SPE/IADC-204035-MS

Detecting Pressure Anomalies While Drilling Using a Machine Learning Hybrid Approach

Aurore Lafond, Maurice Ringer, Florian Le Blay, Jiaxu Liu, Ekaterina Millan, Samba Ba, and Mu Chao, Schlumberger

This paper was prepared for presentation at the SPE/IADC International Drilling Conference and Exhibition to be held virtually on 8 - 12 March 2021. The official proceedings were published online on 8 March 2021.

Abstract

Abnormal surface pressure is typically the first indicator of a number of problematic events, including kicks, losses, washouts and stuck pipe. These events account for 60–70% of all drilling-related nonproductive time, so their early and accurate detection has the potential to save the industry billions of dollars. Detecting these events today requires an expert user watching multiple curves, which can be costly, and subject to human errors. The solution presented in this paper is aiming at augmenting traditional models with new machine learning techniques, which enable to detect these events automatically and help the monitoring of the drilling well.

Today's real-time monitoring systems employ complex physical models to estimate surface standpipe pressure while drilling. These require many inputs and are difficult to calibrate. Machine learning is an alternative method to predict pump pressure, but this alone needs significant labelled training data, which is often lacking in the drilling world. The new system combines these approaches: a machine learning framework is used to enable automated learning while the physical models work to compensate any gaps in the training data. The system uses only standard surface measurements, is fully automated, and is continuously retrained while drilling to ensure the most accurate pressure prediction. In addition, a stochastic (Bayesian) machine learning technique is used, which enables not only a prediction of the pressure, but also the uncertainty and confidence of this prediction. Last, the new system includes a data quality control workflow. It discards periods of low data quality for the pressure anomaly detection and enables to have a smarter real-time events analysis.

The new system has been tested on historical wells using a new test and validation framework. The framework runs the system automatically on large volumes of both historical and simulated data, to enable cross-referencing the results with observations. In this paper, we show the results of the automated test framework as well as the capabilities of the new system in two specific case studies, one on land and another offshore. Moreover, large scale statistics enlighten the reliability and the efficiency of this new detection workflow. The new system builds on the trend in our industry to better capture and utilize digital data for optimizing drilling.

Introduction

Damages to the drillstring or undesired drilling events can have a significant impact on the safety and cost of the drilling process. Therefore, it is essential to detect such events as quickly as possible to maximize the efficiency of the contingency plan or minimize the risk of potentially more damaging events. As an example, stuck pipe costs to the oil industry more than $3 billion each year (Raja 2011). Loss of revenue is due to:

- The loss of drilling time for the whole process
- The time and cost of the fishing (pulling out of the hole the broken part of the BHA)
- The cost of the lost tool in the well if the recovery is impossible or too costly
- The cost of the cementing and sidetracking if part of the well is lost

Abnormal surface pressure is one of the primary indicators of dysfunction in the drilling hydraulic system. An abnormal surface pressure is defined as the observation of any change in surface pressure (standpipe pressure) due to undesired events occurring during the well construction process. Undesired events detected on the surface pressure include the following non exhaustive list:

- A drillstring washout: a hole or cracks in the drillstring (from drillpipe to bit) caused by wear, such as corrosion or tensile stress. It might induce a complete twist-off of the pipe, leading to nonproductive time due to fishing of the lost components, or in worst case abandonment of the well. When a drillstring washout is occurring, a decrease of surface pressure is observed due to the crack in the drillstring, inducing a deviation in the hydraulic system.
- Solids-induced stuck pipe: a stuck pipe mechanism induced by the accumulation of solids in the annulus—pack off—(occurring most of the time at the stabilizer level) due to poor hole cleaning. When a pack off is building up, an increase in surface pressure is observed due to the obstruction generated by the accumulation of solids in the annulus.

Interpretation of many downhole events depends on the reliability of the pressure anomaly detection system that meets the following requirements. First, this detection process is expected on every rig and should be based on classical inputs measurements (such as surface measurements) accessible on every rig to ensure no limitation on its use. Moreover, it must provide early, accurate, and robust detection to ensure that it can be used as a part of the drilling decision-making process. Last, the system must be sufficiently automated to minimize the need for a user intervention in order to detect anomalies.

Current abnormal pressure detection methods are based on advanced flow modeling (Cayeux 2012), statistical approaches, or, more recently, supervised machine learning techniques (Kuesters 2020). Advanced flow modeling approaches might suffer from context unavailability, poor accuracy, and high sensitivity to a lot of drilling parameters (mud properties, drilling tool description …). Statistical approaches have good reactivity to abnormal pressure events but might trigger false alarms during normal drilling events such as connection or during downlinking to downhole tools. In addition, supervised machine learning techniques are promising but require large amount of accurate labelled data, which is not easily accessible in the drilling industry (Kuesters 2020).

The new detection workflow presented in this work is a hybrid approach that aims to take advantage of the previously mentioned approaches. Some physical modeling enables to form an initial estimate of the normal pressure expected given some surface inputs measurements. A statistical approach such as a stochastic sequential segmentation algorithm can be used to identify in real time some potential training periods for the data-driven model. Once the training periods are identified, a machine learning approach is used to complement the physical model and capture the behavior of unknown parameters in real-time.

This real-time adjustment is necessary to capture the expected evolution of the physical model parameters (due to changes in the drilling mud characteristics, for example).

The proposed detection workflow has been tested on several wells, and its capabilities evaluated in terms of false alarms, detection rate, and detection reactivity. Its capabilities are illustrated on two washout cases (severe low abnormal pressure events), on a land rig and on an offshore rig. Because the large-scale estimation of the detection capabilities is a prerequisite to establish trust in a method, the capabilities of the proposed method over several wells are presented using false alarm and true detection rates.

This new method is partially data driven: its detection capabilities are highly dependent on the measurement noise, for example the measured standpipe pressure noise. This dependency is shown by carrying a sensitivity analysis on the alarm's reactivity according to the abnormal event intensity and the noise observed on the pressure measurement.

The challenges of the abnormal pressure detection

One approach to detect abnormal pressure is to compute the difference between a simulated pressure and the measured pressure. Several hydraulic models exist to simulate pressure in real time, but all are based on the same principle. They use real-time input measurements (pumps flow rate and bit depth), infrequent measurements (mud rheology), and contextual information defined by a user (drillstring elements). These models are complex, as they try to reproduce with a high fidelity all the pressure drops in the well (in the drillstring, in the drilling tool, and in the annulus). The pressure at surface is the sum of all the pressure drops along the flow path. Due to the uncertainties associated to the parameters used in this physical approach and the impossibility of capturing every components of the underlying physics in the model, the predicted pressure cannot be considered accurate enough in every condition (Cayeux 2012). Frequently, the simulated and measured pressure do not match, thus an automated detection of abnormal pressure based on this pressure difference cannot be performed with this approach.

Another approach is data driven and relies on statistics with a change point algorithm. The standpipe pressure is dependent on few measurements such as pumps flow, but also surface torque or weight on bit when mud motors are used. Thus, we can track changes in those inputs and check if they match with changes in the measured pressure. An abnormal trend (i.e. a trend that cannot be explained by some other parameters change) will trigger a high probability alert (Aldred 2010). This approach performs well for detecting abnormal pressure periods, mainly in the presence of strong and obvious anomalies.

Machine learning is an alternative method to detect pump pressure anomalies. Yet this kind of technique needs significant training labelled data, which is often not available.

The proposed system combines several methods: a machine learning framework that is driven by a physical understanding of the flow in the wellbore. The physical model in use is simple on purpose and a Gaussian process is used to learn the missing parts of the physics in real time. This approach takes advantage of the machine learning properties: observed data help to build up the model and compensate for weakness in the physical modeling part. Yet, it is not solely data driven and does not require the use of historical datasets to train the model.

There are multiple advantages to this hybrid approach. It is fully automated and uses only standard surface measurements. This is a great advantage, as it means it can be used in a large variety of rig configurations. It does not rely on complex inputs such as mud rheology, wellbore geometry, and full drillstring description. The detection is not based on a deterministic approach with some absolute pressure variation thresholds. The detection capability adapts to every rig condition and to observed noises on the pressure measurement.

Nonetheless, the abnormal pressure detection faces several challenges, such as the two listed below:

- The system needs to account for a downhole motor to avoid missed events, false alarms, or both (Wong 2013). The physical models to capture the normal pressure variations are more complex than in the case with no motor. The pressure measurement varies significantly according to the bit position (on bottom or off bottom) and the kind of drilling (slide or rotary) when dealing with a mud motor.

The global detection workflow needs to be able to differentiate in real time and accurately those drilling states and apply the different pressure models accordingly.

- Another challenge is the data measurement quality. Some quality control on the input's measurements are needed. Identifying abnormal inputs measurements periods avoids misinterpreting them as abnormal pressure situations.

New pressure prediction model

Physics based prior

The proposed approach relies on a simplified model of the hydraulics in the well. This physics-based model is used as a prior for a Gaussian process, which generates the pressure prediction and the associated uncertainty. The model assumes an established steady state flow condition: no predicted pressure is computed during times when the mud flow is changing and considered transient.

The pressure measured at the standpipe is the sum of the pressure drops along the circulation system. The physics based prior is a simplified well pressure loss model and is the sum of:

- A pressure loss in the drillstring that is proportional to the length of drillstring in the well. The flow regime in the drillstring is expected to be primarily turbulent.
- A pressure loss in the annulus that is proportional to the length of well. The flow in the annulus is expected to be primarily laminar.
- A pressure loss at the bit, which is due to the mud flowing through the nozzles: the mud quickly flows from a large diameter pipe (the drill string) into smaller diameter nozzles.
- A pressure loss across any special components of the BHA such as mud motors or reamers. For the sake of this paper, the focus will be placed mainly on the mud motor for special components. It is assumed that the pressure drop in the pipework at surface is negligible in comparison to the pressure drops listed above.

The approach relies on Newtonian fluid approximation for the computation of the pressure drops through the well. This approximation is considered as enough to derive a first simplified model of the standpipe pressure. Indeed, this simplified model will then be used as a prior for the Gaussian process described in the next section.

The pressure drop inside the drillstring is dependent on the friction inside the drillstring, the volumetric flow rate Q, the mud density ρ, and the bit depth D_{Bit} or the length of the pipe (Sindi 2016):

$$\Delta P_{drillstring} = K_1 f_1 \rho D_{Bit} Q^2 \tag{1}$$

With K_1 a constant dependent on the pipe geometry and f_1 the friction factor in the drillstring (a function of the Reynolds number and pipe relative roughness). As flow regime in the drillpipe is mainly turbulent, the friction factor can be approximated by the Blasius correlation (smooth pipe assumption) and we assume that f_1 is proportional to $Q^{-0.25}$, $f_1 \propto Q^{-0.25}$.

Thus, we can write equation 1 as follows:

$$\Delta P_{drillstring} = K_1 D_{Bit} Q^{1.75} \tag{2}$$

where $k_1 \propto \rho K_1$

Similarly, we can express the pressure drop inside the annulus as follows:

$$\Delta P_{annulus} = K_2 f_2 \rho D_{Bit} Q^2 \tag{3}$$

With K_2 a constant dependent on the pipe and well geometries and f_2 the friction factor in the annulus (a function of the Reynolds number and surface roughness). The flow regime in the annular is mainly laminar. In this condition, the friction factor is directly proportional to Q^{-1} and we can write equation 3 as follows:

$$\Delta P_{annulus} = K_2 D_{Bit} Q \tag{4}$$

The pressure loss through the bit can be approximated from the *Drilling Data Handbook* (Institut Français du Pétrole Publications 1999):

$$\Delta P_{bit} = \alpha_1 \rho Q^2 \tag{5}$$

With α_1 a constant dependent on the bit geometry and the nozzle types, ρ is the mud density, and Q is the volumetric flow rate.

Assuming no motor is present in the drillstring, the global hydraulic pressure is the sum of the pressure drop through the drillstring, the annulus pressure drop and the pressure drop at the bit. It can be expressed as follows:

$$\Delta P_{hyd} = k_1 D_{Bit} Q^{1.75} + k_2 D_{Bit} Q + \alpha_1 \rho Q^2 \tag{6}$$

Equation (6) shows a linear combination of power law models. It can be approximated by a single power law function of flow rate, Q. As can be seen from equation 6, the power law index on Q is expected to be more than unity but less than 2. From practical observations and correlations with oilfield data, given the relative contribution of the respective coefficients, it has been seen that a power index of 1.8 has provided a successful approximation of standpipe pressure dependency of flow. Thus, we can express our hydraulic pressure loss model as follows:

$$\Delta P_{hyd} = \beta_Q Q^{1.8} \tag{7}$$

Where β_Q is a global constant dependent on the mud properties (density, rheology), the bit depth, the bit type, the drillstring and well geometries, and roughness. This approximated simple form enables to explicitly express the global pressure drop as a function of one single real time input, the pumps volumetric flow rate Q.

The pressure drop across a motor is proportional to the motor output torque while rotary drilling (Bourgoyne Jr, 1991):

$$\Delta P_{motor,rotary\ drilling} = \frac{T}{a} \tag{8}$$

In theory, the parameter a depends only on the geometry of the motor (the profile, eccentricity and cross-section geometries) and on the motor efficiency. It does not change with flow, bit type, or rock lithology. Thus, the value of a should remain constant. If it begins to decrease, it is likely to be a result of motor wear or rubber damage. Note that torque, T, in this equation refers to output torque from the motor (downhole). This is sometimes measured by sensors in downhole tools (such as an MWD tool) placed close to the motor, but more often, only a surface measurement of torque is available. Provided the drillstring is rotating, the downhole torque T is often correlated to the surface torque T_S. Thus, the latter could be used to estimate the former:

$$T_S \propto T$$

And consequently, we can rewrite the equation (8) in the form

$$\Delta P_{motor,rotary\ drilling} = \beta_T T_S$$

where β_T is a constant dependent on the motor geometry and the well characteristics.

This technique of estimating downhole torque from surface torque cannot be used while slide drilling. In this case, we assume that the downhole torque is proportional to the weight on the bit and thus the pressure drop across the motor is also proportional to the *WOB* with a constant β_w. We can then write the following simplified model while sliding:

$$\Delta P_{motor,slide\ drilling} = \beta_W WOB \tag{9}$$

Thus, the physics based prior can be written as follows:

$$\begin{cases} no\ motor: \ SPP = \beta_Q Q^{1.8} \\ motor,\ slide\ drilling: \ SPP = \beta_Q Q^{1.8} + \beta_W WOB \\ motor,\ rotary\ drilling: \ SPP = \beta_Q Q^{1.8} + \beta_T T_S \end{cases} \tag{10}$$

This physics-based model is deliberately simplified so that its three unknown parameters can be easily estimated during operations using measurements of standpipe pressure, flow, weight on bit and torque. Note, however, that determining the three unknown parameters at a given instant will not be sufficient to predict the standpipe measurement over a complete BHA run. This simple model needs to be updated in real time to account for the expected changes in its parameters. As an example, the β_Q coefficient in the hydraulic pressure loss will evolve while drilling because it is proportional to the bit depth (the deeper the bit depth is, the larger the pressure drops inside the drillstring and the annulus are).

This model has the advantage that its parameters can be easily estimated during drilling operations. However, it is a simplified model and does not capture all the physics present in the well. The resulting prediction of pressure has significant uncertainties. For this reason, we augment this physics-based model with a Gaussian process.

Gaussian process

A Gaussian process is a collection of random variables, any finite number of which follow a (consistent) joint Gaussian distribution (Rasmussen 2006). It computes the probability distribution of all possible functions that can explain the training data. We specify a prior over the function space, compute the posterior distribution based on training data, and predict the posterior distribution on new points of interest. It is a nonparametric regression model.

The prior describes the functions' space through the definition of the mean function m(x) and the covariance function (with x inputs data). Two parameters specify the covariance kernel function: the signal variance and the length scale. The signal variance controls the span of the function vertically between the observed training data. The length scale controls the minimal distance between two uncorrelated input points: two input points with a distance lower than the length scale have similar function outputs.

The Gaussian process outputs a prediction in real time for every new incoming input, the uncertainty associated with this prediction based on training data, and the prior knowledge of the functions' space.

For this application, a Gaussian process is used to characterize the unknown function between each simplified model residuals (error between the simplified modelled pressure and the reference pressure) and the corresponding list of inputs. A Gaussian process is considered for each element of the global pressure model:

- One is defined to model the residuals associated to the hydraulic pressure loss, using as input the pumps flow rate.
- One is defined to model the residuals associated to the motor pressure drop (if any) while rotary drilling, using as input the surface torque.
- One is defined to model the residuals associated to the motor pressure drop (if any) while slide drilling, using as input the weight on bit.

The kernel hyper parameters for the three Gaussian processes are determined thanks to our understanding of the measurements space.

The final output of the combined Gaussian processes is the modeled standpipe pressure (from the simplified physical models) associated to the predicted residuals (from the Gaussian process regression) and the uncertainty associated to this prediction.

Each Gaussian process needs to be trained with real-time measurements to adjust to drilling changes. The training process needs to be smart enough to not train during abnormal pressure periods. In this regard, potential training periods are identified; then the reference pressure to fit is determined for each model. Finally, those periods are automatically checked to decide if they are suitable for the update of the Gaussian process or not.

For the simpler case where there is no mud motor, only the Gaussian process related to the hydraulic pressure loss needs to be trained. Indeed, the standpipe pressure measurement is mainly explained by this type of pressure loss, thus the measure standpipe pressure is directly used as reference for the hydraulic pressure drop.

For the motor case, the identification of the correct potential training periods for each Gaussian process is more challenging. Indeed, the only measured pressure is the standpipe pressure, and there is no direct measurement of the motor pressure drop. This challenge can be overcome thanks to the understanding of the drilling operations. During off-bottom periods, the only pressure drop through the motor is the no load pressure, thus, the hydraulic pressure drop is equivalent to the measured standpipe pressure. Off-bottom periods can be used as reference to train the Gaussian process related to the hydraulic pressure loss.

$$SPP_{off\ bottom} = \beta_Q Q^{1.8} \tag{11}$$

While being on bottom, the motor influence starts to appear, and there is an extra pressure drop occurring on the standpipe pressure, as illustrated in Fig.1. Using the off-bottom pressure baseline (dependent solely on the pumps flow), the pressure reference can be derived for the training of the Gaussian processes related to the motor pressure loss. This motor pressure drop is equal to the measured standpipe pressure minus the computed hydraulic pressure drop.

$$SPP_{on\ bottom} - \beta_Q Q^{1.8} = \Delta P_{motor} \tag{12}$$

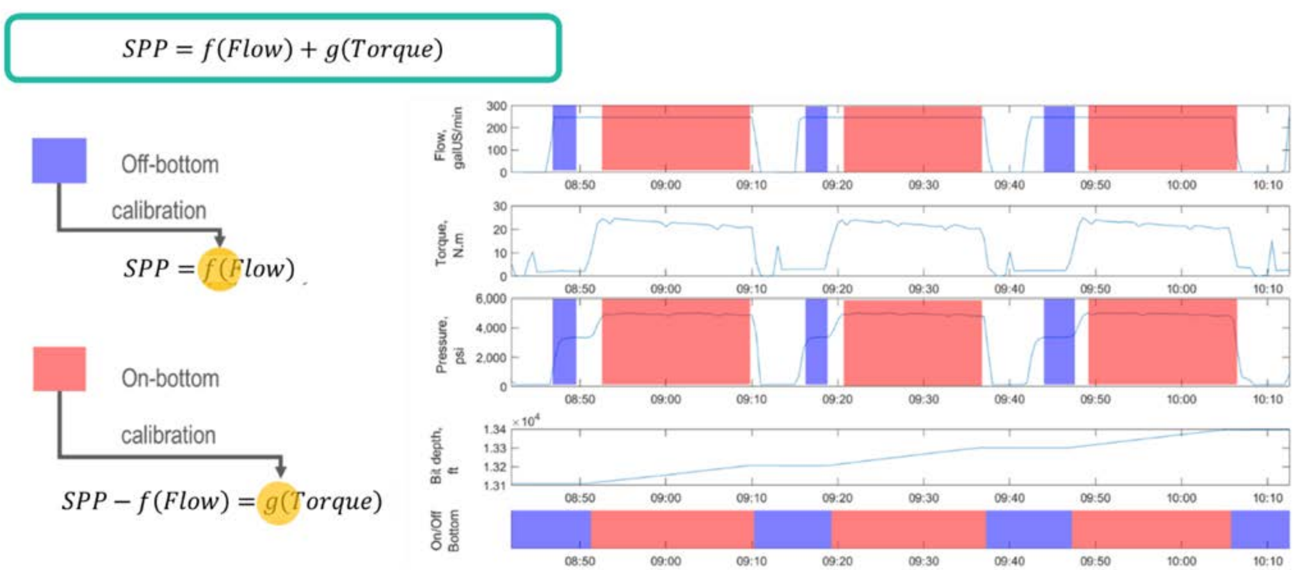

Figure 1—Pressure decomposition between off-bottom and on-bottom periods with the motor case in rotary drilling

Two models exist for the motor pressure drop according to the kind of drilling configuration, slide or rotary. It must be emphasized that the on-bottom models can only be trained if the hydraulic pressure loss model has been calibrated first.

Gaussian process training

To avoid NPT related to dedicated training periods and to automate the calibration workflow (no operator inputs to select a period for training), a real-time model training under automatic supervision is implemented. To test if a potential training period is a good candidate to update the models training tables, the prediction's uncertainty (proportional to the standard deviation of the prediction) performed by the Gaussian process is used.

For each potential training period, the model inputs (pumps flow, surface torque, or WOB) and the model pressure references (for example, in the motor case, standpipe pressure measurement for the off-bottom periods) are extracted. For those new inputs, the current model is used to estimate the predicted model pressure and its associated uncertainty. An authorized recalibration range is computed based on the prediction's uncertainty (and consequently proportional to the standard deviation of the prediction): if the observed model pressure reference is far from the prediction (or outside of the recalibration range), the potential training period is not going to be used to retrain the Gaussian process. If the reference pressure is within the recalibration range, this period can be used to update the training table, as illustrated in Fig.2.

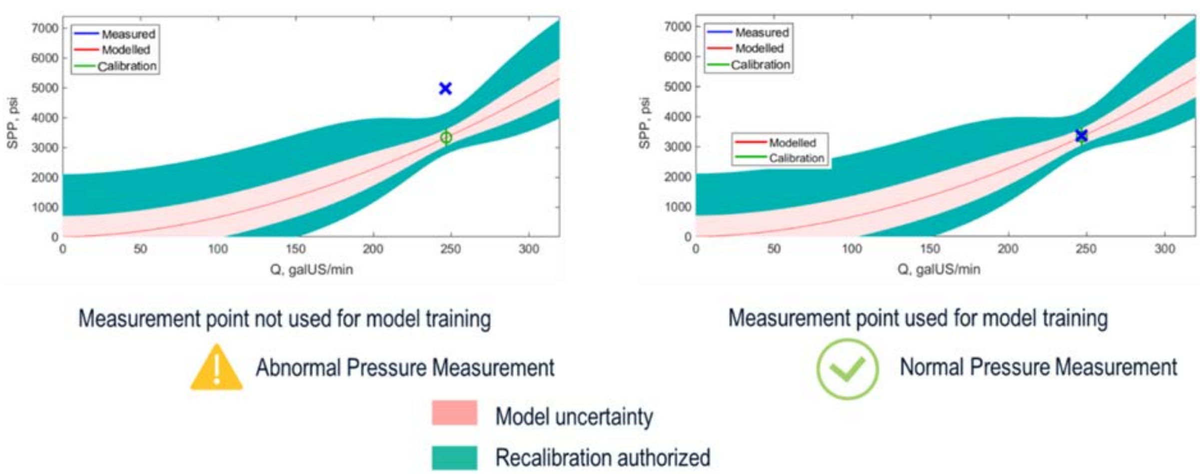

Figure 2—Training authorization

The predicted pressure (for both motor and no motor cases) is derived based on the different real time Gaussian processes trained. If new inputs are encountered that do not belong to the training tables, the physical pressure loss prior is mainly used to predict the pressure with a higher uncertainty. The difference between the measured pressure and the modelled one is computed and compared to the global uncertainty at given input conditions. The global uncertainty is derived from the uncertainty of each Gaussian process. The normalized pressure difference is equal to the pressure difference divided by the computed global uncertainty.

The pressure anomalies alarm is derived from this normalized pressure difference. There is no constant and absolute pressure threshold for the anomaly detection: it will depend on the level of uncertainty of the models at the given observed conditions. There are two levels of alarms: one is intermediate, the other one is severe, and they are based on the intensity of the deviation. This method ensures agility in the detection and a standardized evaluation of the pressure anomalies. The models' uncertainties depend on the level of noise of the pressure measurement. The quality of the measurement acquisition is key for the detection reactivity as it affects the detection thresholds.

Pressure anomaly detection results

The workflow has been used on several wells and has shown its robustness and detection capabilities. The workflow is automated; it adjusts itself to different rig conditions. Its concrete capabilities are displayed on two examples: one onshore with a downhole motor and another one offshore with no motor. Both examples suffer from washout events (severe loss of pressure). The workflow is run on those datasets, starting at the beginning of the BHA run, up to the last abnormal event. This is a "postmortem" analysis to check the capabilities of the workflow in terms of:

- False alarms: how many false alarms are triggered when everything is normal (i.e. the day before the events)?
- True detection: can we detect the actual events? How long does it take to detect them?

On both cases, the labelling of the events (start time–end time) is done posteriori thanks to experts, based on measurements only.

Alarms are displayed on the bottom graph with flags: green flag means no abnormality detected, orange flag means an intermediate level of low-pressure anomalies, and red flag means a severe low-pressure event (such as a washout). Periods with no colored flag are periods where no predicted pressure is computed (for example during transient flow periods): no detection can be done.

Example 1: offshore rig

On an offshore rig, during the 8.5-in section, a washout event started at 13,510 ft, with a decreasing trend of 680 psi/h. Over the two days prior to the washout event, no false alarms were triggered. The event was detected with a high level of confidence (red flag) less than 15 min after the observed start of the pressure decrease (Fig.3).

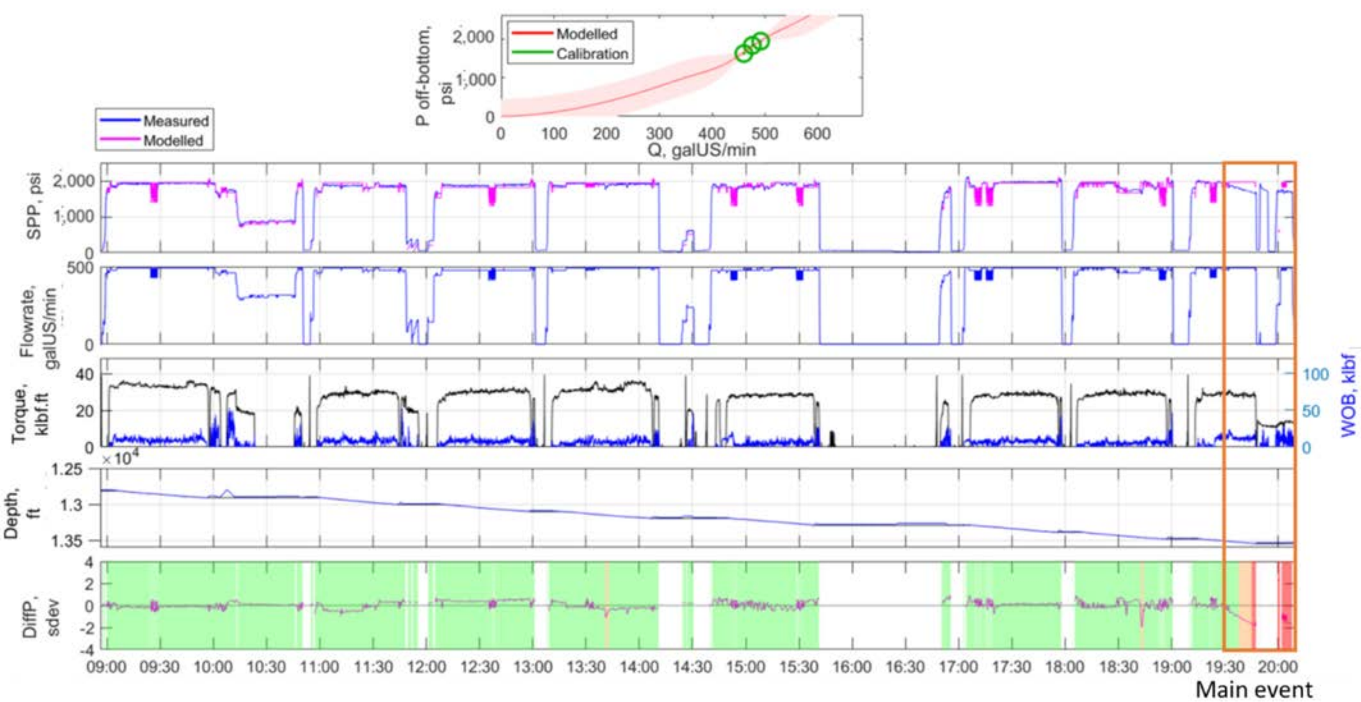

Figure 3—Off-shore pressure loss detection example

Example 2: land rig

On a land rig, during the 12.25-in section, several severe drops of pressures were observed: at 5,723 ft, the SPP lost 1,885 psi momentarily, with no relation to any drop in some other inputs (event 1). The pressure was recovered and the drilling continued. A second short drop of −800 psi occurred 10 min after during a longer period at 5,749 ft (event 2). The pressure was again recovered, and the drilling continued. Yet a continuous SPP drop restarted two hours later (main event) and lasted for three hours. The decreasing trend was around 83 psi/h. This decrease has been confirmed as a washout later.

Over the two-and-a-half days prior to the first abnormal events, no false alarms were triggered. Some intermediary (orange) alarms were raised punctually, but they are related to circulating pill events.

The two first events were detected with intermediate alarms (orange alarms), raising a first level of awareness. The main event was detected with a higher level of confidence (red alarm) less than 25 min after the start of the pressure decrease, as it can be observed in Fig.4.

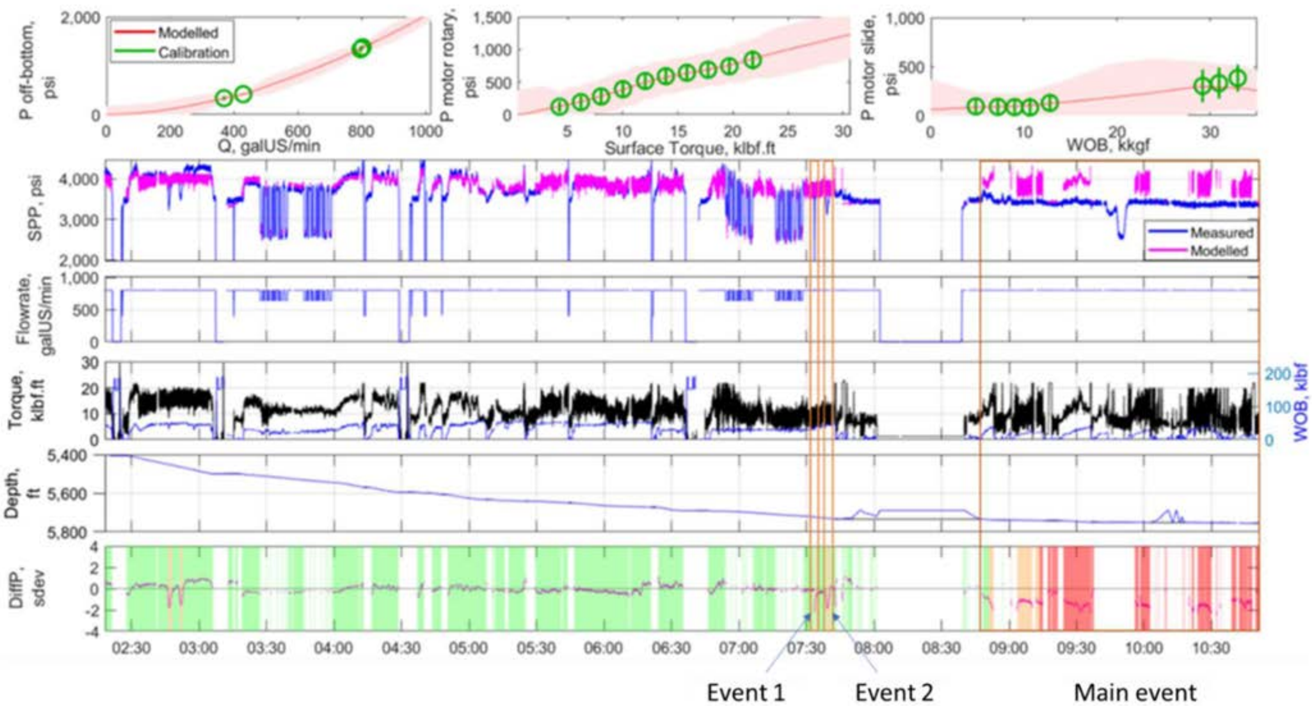

Figure 4—On-shore pressure loss detection example

Large scale capabilities

Capabilities of the workflow on several datasets are presented through a statistical analysis. The detection capabilities and the false alarm rates have been computed on several datasets to estimate the reliability and the accuracy of the workflow.

First, estimating capabilities on numerous datasets is challenging. Indeed, it requires having datasets with events labelled by subject matter experts (SMEs). This labelling effort is time consuming and must be performed by several experts. Indeed, those labels are going to be used as the true reference. It might happen that multiple experts might label the data differently. This uncertainty in the labelling must be accounted for: the most recurrent label among the experts is the true label. We should not rely on only one expert to define the true events on every dataset because this will not protect us from human mistakes; every expert's timing might be subjective.

Moreover, estimating capabilities can also be challenging because typical labels from experts often focus on severe events such as a washout for the low-pressure anomaly cases; less severe events are not always identified or accounted for. Thus, solely using priori labels from experts could lead to wrongly classifying some alarms as false. Indeed, the current workflow tends to capture a large variety of abnormal pressure situations, even the less intense ones.

False alarm rate

One strategy adopted has been to analyze all alarms triggered by the workflow for more than 50 wells over several runs. Each alarm triggered has been observed to check if it was a true or a false abnormal pressure event (whatever its intensity). Over 120 alarms triggered for all those wells, 45 are considered as false alarms. In terms of time spent in false alarm state, it represents less than 7% of the total drilling time. This percentage is not equivalent to 45 divided by 120 because all the alarms triggered might not have lasted the same amount of time.

There is an upstream data quality check workflow. Indeed, some data quality issues can undermine the capabilities of the abnormal pressure detection workflow. The detection workflow is highly dependent on the rig state detection to identify on- and off-bottom periods but also the kind of drilling (slide or rotary).

Any rig state classification issue has a strong impact on the abnormal pressure detection capabilities. Due to rig acquisition issues, the following problems could occur: improper unit definition, uncalibrated WOB or flow rate, noisy surface torque, and WOB. The correct upfront detection of those inputs issues has enabled reduction in the number of false alarms in the pressure anomalies by a factor of two.

The presented workflow still has some false positive alarms (less than 10%). Those issues are related to some known algorithm limitations. When dealing with mud motors, the modeling relies on two steps. First, the off-bottom baseline is estimated, then the motor pressure drop is deduced. The hydraulic pressure reference (from off-bottom periods) needs to be updated regularly to account for depth and mud variations for example. This update could not be performed sometimes due to the limited amount of time spent off bottom and circulating. This means that at some point, the on-bottom models cannot be trained anymore, and the predicted pressure baseline cannot explain the observed data. This issue is related to the way the drilling is done: little time is spent off bottom prior to going on bottom to drill fast. Similarly, it can take a bit of time to start the prediction process. Indeed, the prediction will require spending enough time in off-bottom state and circulating to start the training of the model.

Detection capabilities

Some SMEs have identified some severe low-pressure events (washouts) on several wells. Those kinds of events are of particular interest while drilling as it can produce a significant amount of Non-Productive Time. Those wells with severe low-pressure events are used to compute the severe event detection capabilities. Indeed, those kinds of situations are the most straightforward to identify by an expert. Over 10 washout cases, 9 events are correctly identified by the new system. The missed event is related to the impossibility for the workflow to be trained, thus, no predicted pressure was computed. For that case, which was with a motor, no off-bottom training periods could be identified to start the computation.

The detection capabilities rely on the pressure prediction uncertainty. This uncertainty is computed from the Gaussian processes and is dependent on the SPP measurements noise. Some analysis is made to estimate the impact of the noise on the abnormal pressure detection. The focus is on low-pressure anomalies such as washouts. Artificial washouts of various intensities are created (from 100 psi/h to 800 psi/h) as additional negative slopes on the measured SPP for cases with or without downhole motor.

For the same intensity washout, the detection reactivity is decreased if the measured SPP is noisy, as can be observed on Fig. 5. This has a direct impact on mitigation measures that can be taken to overcome those problems when they occur on the rig. Indeed, if the event is detected late, the size of the washout might be too large at the time of the detection, and it might be hard to avoid fishing of lost elements. The objective is to be able to detect as soon as possible, and this cannot be done if the measurement quality is low.

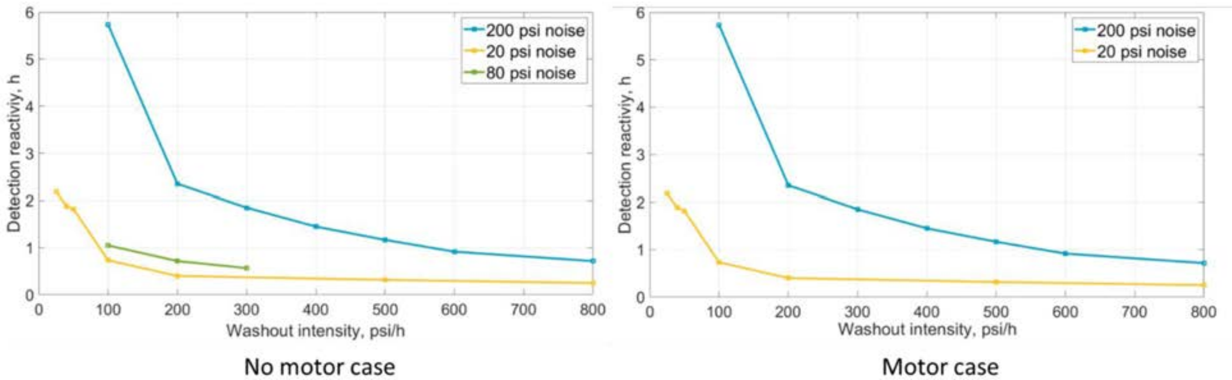

Figure 5—Detection reactivity as function of the washout intensity and pressure measurement noise

Conclusion

The new detection algorithm for abnormal pressure events has the advantage of being fully automated, relying on few surface measurements inputs. It is data driven, but it does not require historical data from other wells to be run; it will adjust itself based on real-time observations. Its detection capabilities are rig adaptive and dependent on the measurement quality: no fixed threshold is used, but adaptive thresholds based on the pressure prediction uncertainty. This balance enables good reliability results combined with efficient detection capabilities, provided that the underlying assumption of the algorithm are satisfied for the utilized Gaussian processes.

The capabilities analysis should remain an ongoing effort, relying on a large-scale labelling strategy by experts. It is a tedious effort, but it is an important step for the development of efficient and reliable algorithm. Moreover, any new improvements or adjustments in the algorithm will be quickly tested and quantitatively estimated in terms of detection capabilities thanks to those registered labels.

Acknowledgement

The authors would like to thank Can Evren Yarman (Schlumberger), Ashley Johnson (Schlumberger) and John L. Thorogood (Drilling Global Consultant) for their help and support during the writing of this paper.

References

1. Raja H. and Dodds, R., 2011, Innovating While Drilling®, March/April. Remote workflows put digital resources to work to reduce NPT. *Drilling Contractor – Official Magazine of the International Association of Drilling Contractors*, https://www.drillingcontractor.org/remote-workflows-put-digital-resources-to-work-to-reduce-npt-8783
2. Cayeux, E., Daireaux, B., Dvergsnes, E. 2012. Early Symptom Detection on the Basis of Real-Time Evaluation of Downhole Conditions: Principles and Results From Several North Sea Drilling Operations. Presented at the SPE Intelligent Energy International, Utrecht, the Netherlands, 27-29 March. SPE-150422-PA.
3. Kuesters, A., Mason, C., Gomes, P., Cockburn C., Lodhi, H. 2020. Drillstring Failure Prevention - A Data Driven Approach to Early Washout Detection. Presented at the SPE/IADC International Drilling Conference and Exhibition held in Galveston, Texas, 3–5 March 2020. SPE-199610-MS.
4. Aldred, W.D., Dunlop, J. and Belaskie, J. 2010. System and Method for Online Automation. International Patent Application PCT/IB2009/007127, Publication number WO 2010/043951 A2.
5. Wong, R., Liu, Q., Ringer, M., Dunlop, J., Luppens, C., Yu, H., Chapman, C. 2013. Advances in Real-Time Event Detection While Drilling. Presented at the SPE/IADC Drilling Conference and Exhibition held in Amsterdam, The Netherlands, 5-7 March 2013. SPE-163515-MS.

6. Sindi, W., Prohaska-Marchried, M., Thonhauser, G. 2016. Successful Real-Time Modeling of Wellbore Hydraulics Using Rheology Obtained According to API Recommended Practice 13D. Presented at the Abu Dhabi International Petroleum Exhibition & Conference held in Abu Dhabi, UAE, 7-10 November 2016. SPE-183398-MS.
7. Institut Français du Pétrole. 1999. Drilling Data Handbook, seventh edition. Paris: EditionsTechnip. https://epdf.tips/queue/drilling-data-handbook-institut-francais-du-petrole-publications.html
8. Bourgoyne A.T., Millheim, K.K., Chenevert M.E., Young Jr, F.S., 1991, *Applied Drilling Engineering*, SPE textbook Series Vol **2**
9. Rasmussen, C. E., and Williams, C. K. I. 2006. *Gaussian Processes for Machine Learning*, the MIT Press.