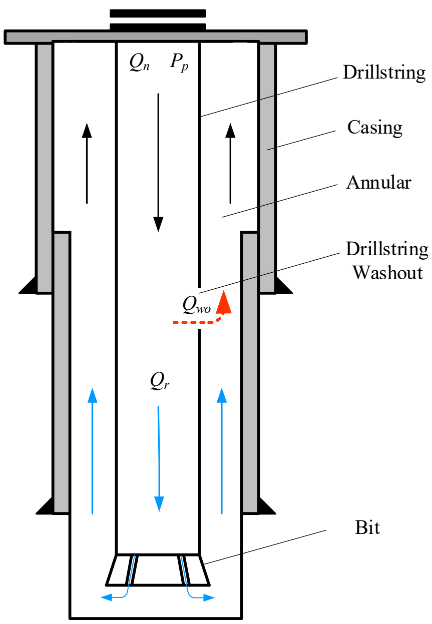

Fig. 1. Drilling fluid flow regularity with a drillstring washout.

Drillstring washout failure is a time-varying process since the washout hole develops over time after it was formed (Lu and Feng, 2005). After a drillstring washout occurs, there is a split flow in the drill pipe when the drilling mud flows pass the washout hole with a certain flow rate (Q_{wo}), leading to a decrease in the flow rate through the well under the washout position (Q_r). The standpipe pressure (P_p) and bottomhole pressure (P_{wf}) decrease gradually due to the reduction of pressure loss of circulation. In the annulus, the flow rate over the washout point changes back to normal due to the confluence flow near the washout hole. As a result, the outlet flow rate of the well (Q_{out}) is almost equal to the inlet flow rate (Q_{in}), which can be obtained by pump rate (Q_p) on the spot.

Conservation equations of the normal flow area

The continuity equation and the momentum conservation equation, which govern the flow parameters of the drilling fluid in the normal drilling process, also can be used to calculate the wellbore flow parameters excepting the region near the washout hole after a drillstring washout occurred. The govern equations are shown as following:

In the drillpipe:

$$\frac{\partial \rho_m A_{di}}{\partial t} + \frac{\partial \rho_m v_{di} A_{di}}{\partial z} = 0 \tag{1}$$

$$\frac{\partial \rho_m v_{di} A_{di}}{\partial t} + \frac{\partial \rho_m v_{di}^2 A_{di}}{\partial z} = -\frac{\partial p_d A_{di}}{\partial z} - \frac{\partial F_f A_{di}}{\partial z} + \rho_m g A_{di} \cos\theta \tag{2}$$

In the annulus:

$$\frac{\partial \rho_m A_{ai}}{\partial t} + \frac{\partial \rho_m v_{ai} A_{ai}}{\partial z} = 0 \tag{3}$$

$$\frac{\partial \rho_m v_{ai} A_{ai}}{\partial t} - \frac{\partial \rho_m v_{ai}^2 A_{ai}}{\partial z} = -\frac{\partial p_a A_{ai}}{\partial z} - \frac{\partial F_f A_{ai}}{\partial z} + \rho_m g A_{ai} \cos\theta \tag{4}$$

Where ρ_m is the density of drilling fluid, kg/m^3; v_{di} and v_{ai} are the flow velocity in the drillpipe and annulus, m/s; A_{di} and A_{ai} are the flow cross-sectional areas of the drillpipe and annulus, m^2; g is gravitational acceleration, 9.8 m/s^2; p_d and p_a are the fluid pressure in the drillpipe and annulus, Pa; F_f is the flow friction, Pa; θ is the deviation angle, rad and i is the wellbore section above or below the washout, i =1, 2.

Dual-path flow model at drillstring washout

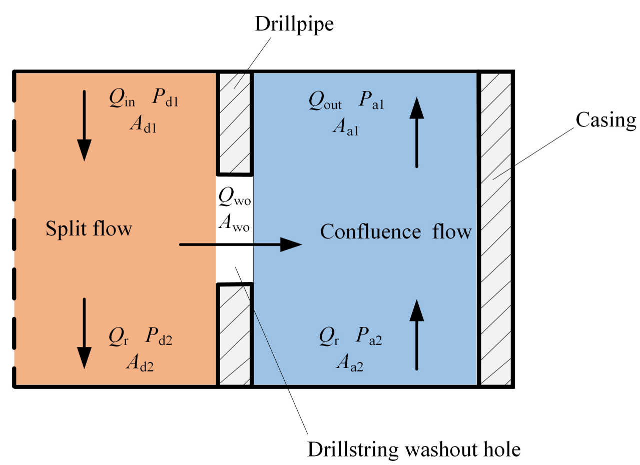

Fig. 2. Drilling fluid flow regularity at a washout hole.

As a new path for drilling fluid to flow from the drillpipe to annulus, the drillstring washout on the drillpipe leads to the split and confluence at this position. Therefore, a minor pressure loss will occur when the drilling fluid passes through the washout point, as shown in Fig. 2. The pressure distribution near the washout point can be calculated based on the Bernoulli equation (Segletes and Walters, 2002).

$$\rho_m \frac{Q_{in}^2}{2gA_{d1}^2} + P_{d1} = \rho_m \frac{Q_r^2}{2gA_{d2}^2} + P_{d2} + M_d \frac{\rho_m Q_{wo}^2}{2gA_{wo}^2} \tag{5}$$

$$\rho_m \frac{Q_{out}^2}{2gA_{a1}^2} + P_{a1} = \rho_m \frac{Q_r^2}{2gA_{a2}^2} + P_{a2} + M_a \frac{\rho_m Q_{wo}^2}{2gA_{wo}^2} \tag{6}$$

where A_{d1} and A_{d2} are the cross-sectional areas above and below the washout hole in the drillpipe, m^2; A_{a1} and A_{a2} are the cross-sectional areas above and below the washout hole in the annulus, m^2; A_{wo} is the cross-sectional area of the washout hole, m^2; P_{d1} and P_{d2} are the pressure above and below the washout hole in the drillpipe, kg/m^2; P_{a1} and P_{a2} are the pressure above and below the washout hole in the annulus, kg/m^2; M_d and M_a are the drag coefficients of the split and confluence, dimensionless. The relationship between different flow rates can be expressed as:

$$Q_p = Q_{in} = Q_r + Q_{wo} \approx Q_{out} \tag{7}$$

The area and shape of washout hole will be changed over time due to the erosion and stress concentration effects, which has an impact on the hydraulic calculation in the wellbore (Fangpo and Yonggang, 2011). At present, an approximate model has been proposed to describe the temporal geometrical feature of drillstring washout hole and the washout hole is approximated as a circular hole with the same hydraulic effect (Millheim, 1982). However, its assumption for the initial stage of washout ignores the influences of the rapid expansion of the washout hole. In this paper, in order to extract the main feature variations of measurement after a washout occurred, the approximate washout hole is assumed to be formed with a certain hydraulic diameter and a safety factor is considered. The proposed approximate model is given as:

$$d_{wo} = kd_{in}(1 - e^{-\frac{T+T_0}{\Gamma}}) \tag{8a}$$

$$\Gamma = \frac{\alpha}{Q_{wo}{}^{\beta}} \tag{8b}$$

where d_{wo} is the hydraulic diameter of the approximate circular hole, m; d_{in} is the drillpipe inner diameter, m; k is the safety factor, dimensionless; T is the time after a washout failure occurred, s; T_0 is the time constant, s; α and β are experimentally determined constants; and Γ is the time factor for the development of washout.

In this model, bottom-hole flow rate is one of the key parameters for calculating bypass flow rate at the washout hole. Relying on the BHA (Bottom Hole Assembly) and signal transmission system, bottom-hole flow rate can be obtained by the rotary speed of a downhole turbine (Arakkal and Belavadi, 2008). Under certain flow ranges and fluid properties, the volumetric flow of drilling fluid is a function of the rotation speed of the downhole turbine (Baker, 1991).

$$Q_r = \frac{RPM}{K} \tag{9}$$

where Q_r is the bottom-hole flow rate, L/min; RPM is the rotary speed of downhole turbine, r/min; and K is the coefficient of downhole turbine, r/L.

Drillstring washout and non-washout modes

Based on the dynamic wellbore flow model with a washout in Equation (1) ~ (9), the bottomhole pressure (P_{wf}) and standpipe pressure (P_p) can be solved by the following equations, respectively.

$$P_{wf} = \int_H^h f_a \frac{\rho_m \left(\frac{Q_r}{A_a}\right)^2}{2(d_{cin} - d_{out})} dz + M_a \frac{\rho_m (Q_{in} - Q_r)^2}{2gA_{wo}^2} + \int_h^0 f_a \frac{\rho_m \left(\frac{Q_{out}}{A_d}\right)^2}{2(d_{cin} - d_{out})} dz + \int_0^H \rho_m g \cos\theta A_a dz + \sum \Delta P_{fa} \tag{10}$$

$$P_p - P_{wf} = \int_0^h f_d \frac{\rho_m \left(\frac{Q_{in}}{A_d}\right)^2}{2d_{in}} dz + M_d \frac{\rho_m (Q_{in} - Q_r)^2}{2gA_{wo}^2} + \int_h^H f_d \frac{\rho_m \left(\frac{Q_r}{A_d}\right)^2}{2d_{in}} dz + \int_0^H \rho_m g \cos\theta A_d dz + P_{bit} + \sum \Delta P_{fd} \tag{11}$$

where h is the depth of the washout hole, m; H is the total depth of the well, m; f_d and f_a are friction coefficients in drillpipe and annulus, which are related to the fluid type of drilling mud (Jensen, 1987); d_{out} is the drillstring outer diameter, m; d_{cin} is the casing inner diameter, m; ΔP_{fd} and ΔP_{fa} are minor losses in drillpipe and annulus, Pa; and P_{bit} is pressure loss through the drill bit, Pa.

The variation of the standpipe pressure during the development of a drillstring washout is calculated by the Equations (10) and (11), as shown in Fig. 3.

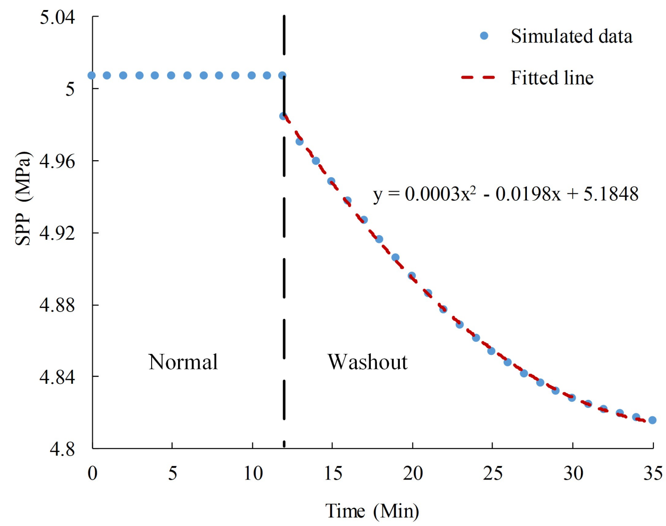

Fig. 3. Variation of the standpipe pressure during a drillstring washout. (Well depth: 2300m; drillstring inner diameter: 0.1086m; drillstring outer diameter: 0.127m; casing inner diameter: 0.224m; density of drilling mud: 1.19kg/m^3; equivalent viscosity of drilling mud in annulus: 0.02Pa·s; pump rate:1890 L/min; washout position: 1382m).

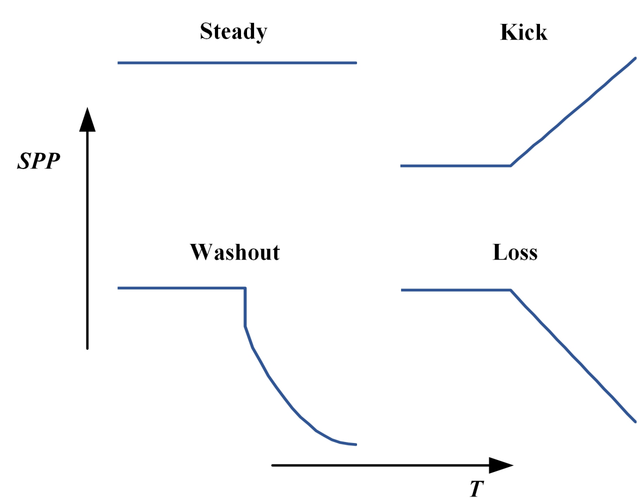

Fig. 4. Modes of SPP variation in different conditions

When the drillstring washout occurs, a sudden decline of SPP was observed in case of the neglected consideration of the washout hole rapid expansion in the initial short duration. Then, with the expansion of the washout hole, SPP shows an obvious decreasing trend, which is proved to be a quadratic decline by data fitting. This variation trend is qualitatively similar to the result in the literature (Reisma, 2010) and gives more features of washout event. The parameter variation mode of drillstring washout is established on the basis of the simulation results. In order to prevent false alarms, other modes of non-washout events such as kick and loss are also considered in this method, as shown in Fig. 4.

Moreover, the monitored variation trends of drilling parameters were compared with the developed washout and non-washout modes. Then, the results can help to detect the drillstring washout. In the pattern recognition method, trend features extracted from different modes are used to identify the variation of drilling parameters, which is related to different drilling events. Therefore, the drillstring washout failure can be monitored in real time and the washout probability can be estimated based on the similarity measure. Compared with the traditional thresholding value or model-based calculation result, a variation trend is able to reflect the characteristics of basic data in time dimension, which improves the noise tolerance of the proposed method and reduces the dependence on the calculation results of wellbore dynamics simulations.

Pattern recognition model for drillstring washout

Piecewise approximation and pattern recognition

In recent years, many researches on pattern analysis of time series have been conducted (Janacek, 2010), which can be applied to data mining in many fields. In order to identify the characteristics of known information, dimensionality curse of time series should be effectively reduced (Ding, 2008), and the piecewise linear approximation (Eriksson, 2004) is an effective dimension reduction method. Previously, the pattern recognition method built on piecewise linear approximation has been developed and successfully applied in the early gas kick diagnosis (Sun, 2018). In this paper, the pattern recognition model is also used to detect the drillstring washout failure based on different variation modes extracted above.

Although the piecewise linear approximation has good noise reduction ability, moving-average filter (Sato, 2001) was used in this paper to preprocess the measured data in consideration of the high sensitivity of the calculation result to the noise. The filtered data can be expressed as the time series Q_{all}:

$$Q_{all} = \{(q_1,t_1),(q_2,t_2),\cdots,(q_i,t_i),\cdots,(q_l,t_l)\} \tag{12}$$

Suppose the time series Q_{all} with length l is divided into N segments, and each segment Q_n can be approximated to a polynomial function, denoted as P_n ($1 \le n \le N$). Each polynomial function P_n only needs to represent the change characteristics of the corresponding time series Q_n obtained by segmentation, effectively reducing the dimension of the entire time series Q_{all}.

$$P_n = r_{n,K_n} t^{K_n} + r_{n,K_n-1} t^{K_n-1} + \cdots + r_{n,1} t + r_{n,0} \tag{13}$$

For better recognizing the variation features of parameters under different conditions, modes of washout and non-washout events are used to restrict the piecewise approximation of time series. The variation characteristics of different segmented measurements obtained in this paper are listed in Table 1.

Table 1. Piecewise features of different events

Measurements	Event	N	P_1	P_2
Pit gain	Steady	1	$K_1 = 0$	
	Kick	2		$K_2 = 1, r_{2,1} > 0$
	Washout	1		
	Loss	2		$K_2 = 1, r_{2,1} < 0$
SPP	Steady	1	$K_1 = 0$ $r_{1,0} > 0$	
	Kick	2		$K_2 = 1, r_{2,1} > 0$
	Washout	2		$K_2 = 2, r_{2,2} > 0$ $-r_{2,1} / (2r_{2,2}) > t_m$
	Loss	2		$K_2 = 1, r_{2,1} < 0$

With the combination of the piecewise features in Table 1 and the search algorithm proposed by Sun (2018), the piecewise approximation results of time series Q_{all} can be obtained. The approximated lines show the variation features of the different measurements. Besides the implement of washout early detection, another advantage of this method is that the start time of washout failure can be estimated, which is helpful to judge the drilling working state.

Similarity measure and washout probability

After approximating the measurements with different modes, the difference between the fitting line and original data is calculated by a similarity measure. As a useful similarity measure, the Euclidean distance is extremely sensitive to abnormal data in time series and cannot reflect the trend information of measurements (Fu, 2007). To measure the similarity of two time series in terms of fluctuation degree, time span and variation trend, Sun (2018) proposed a measurement criterion of similarity called morphological distance, which is defined as:

$$D = \sqrt{D_0 \times D_{KM}} \tag{14}$$

$$D_{KM}(S_1, S_2) = \left| \sum_{i=1}^{l} \Delta t_i W_i (k_{1,i} - k_{2,i}) / t_l \right| \tag{15}$$

where, D_0 is the Euclidean distance; D_{KM} is the modified slope distance; $S(1{:}l\text{-}1)$ is the slope time series corresponding to $Q(1{:}l)$ and W_i is the weight coefficient of segment i. Based on the morphological distance, the relative probabilities of washout and non-washout events obtained from a single measurement can be expressed as:

$$(P_1,...,P_t,...,P_T) = \left[\left(\frac{1}{D_1} / \sum_{i=1}^{T} \frac{1}{D_i} \right),...,\left(\frac{1}{D_t} / \sum_{i=1}^{T} \frac{1}{D_i} \right),...,\left(\frac{1}{D_T} / \sum_{i=1}^{T} \frac{1}{D_i} \right) \right] \tag{16}$$

where, T is the number of all the types of events contained in the model. The synthetic diagnosis with multiple parameters provides more reliable results in event diagnosis (Abu-Mahfouz, 2003). However, during the drillstring washout, the producing and expanding of washout hole have little impact on the measurements of pit gain, which leads to the unsatisfactory prediction probability with this parameter. Synthetic probability based on confidence degree, which has been successfully used in gas kick detection, is also affected.

CASE STUDY

The measurements of a washout state in a field well are shown in Fig. 5. There is a significant change in preset pump rate during this time, which has an impact on the original variation trend of SPP. In order to avoid the impact on the washout early detection, measured data in the first 10 minutes, which can provide enough information, is selected to test the predictions of proposed method.

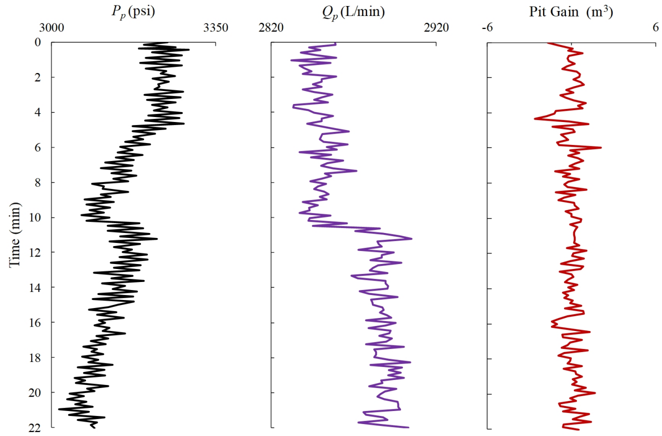

Fig. 5. Variation in different parameters during a drillstring washout

Drillstring washout detection

Based on the extracted washout and non-washout modes, the pattern recognition method is used to mine event information of pit gain and SPP and the results is shown in Fig. 6 and Fig. 7.

In Fig. 6, horizontality states of pit gain are recognized at different times. But it is unknown whether there is a washout state or a steady state because both of them have the same variation trend of pit gain. Compared with pit gain, SPP has a higher distinguish efficiency for washout early detection. In Fig. 7, different events are detected over time. As both events will result in a decline in SPP, the washout and loss are observed at the early stage. Then with the declining velocity reducing, drillstring washout is considered more likely to occur in the wellbore.

With the pattern recognition results of pit gain and SPP, drillstring washout failure is detected when washout mode is discovered in all of the measurements. On this basis, similarity measure is utilized to quantify how well the measurements match different event modes, which can by used for further calculation of the washout probability. In the proposed method, the drillstring washout probability estimated based on the historical measurements is obtained at different times, as shown in Fig. 8.

Since the washout failure will change the pressure distribution in wellbore with little impact on the difference in inflow and outflow rates, the predicted washout probability of pit gain has lower reliability compared with results of SPP. In Fig. 8, a drillstring washout is confirmed when the probability is higher than 50 percent, meaning that the probability of washout event is higher than the sum of the probabilities of other events. With the measurements of SPP, a washout is detected around 6 min, which is earlier than the comprehensive analysis based on weight coefficient. The SPP only decreases about 80 psi when the fault is diagnosed.

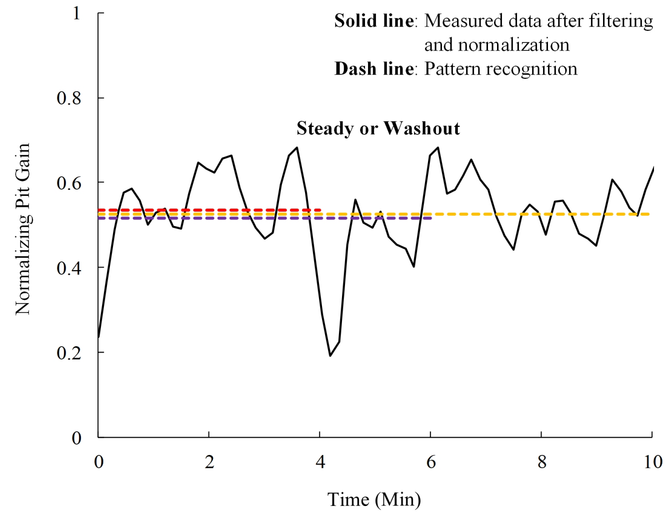

Fig. 6. Pattern recognition results of Pit Gain at different times

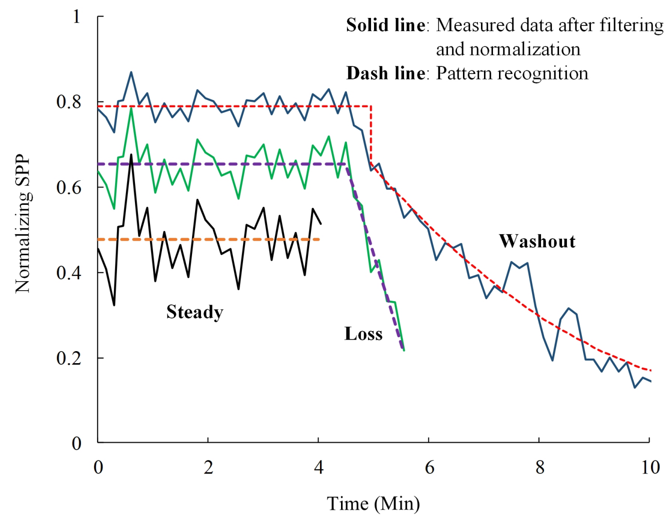

Fig. 7. Pattern recognition results of SPP at different times

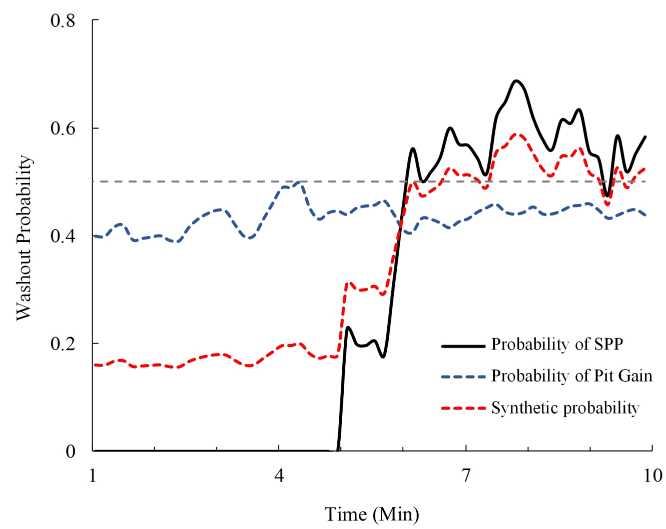

Fig. 8. Probability log of washout detection

Performance discussion

It was noted (Cayeux, 2012) that the tendency of SPP provides the most obvious information of a drillstring washout. In Fig. 9, the detection results of the proposed method are compared with the diagnosis outcomes of a SPP thresholding method. Based on the pattern recognition model, the predicted probability of SPP increases gradually with time and a washout state is diagnosed at an early stage. However, noise in the measurements causes a certain degree of delay and fluctuation in the results of SPP thresholding method.

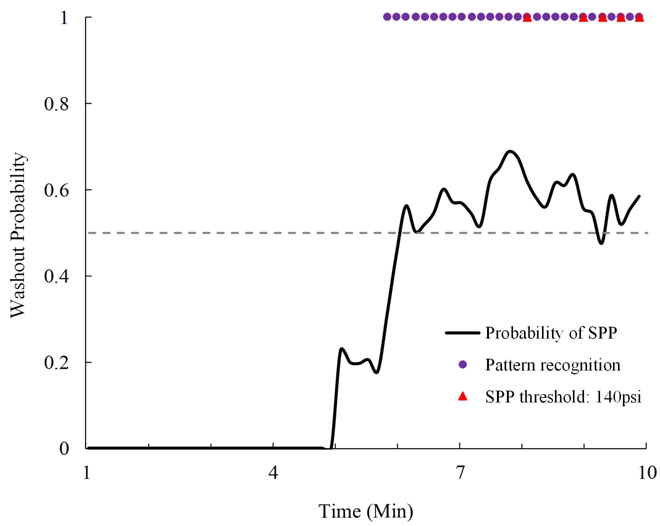

Fig. 9. Comparison with the proposed method and a SPP thresholding method

CONCLUSIONS

In this study, a drillstring washout detecting method based on the hydraulics model and pattern recognition technique was proposed. In the hydraulics model, drilling mud flow regularity in wellbore during a drillstring washout is analyzed by coupling of normal flow model and dynamic dual-path flow model at the washout hole. Then, the variation trend of the key parameters after a drillstring washout occur is simulated and the corresponding features of washout mode is extracted. Furthermore, pattern recognition with piecewise linear approximation and washout probability estimation method is used to implement early detection of drillpipe washout failure.

A drillstring washout accident in the real field was analyzed using the proposed method, and the washout failure is successfully detected with trend identification and similarity measure. Because of the particularity of drillstring washout, the predicted results of SPP has a better performance in faults diagnosis than the results of pit gain. A drillstring washout is confirmed after the SPP readings decreased about 70 psi, which is a small decline comparing with the traditional thresholding technique. The results of performance discussion show that the proposed method has a good recognition sensitivity and higher noise-tolerant level.

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