IADC/SPE-199610-MS

Drillstring Failure Prevention - A Data Driven Approach to Early Washout Detection

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This paper was prepared for presentation at the IADC/SPE International Drilling Conference and Exhibition held in Galveston, Texas, 3–5 March 2020.

Abstract

Drillstring washouts occur when a leak path develops through the drillstring, leading to the loss of pressure integrity. These events often lead to significant non-productive time across the industry, with many operators experiencing multiple events per year across their global operations. Data driven techniques were applied to detect washouts and prevent them developing into twist-offs. Statistical techniques, rules-based logic and machine learning approaches were assessed against various operations where washouts had occurred. The results showed that data driven techniques can provide effective solutions for detecting the onset and development of drillstring washouts.

Introduction

The project was developed to use data driven techniques to reduce the number of catastrophic drillstring events that are persistently experienced. In most incidences of parted drillstrings, the precursor appears in the form of a drillstring washout, Figure 1, where the pressure integrity of the string is lost and a pressure decrease can be observed at surface. In some cases, this pressure drop is significant and immediately obvious but, in other cases, the pressure drop can be much harder to recognize.

Figure 1—Examples of loss of integrity in the drillstring: at the connection (left) and mid-body (right).

The goal is to detect the onset of the washout as soon as possible so that the string can be recovered to surface intact. Failure to do this may result in further loss of drillstring integrity and ultimately a twist-off, Figure 2. The consequence of a twist-off may result in expensive fishing or other remedial operations, such as sidetracking.

Figure 2—Example of a twist-off.

Historically, rigsite teams have relied on close monitoring to detect the development of washouts. In some instances, service companies have applied simple algorithms to analyze the relationship between MWD (Measurement While Drilling) turbine speed and flow rate. These methods are dependent on having an MWD in the string and therefore are not universally applicable to all operations.

The project objective was to develop a solution for detecting drillstring washouts, which could be deployed in a remote monitoring center and is applicable to all drilling operations, regardless of whether or not a downhole MWD system is available.

The paper starts by presenting the business case followed by an overview of previous work. Both data requirements and different types of pressure anomalies are then discussed. Next, the data driven techniques applied in this work are described and results are illustrated through case studies. Finally, the deployment strategy is mentioned followed by future work and conclusions.

Business case

Based on operator experience, 5 incidents of parted drillstrings are typically experienced per year. On average, the Non-Productive Time (NPT) for each incident was 9 days, although one case resulted in 44 days of NPT. This illustrates the variability and the impact of a twist-off. The financial cost of these events was, on average, $25M per year, and this accounts purely for lost time, not including additional equipment or delayed production. In addition, reducing the frequency of drillstring failures improves operational safety by reducing rig crew exposure to unplanned rig floor operations.

Literature review

McCann et. al. in 1990 [1] describes a way of detecting circulation events at their early stages of development, such as washouts in the drillstring, loss in pump efficiency and plugging/loss of bit nozzles. Their method triggers an alarm if standpipe pressure varies by 35 psi or more when all other parameters are constant, such as flow rate and drillstring movement. The data collected is displayed for interpretation and recorded for later use.

Paul et. al. in 2008 [2] monitor the rotary speed of a downhole MWD turbine. Their expectation is to identify washouts at early stages of development before the rig crew does. Paul et. al. caution that the method does not identify washouts exclusively. A drop in downhole turbine Rotations Per Minute (RPM) could also be caused by variations in parameters such as flow rate, mud properties and pump pressure. Their approach appears to be a comparison of real-time values versus an expected trend.

In a more recent approach, Ambrus et. al. 2018 [3] use machine learning to identify drillstring washouts and mud pump failures. Their method uses a Bayesian network that models the drilling hydraulics and aggregates past and present trends with real-time sensor data from standpipe pressure and flow rates in and out of the wellbore. Results are then post-processed into alerts when some values deviate from the expected trend. The paper further discusses ways to improve the model by reducing the number of false positives and how these are linked to transient states in drilling operations.

Data requirements

Surface logging parameters were used as primary inputs for the various data driven solutions. Although many parameters can be utilized to support detecting the onset of a washout, the primary variables chosen were flow rate and pump pressure. Other control parameters, such as block position and string rotary speeds were also assessed but were considered to have second order effects on washout detection.

Data from downhole tools was also considered, but the availability and variety of this information add to both complexity and additional configuration requirements. It was recognized that MWD turbine speed data is of high value and should be used, if available. However, in terms of deriving a generalized solution only parameters that were always present were included in the analysis.

To support the development phase of the various solutions, 9 washout events were identified. These originated from various land and offshore platform operations and had occurred over several years. It was found that data quality, data frequency and sensor calibration accuracy varied significantly between the different operations. At best, surface logging data was recorded at a 1 second data frequency and at worst, a 30 second data frequency. For practical purposes, a data frequency of at least 5 seconds is recommended. Data gaps were also a common occurrence together with occasional outliers.

One common challenge is the variation of flow rate data. A formula based on pump efficiency, liner size and number of pumps being used is used to calculate how much fluid volume is pumped per stroke. This flow volume is then multiplied by SPM (Strokes Per Minute) to create the flow rate value. It was observed, in some cases, that the flow rate parameter is relatively noisy. For example, flow rate values can change by +/- 40 gpm in 1 second. In Figure 3, it can be seen that once the pumps have been through their start-up phase, flow rates have stabilized after about 90 seconds. In comparison, the pressure response curve is much smoother confirming that the variation in flow rate is unwanted noise. This means that it can be challenging to identify if the driller has made a flow rate change or if underlying noise has resulted in a flow rate spike.

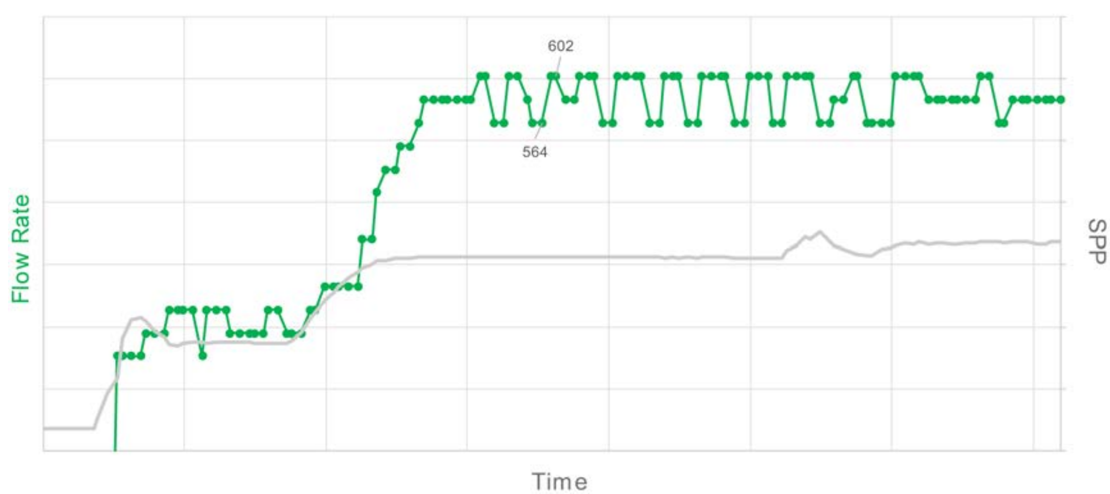

Figure 3—Example of flow rate and standpipe pressure variation

Negative Pressure Anomalies

It was necessary to establish the symptoms of a wash out, and to consider what other drilling events could present similar symptoms, leading to false identification of a wash out. These are summarised in Table 1.

Table 1—Description of negative pressure anomalies

Pressure Anomaly Type	Observation Time	Magnitude	Comment
Washouts	minutes / hours	medium / high	Continuous pressure decrease at constant flow rate
Pump problems	seconds / minutes	medium / high	Continuous pressure decrease at constant flow rate / erratic pressure
Downlinking	minutes	medium / high	Pressure fluctuations during transmission (flow rate may also change depending on downlink system). Sharp decrease (>100 psi in seconds) followed by approx 5 mins of fluctuations
Opening under reamer or circulating sub	seconds	medium / high	Pressure decreases (150 psi approx. – this varies) when underreamer opened. Reduced flow rate possible as the ball is pumped down the string (if ball activated)
Mud property changes - mud weight decrease	hours	medium / high	Continuous pressure decrease at constant flow rate. No way to know by surface parameters alone
Pump ramp down	minutes	high	Delayed pressure response
Pumping pills (pill density higher than mud density)	minutes / hours	low	Variation in pressure as pill passes through the system.
String obstruction released	seconds / minutes	medium / high	Rapid pressure decrease (e.g. unblocked nozzle) preceded by pressure increase (obstruction build up).
Mud motor WOB decrease / come off bottom	minutes	medium / high	Reduced WOB decreases pressure drop across motor. 150-300 psi for example when coming off bottom
Tool failures	minutes	medium / high	Pressure decrease (e.g. turbine failure). Variable response depending on failure type
Temperature effects	hours	low / medium	Pressure changes as mud heats up / cools. Most likely after a period of static conditions
Backreaming / Pumping Out of Hole	minutes / hours	low / medium	Continuous pressure decrease as bit moves up. Potential effects from changing pipe configuration.
Rapid backreaming	seconds / minutes	low / medium	Swab effect (e.g. when circulating off bottom prior to tripping out, or when performing a friction test)
Improved hole cleaning	minutes / hours	low / high	Cuttings bed removal can lead to a pressure decrease
Bit moves on bottom to off bottom	seconds	low	Pressures decrease as bit moves off bottom from drilling at constant flow rate
Downhole losses	minutes	low	Pressure decrease at constant flow rate, as less fluid returned through annulus. Active volume would decrease, flow out would decrease
Influx	minutes	low	Pressure can decrease as lower density fluid enters annulus.
String rotation speed decrease	minutes	low	Annulus pressure decrease as RPM decreases
Wellbore breathing	minutes	low	Pressure changes according to loss /gains. Detected mostly on connections

The activities which display the strongest similarities to a washout include:

- Pump problems
- Downlinking to downhole tools
- Activation of under reamers / circulating subs
- Mud property changes

In a drillstring washout, the standpipe pressure will decrease with constant flow rate which can develop over a period of minutes or several hours. It was considered that a rapid, severe washout should be readily detected by the driller. Therefore, the deployed solution in a remote monitoring center should focus on identifying the longer, harder to detect washouts. Analysis showed that drillstring washouts which occurred at connections were generally more severe events (larger and faster pressure drop) compared with washouts which were located on the pipe body.

Methodology: Data driven techniques applied in this project

Change Point Detection (CPD). A Change Point Detection (CPD) algorithm is a statistical method looking for changes in trends in data. It is a technique which has been applied successfully to several data driven projects [4, 5] with low dimensional input data, i.e. only a few relevant parameters to consider. In the case of washout detection, flow rate and pressure are the two key parameters. As a washout develops, the pressure decreases, marking a change in trend which triggers the alert for a pressure anomaly.

There are multiple formulae for change point detection, for example using z-score, Bayesian or frequentist probabilistic approaches [4, 6, 7, 8]. Whilst all may be valid, focus was given to the z-score, where the distribution of local data is compared against reference data. Local data applies to a small rolling window leading up to the most recent data point. Reference data applies to a wider rolling window up to the most recent data point. When the difference in distribution between the local data and the reference data exceeds a specified threshold an alarm for a pressure anomaly is raised. This method would allow monitoring for all changes in trend. However, only decreases in pressure produce alarms for the case of washout detection.

There is an established relationship between pressure drop and flow rate. This suggests the use of the SPP/(flow rate)^2 parameter, which is based on Bernoulli's equation for flow. This relationship has also previously been used Ambrus et. al. [3] and Aldred et. al. [9].

Connection practices and downlinking could create false alarms. However, they tend to have clear pressure and flow signatures and are filtered out using minimum flow thresholds, or maximum standard deviation pressure limits.

Figure 4 shows a typical example of the output of the algorithm. In the top panel, the raw data for SPP (grey) and flow rate (green) are plotted. The panel below shows the model outputs in blue and in red when an alarm is raised. There are 4 instances when the model results dipped below the threshold, however, these are due to filtered out events and hence do not have a red colour.

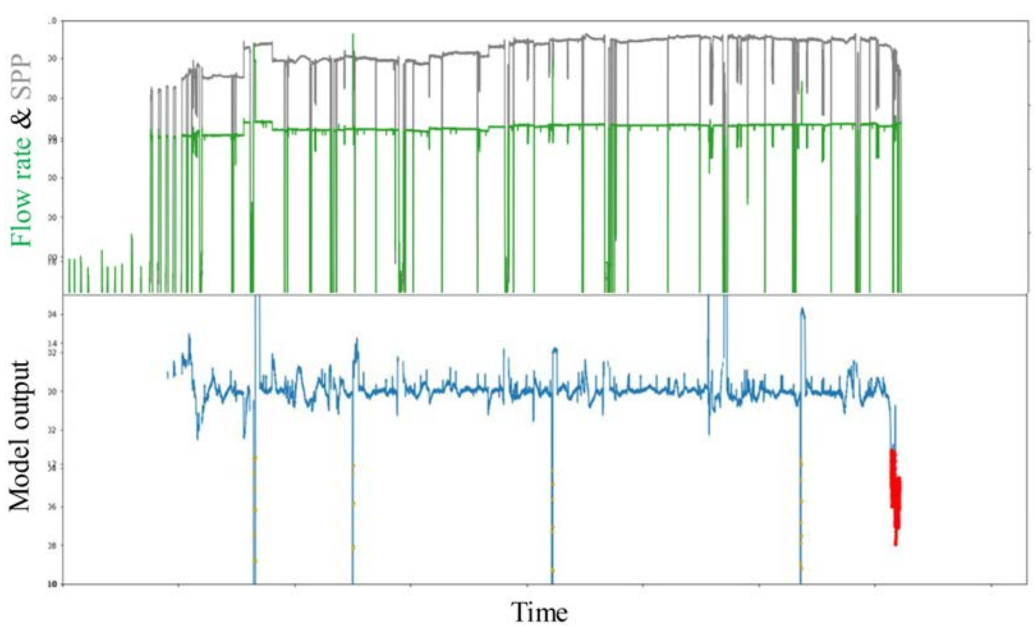

Figure 4—Typical output from the change point detection algorithm

Rules-based Approach. The rules-based solution attempts to codify the knowledge of an expert. The underlying principle is relatively simple, however, due to the nature of real-time data, there are many edge cases that require careful management. This approach identifies periods whenever flow rate is considered stable. This typically occurs after the driller has changed the target flow rate. Due to the response of the rig control system, there is a time lag between the drillers command and the flow rate reaching its desired set point.

Once the flow rate is considered stable, pressure values are then processed to identify when they too are considered stable. Once stability has occurred, pressures are continuously monitored to identify sustained increases or decreases. Should the driller change the flow rate, then the cycle of identifying stable parameters begins again.

In theory, as each stand of drillpipe is drilled down, pump pressures should increase, usually by an incremental amount, due to the increasing length of the wellbore. However, due to the dynamics of the drilling process, pressure fluctuations will occur due to changes in drilling parameters, cuttings loading effects, fluid rheology and density variations, different shock and vibration modes, and circumferential and axial changes of the string position in the wellbore. Normal pressure variations are typically in the range ± 100 psi from the average pump pressure.

The workflow for this approach involves the following steps

- Identify a stable flow rate
- Identify a stable pressure
- While flow rates and pressures remain stable with pre-defined threshold values calculate rolling averages of flow rate and pressure values
- If pressures trend away from a rolling average by more than a specified limit, then flag this as a pressure anomaly
- Test to see if any pressure anomaly is characteristic of a downlink, or a survey, and if so, ignore it.
- If a washout is predicted, generate an alert

During drilling, flow rates can go through many changes as dictated by the driller. It is common practice for flow rates to go through a sequence of hierarchical changes at the start of each stand, to break gels and avoid generating unwanted pressure spikes. The driller may also adjust flow rates to manage Equivalent Circulating Density (ECD) and will make other ad-hoc changes from time to time.

It has also been mentioned previously that flow rate is a relatively noisy parameter, due to the way it is calculated. This means that the rules-based logic differentiates between the case when the flow rate has been changed and edge cases where an outlier flow rate value might falsely indicate the flow rate has changed when in fact it has not.

Monitoring pressure for anomalies has similar challenges. Pressures continually change during the drilling process so identifying an underlying average value is essential when seeking deviations from the predicted trend. The ability to differentiate between a washout and normal pressure fluctuations can be complex, particularly when the washout is developing slowly.

One disadvantage of this rules-based solution in its current form, is that it only considers local changes to flow rates and pressures. This means if a slowly developing washout was occurring in a previous stand, this would not be accounted for in the subsequent stand, so will not get alerted.

Supervised Approach. In addition to the above-mentioned approaches, supervised machine learning algorithms were also tested. However, it was found that these algorithms behaved poorly for washout detection, resulting in a significant number of false positives and low detection rate.

The main challenge with the supervised approach is accurately labelling the data and allowing the algorithm to learn from it effectively. Firstly, it is challenging to pinpoint the onset of the washout. Secondly, when the washout is at the early stage of development, the characteristic pressure trend signature may not be fully developed yet. In some datasets, there were instances of steady, or even increasing pressure, when it was believed a washout was present.

Case Studies

The change point detection and rules-based algorithm were run for 9 data sets where washouts have occurred, 3 of which resulted in twist-offs. Table 2 shows a summary of the data sets, including information on the run such as hole section, duration of run, drilled interval and data frequency available. The datasets were predominantly drilling assemblies with one clean-out run; the shortest run lasted 1.7 days and the longest 8.6 days. As can be seen in the table, the runs occurred in a variety of different hole sizes.

Table 2—Datasets with washouts which were analysed.

Dataset	Hole section (in)	Run time (days)	Drilled interval (m)	Data frequency (s)
Land 1	8 ½	4.1	170	5
Land 2	8 ⅜	8.6	211	5
Land 3	5 ⅞	2.5	clean-out	5
Land 4	8 ¾	3.6	1623	30
Land 5	8 ½	4.2	2448	10
Land 6	12 ¼	1.9	834	30
Offshore 1	12 ¼ x 13 ½	4.3	2103	1
Offshore 2	8 ½ x 10 ¼	7.3	1144	1
Offshore 3	12 ¼	1.7	575	1

For each dataset the change point detection and rules-based algorithm were applied. All runs with the change point detection algorithm were carried out using consistent parameters and thresholds. The thresholds and parameters were chosen in such a way as to minimise the number of false positives whilst still getting a clear indication of the washout. It is possible to select other parameters to reduce the number of false positives, but this will result in reduced confidence of the identification of the washout.

Table 3 shows the results for both algorithms. An operations specialist reviewed all runs and identified the most likely washout time, i.e. when it should reasonably be detected at a remote monitoring center. The detection offset time in Table 3 shows how many minutes earlier (negative values) or later (positive values) the washout was picked up by the CPD and rules-based solutions. The detection offset time is colour coded showing values in green when the algorithms picked it up before the washout time, yellow when the algorithm picked it up around the same time, orange when it picked it up later and red when it did not detect the washout.

Table 3—Results of change point detection and rules-based approach

	CPD		Rules-based (100 psi)		Rules-based (200 psi)	
dataset	detection offset (min)	false positives per 24 hours	detection offset (min)	false positives per 24 hours	detection offset (min)	false positives per 24 hours
Land 1	-56	0.0	-57	0.7	-53	0.2
Land 2	-1	1.3	2	0.9	3	0.1
Land 3	-1	1.6	0	1.6	5	0.4
Land 4	-50	3.6	-50	1.9	-48	1.1
Land 5	-3	0.9	-3	1.4	-1	0.0
Land 6	-34	2.1	-18	2.6	-9	1.0
Offshore 1	0	0.7	0	1.2	0	0.0
Offshore 2	14	0.1	-62	0.5	-42	0.0
Offshore 3	-22	1.2	Not detected	0.0	Not detected	0.0

Table 3 also shows the number of false positives per 24 hours. The Land 4 and Land 6 cases have the highest number of false positives but for these datasets only 30 second data frequency was available. As discussed in the data requirements section, the models are predominantly built for data with frequencies of 5 second or higher. Even though both algorithms work for a lower time frequency, the number of false positives increases. In all other cases the average number of false positives is below 2 per 24 hours, meaning that a remote monitoring center would expect one alarm per 12 hours shift, which is considered acceptable.

In terms of performance, the CPD and rules-based solutions have a similar number of false positives where pressure loss thresholds are similar, i.e. the 100 psi case. Increasing the pressure loss threshold to a higher value significantly reduces the number of false positives but at the expense of detecting the washout later or possibly not at all.

There are 3 cases which are discussed in more detail below. Firstly, the Offshore 2 well, which was identified by the CPD algorithm after the rig site would have expected to have noticed it. Secondly, the Land 2 case, which had an unexpected pressure change in behaviour before and after connections. Finally, the Offshore 3 case where the rules-based solution failed to identify the washout.

In the Offshore 2 case, the washout was slowly developing over a 6 hour period. Figure 5 shows SPP (grey), flow rate (green) and bit depth (black) trends from the detectable onset of the washout. The red arrow in this diagram identifies the time at which the washout should have reasonably been detected. It was another 2 hours after this time that the rig crew made an intervention. Initially the pressure loss was subtle and built up slowly. This slow pressure decay is challenging for the algorithm to detect as a washout, and therefore is only picked up later. Configuration parameters could have been adjusted to detect the washout sooner, however, the aim of the CPD solution is to create a general solution by maintaining constant parameters, thus ensuring it is comparable between different runs.

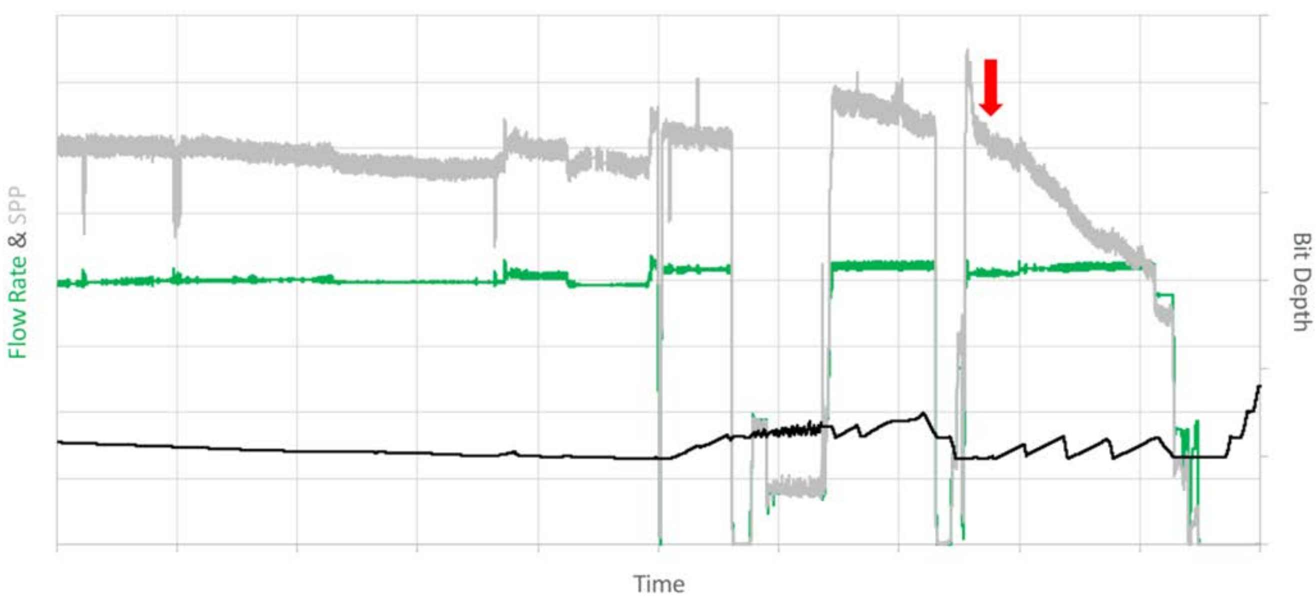

Figure 5—SPP (grey), flow rate (green) and bit depth (black) from onset of the washout for Offshore 2

Incidentally one of the practical reasons the washout was detected later than expected at the rig site was that the hole was circulated clean, and then a 42 bbl high viscosity pill was pumped which would have initially increased pump pressure. However, as the pill was displaced out of the annulus, the rig crew were expecting a pressure decrease and therefore they were not suspicious that a washout might be occurring. The rig crew finally made an intervention 2 hours after the red arrow in Figure 5, i.e. when it should have been identified.

In Land 2 case, an interesting pressure behaviour at multiple connections was observed. A pressure decrease was noticed before and after a connection on many occasions. Figure 6a shows typical flow rate (green) and SPP (grey) curves before and after a connection. Figure 6b shows a zoomed in version of the same connection. It can be seen that with a constant flow rate, the pressure is significantly lower at the beginning of a connection and takes significantly longer to recover to its previous level. Given that the change point detection algorithm monitors from one stand to the next, this drop and slow adjustment in SPP is sometimes picked up as a false positive.

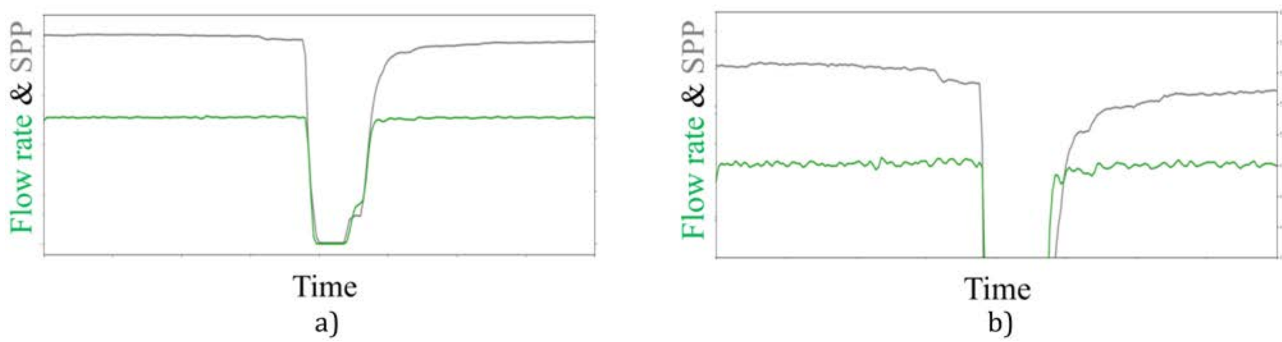

Figure 6—SPP and flow rate for a connection on Land 2 case (a) and zoomed in on y-axis (b)

In the Offshore 3 case, the washout was occurring over a 4.5 hour time period, as five stands were drilled. The pressure loss was on average about 40 psi per stand, until the washout increased in severity. The CPD solution worked well in this case as it considers cumulative pressure losses before and after a connection, whereas the rules-based solution only considers local changes in pressure whenever the flow rate changes. This meant the rules-based approach failed to detect the washout in this case.

Overall the results of both approaches look promising and valuable. The number of false positives is manageable by a remote monitoring center with the algorithms detecting the majority of washouts either earlier or about the same time it was picked up by the specialist. Note that even in the cases where it was detected at about the same time, the solutions are still beneficial because the specialist may not always be focusing on that particular well or even looking out for a washout.

Deployment

The washout detection solutions are intended to be deployed into remote monitoring centers. These will assist the specialists in quickly identifying potential washouts and then alert the rig site using an escalation protocol so that the string can be recovered before a twist off occurs.

It is anticipated that the tool will be most useful when subtle washout trends are occurring. It is considered that more rapidly developing washouts would be first identified at the rig site without the requirement for monitoring center intervention.

The final deployment platform is still under discussion. The intention is that the washout solutions will run in the background during all drilling activities. A requirement is to have minimal configuration, as the system is designed to use only flow rate, and SPP (and potentially MWD turbine RPM) parameters. Once a washout is suspected an alert will flag that a pressure anomaly is detected, as in Figure 7.

Figure 7—Initial Washout Alert

This alert would include a link for the monitoring engineer to immediately access more contextual information, to support their interpretation of the event. This contextual display is envisaged to include logs of the drilling parameters, mudlogger comments and information relevant to the algorithm parameters. A log of events would also be included, together with a record of pressure anomalies and the associated responses.

Washout detection using Deep Long Short Term Memory (LSTM) – Preliminary approach

In recent years deep learning has been applied very effectively in many industries ranging from health care to finance. These techniques are now being adopted to improve operations in the oil and gas sector. A novel methodology, based on the use of deep long short-term memory (LSTM) networks, could be applied for washout detection. It is based on learning to reconstruct sensor data in an unsupervised framework. LSTM [10] is an instance of Recurrent Neural Network (RNN) and is characterized by its ability to learn long term dependencies. These networks have memory units and can add, delete and update information.

To detect anomalies like washouts a deep network comprising LSTM layers is trained. The structure of the network is shown in Figure 8. It is trained on non-anomalous multi-variate time series data using Hookload, Weight on Bit, RPM, Torque, Rate of Penetration (ROP), Flow Rate and SPP parameters. During the training process, characteristics of normal data are observed and the model learns how to reconstruct the data. Once the training is finished, the model is applied to reconstruct unseen data including anomalies. As the model has not seen washouts and other anomalies, it fails to reconstruct these. Figure 9 illustrates this process where the anomaly can be seen towards the end of the plot. Application of this method to two wells shows positive results. It is interesting to note that the network learns interactions between pressure and flow and determines that these two parameters are directly proportional.

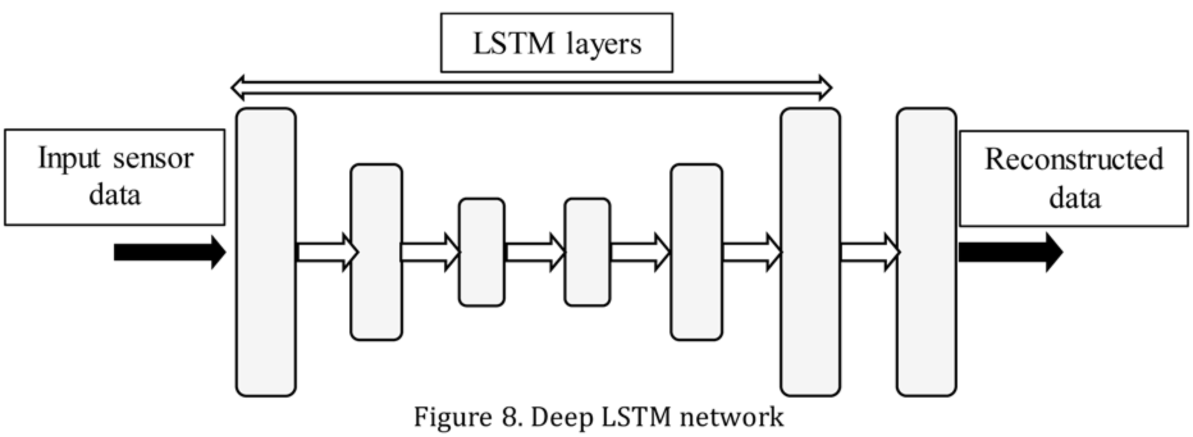

Figure 8—Deep LSTM network

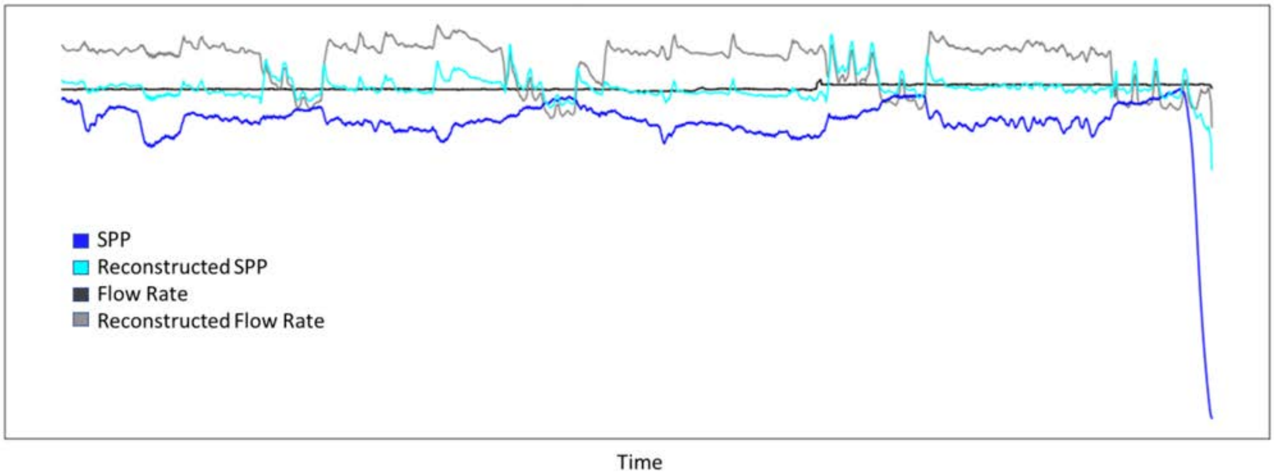

Figure 9—Target and reconstructed pressures and flow sub sequences

Conclusion

It is recognized that drillstring washouts are an industry wide problem, significantly adding to non-productive time. Data driven solutions are enablers to help reduce the number of washouts and mitigate their consequences. This paper focused on solutions for early detection of washouts to prevent drillstring twist-offs.

The nature and onset of washouts is highly variable in the way they originate and manifest themselves. Typically, the rig site should detect washouts that result in rapid pressure drops. Slowly developing washouts are harder to detect and this is where data driven solutions should prove more effective.

The Change Point Detection and Rules-Based Approach were successful in the early detection of washouts. An alternative Deep Learning Method was assessed and showed promise for further work. A consequence of developing these methods is that other pressure anomalies can be readily detected. Strategies were applied to recognize and discount the most frequent false positives. A balance between accurate washout detection and the number of false positives can be achieved by optimizing the detection threshold.

The developed solutions consider only pressure and flow rate to allow deployment to all operations. It is recognized that MWD turbine RPM may provide an alternative washout indicator, if available. Also, other input parameters to consider are block position, RPM and WOB. This information could be incorporated in future versions.

Potential limitations are poor data quality and application to floating rigs, as significant wave motion will superimpose surge and swab pressure cycles onto the underlying pump pressure trends.

Acknowledgements

The authors would like to acknowledge the help and support received from the BP Upstream Technology Wells Team Lead, Riaz Israel, the BP Global Wells Organization Discipline Manager, Matthew Rhodes, and the BP Remote Collaboration Center Manager, John Sutler.

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