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Self-Learning Probabilistic Detection and Alerting of Drillstring Washout and Pump Failure Incidents During Drilling Operations

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Abstract

The mechanical failure of drilling equipment is an operational risk that can be limited through a robust detection and alerting system, particularly for Drill String Washouts (DSW) and Mud Pump Failures (MPF). The detection of these issues focuses primarily on the time signatures of the real-time and modeled pump pressure in relation to the flow rate trends. Together, these parameters describe the state of the equipment which can be assessed through real-time alerts.

A new methodology for real-time detection of washout and pump failure incidents during drilling operations was developed. The methodology behind the detection system uses a Bayesian network that models the drilling hydraulics and their associated failure modes. The network aggregates data from real-time rig floor sensors (standpipe pressure, pump rate, flow out, etc.), contextual information (rig state, mud properties, etc.), and predictions from hydraulic modeling. Cumulatively, they are the determinants of a probabilistic belief system indicative of DSW and MPF. The probabilistic model outputs belief values for DSW and MPF between zero and one. Given past and present trends, the model increases accuracy though self-learning and self-calibration that adjusts for poor sensor data, drilling conditions, and model uncertainty.

The Bayesian network was integrated into decision support software with real-time alerting capabilities. The software was then validated by an operator's 100+ onshore wells in North America, some of which contained MPF and DSW incidents with varying degrees of severity. Several case studies drawn from these wells are presented in the paper.

Each failure event that exceeded a programmed threshold for a specified period of time generated an alert in the form of a PDF report containing real-time sensor traces and DSW and MPF prediction outputs. The alerts were also displayed on a dashboard on the rig site user interface. Software thresholds were optimized to reduce false alert reports presented to the driller. Through continuous improvement and validation, DSW and MPF detection reached a level of accuracy which, in some cases, detected the warning signs of a failure hours before the problem was noticed at the rig site. Conclusively, the value added by the early detection of mechanical failures is the decreased amount of non-productive time due to pump downtime and maintenance, as well as trips and fishing jobs due to washed out pipe.

Introduction

As drilling operations are faced with an increasing need for efficiency and reduced non-productive time, early detection and prevention of costly equipment failure is becoming a prominent feature of real-time decision support and data analytics tools. In recent years, intelligent event detection and alerting systems have been deployed in a variety of scenarios, such as influx and loss identification (Pournazari et al., 2015; Unrau et al., 2017), monitoring of drilling dysfunctions and performance (Ambrus et al., 2017), or prediction of stuck pipe incidents (Salminen et al., 2016).

Drillstring washouts represent another problem area which can greatly benefit from improved detection algorithms. Drill pipes, tool joints and BHA components are exposed to mechanical fatigue, wear and corrosion throughout their life span. As a result, cracks start to develop, often accompanied by leakage of drilling mud into the annulus. Depending on the location of the washout, a noticeable pressure loss (of several hundreds of psi or more) may be observed on the standpipe, along with reduced flow rates in the pipe section below the washout. The cracks enlarge in the presence of high torsional loads, and may ultimately result in a drillstring twist-off and subsequent fishing operation to retrieve the components lost in the hole. A particular washout scenario investigated in this study resulted in a twist-off in the rotary steerable system. This was followed by 4.6 days of fishing, with an estimated price tag of $300,000 based on the spread rates and fishing equipment costs for a typical land rig.

A standard approach to identification of washout signatures relies on measurements commonly available on a drilling rig, such as standpipe pressure and pump rates. A drop in standpipe pressure at constant flow rate is the most basic indication of an ongoing washout. A simple hydraulic coefficient relating standpipe pressure to pump rate has been used as part of a rig-based event detection system (Ritchie et al., 2008). If a downhole motor or turbine is used and MWD data is available, downhole RPM measurements can be used to infer the actual flow rate through the motor (Wong et al., 2013). Alternatively, annular pressure measured in the MWD can also be used to track changes in downhole hydraulics (Arakkal et al., 2008). Regardless of the method used, detecting washout signatures can be a challenging task due to the accuracy and quality of sensor data, as well as other factors which may affect pressure and flow rate readings, such as transients and delays due to drilling fluid compressibility, mud pulse telemetry and downlinking, cuttings build-up, plugged drill bit nozzles, or loss of pump efficiency.

Mud pump failures or partial degradation (e.g. damage to pump liner, piston, and suction or discharge valve) also result in a drop in standpipe pressure, in addition to a deviation between the expected flow rate into the well and the actual flow rate. High frequency pump pressure data can be utilized to improve detection of pump wear (Spoerker and Litzlbauer, 2002). Alternately, accelerometers can be fitted to the suction and discharge lines and the recorded vibration data may be analyzed to infer leaks in the valves (Kyllingstad and Nessjoen, 2011). However, high frequency data or additional sensors may not be practical in most field setups, and therefore, it is preferred to develop a methodology that can distinguish between different failure modes using a basic set of rig sensors and contextual.

This paper proposes a methodology employing a Bayesian network representation of the drilling hydraulics. The self-calibrating Bayesian network aggregates past and present trends in real-time sensor data as well as hydraulic calculations, and infers the individual beliefs for events such as washouts and pump failures. These beliefs are post-processed into an alerting and reporting module deployed as part of a driller-friendly real-time data aggregation system (Behounek et al., 2017). The paper provides several case studies detailing the application of the system in field operations across a number of onshore rigs in North America.

Methodology

Bayesian Network for Event Detection

The event detection back end engine utilizes a Bayesian Network (pictured in Figure 1) which aggregates all the key sensor inputs, modeled variables and contextual data. Bayesian Networks are a class of probabilistic graphical models which consist of discrete or continuous-valued nodes representing the process variables of interest (Koller and Friedman, 2009). The nodes in a Bayesian Network are connected among each other via conditional probability tables (CPT) and visually linked by arrows representing the direction of causation. Each of these arrows can be assigned a specific weight based on the relative importance in determining a specific outcome. A learning algorithm can be applied to update the CPTs. This will be detailed in a later section.

The key node for the event detection in the Bayesian Network shown below is Unplanned Event, which includes several possible event types and their associated probabilities (beliefs). While the focus in the current paper lies exclusively on washout and pump failure incidents, the present setup can also detect other events related to well control and hydraulics, such as kick, lost circulation, wellbore breathing, pack-off etc. A prior probability value is assigned to each of these events. In addition to the "unplanned events", the network can also determine "planned events" such as pump start/stop routines or changes to the mud volume by the rig crew. The Planned Event node is necessary to eliminate false alarms in the detection of unplanned events; for instance, the washout probability should be low during and right after pump start-up, since a washout signature is easier to detect with a steady pump rate.

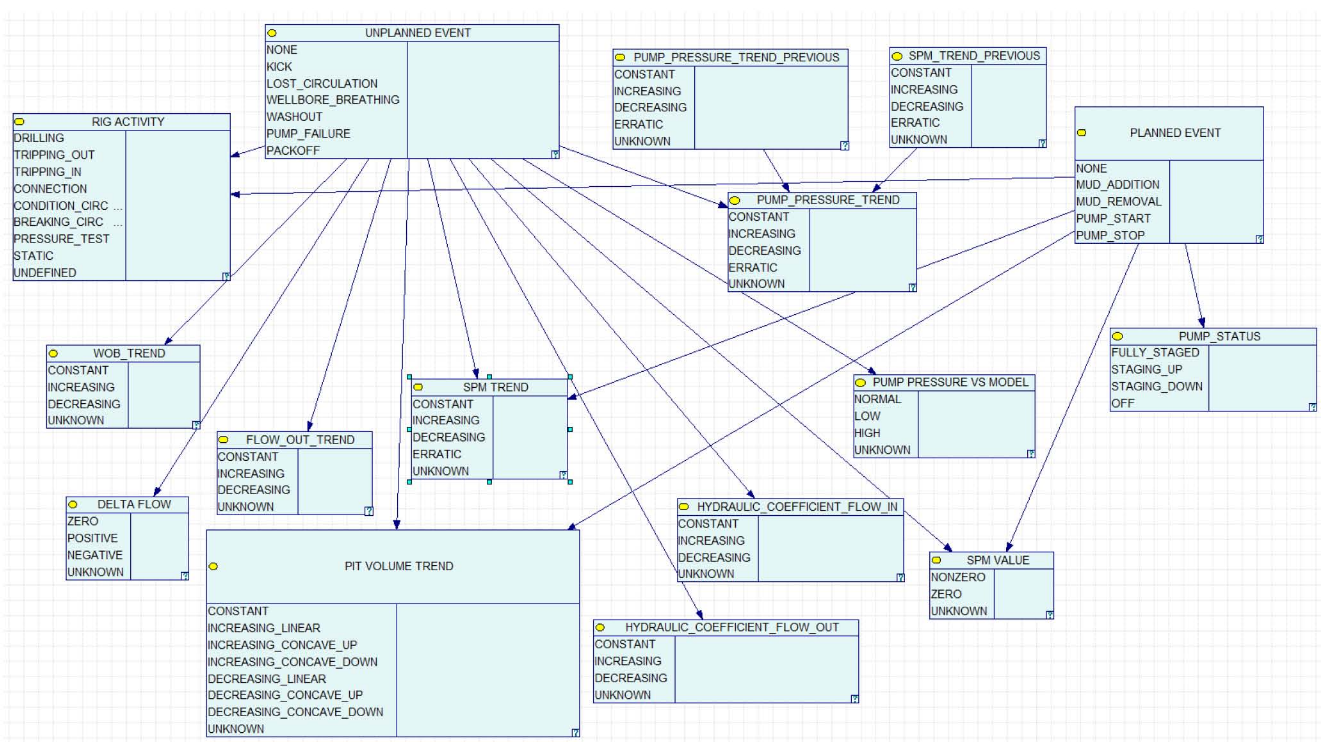

Figure 1—Bayesian Network used for detection of different events in a drilling operation. The network takes real-time data inputs, modeled values and contextual information to infer the probability that a certain event is occurring.

The other network nodes include processed real-time inputs, such as the current and previous trends in pump pressure and pump strokes per minute (SPM). These trends are continuously monitored over a 2-minute moving window, and simple statistics (mean, standard deviation) and curve fitting are utilized to determine whether a constant, increasing, decreasing, or erratic trend is present (e.g. a cyclic trend in pressure and/or pump rate indicative of a downlinking sequence). The previous trend indicates the state of the variable at the beginning of the moving window, as opposed to the current trend recorded at the end of the window. If insufficient data samples are available, an "Unknown" state is entered, lowering the reduced conditional probability for that particular node. The network also includes weight on bit (WOB) trends, used as an additional feature to distinguish a washout or pump failure from differential pressure changes occurring while drilling, as well as pit volume, flow out, and delta flow (i.e. difference between flow out and flow in). The last two are used primarily for kick/loss detection, but also for a clearer distinction between washout and pump failure.

The relationship between pump pressure and flow rate is also modeled through the hydraulic coefficient, defined according to (Ritchie et al., 2008):

$$h_{flow-in} = \frac{P}{Q_{in}^2} \tag{1}$$

where P is the pump pressure (measured at the standpipe) and Q_{in} is the flow rate into the well (computed from the pump strokes). We introduce a similar coefficient for the flow out (Q_{out}):

$$h_{flow-out} = \frac{P}{Q_{out}^2} \tag{2}$$

If the flow out is measured with a flow paddle, additional calibration needs to be performed to scale the flow out percent to the range of flow in values. This calibration process is automatically performed at several different pump rates. If the flow out sensor is faulty or not connected to the data acquisition system, this feature is entered into the network as an "Unknown" state which carries a lower weight in the CPT. The hydraulic coefficients defined in Eqs. (1) and (2) are calculated over a 10-minute window with steady pump rate, and their overall trend is computed over a 5-hour moving window. This allows slowly developing washouts and pump failure to be detected more easily, whereas a more sudden occurrence will be handled by the pressure trends averaged over the 2-minute moving window. A decreasing flow-in hydraulic coefficient is expected to be observed over time in both a washout and pump failure case, whereas the flow-out hydraulic coefficient will stay roughly constant in a pump failure event, since both flow out and pressure will drop as the pump condition degrades. If an additional flow meter were available on the inlet side, the relationship between pump strokes and measured flow in could be used to more easily distinguish the pump failure.

The measured pump pressure is also continuously evaluated against a modeled value obtained by calculating the steady-state pressure losses in the circulation system. If the measured pressure falls below the modeled pressure, the likelihood of a washout or pump failure is increased. The total pump pressure is a sum of the surface pressure losses, pressure drop through the drill bit, friction losses in the drillstring and annulus sections, and differential pressure across the mud motor. The model requires accurate mud properties, BHA and pipe dimensions, bit nozzle flow area, as well as hole size and casing inner diameter. The BHA, casing, bit and mud properties are automatically retrieved from a data aggregation system containing the most recent digitized information (Behounek et al., 2017). The pressure loss calculations account for the effects of pipe rotation, eccentricity and Bingham Plastic fluid rheology. For more detailed information regarding the hydraulic model, interested readers can refer to Shahri et al. (2018).. A calibration factor is applied to the pressure model to account for uncertainty in the mud properties and drillstring components. The calibration procedure results in a map of scaling factors at different pump rates, which are multiplied by the measured pump rate and added to the total pressure loss value.

Additional contextual information, such as rig activity and pump status (pumps off, ramping up / down or fully staged), is included as nodes in the Bayesian Network. The rig activity is computed by a separate engine running in the back end, and is used to skew the detection of certain events based on the activity during which they are more likely to occur. For instance, a washout is more likely to develop during drilling or reaming operations, when the drillstring is subject to high torque values. Other events, such as kicks and wellbore breathing, may be more likely to happen during connections or tripping out periods (e.g. swab kicks), and the CPTs need to account for all the possible scenarios.

Figure 2 illustrates the Bayesian Network predictions during a hypothetical washout scenario, where all the relevant signatures are fully satisfied. In this case, it should be noted that the washout detection probability only goes up to 80%, which is the maximum attainable value for this network configuration and CPT definitions. If only partial signatures are observed (e.g. the pump pressure decreases, but the difference between measured and model pressure is not significant, or the model value falls below the measured pressure), the washout probability will be further reduced. Figure 3 presents a similar calculation for a hypothetical pump failure incident, where the maximum detection probability goes to 93%. These peak probabilities can be increased by changing the priors in the Unplanned Event node, or by updating the CPTs (e.g. using a learning algorithm), however this should be done carefully, since it will impact the detection of other events. One key assumption in this current setup is that the events detected at a particular time instant are mutually exclusive, so if two of these events were to occur simultaneously (e.g. washout and pump failure), and a detection probability threshold were imposed (e.g. 50%), it would not be possible for the software to detect both of them. Also there can be circumstances under which two different events yield the same detection probability. One such scenario is illustrated in Figure 4, where due to an unavailable flow out measurement, the washout and pump failure events both show a probability of 45%, unless any of the other detection features change. In order to observe which features carry the most weight in the event detection, the thickness of the arrows connecting each feature to the event nodes can be displayed in the Bayesian Network visualization toolbox used to generate the figures below. The thicker arrows indicate a higher influence in the inference process.

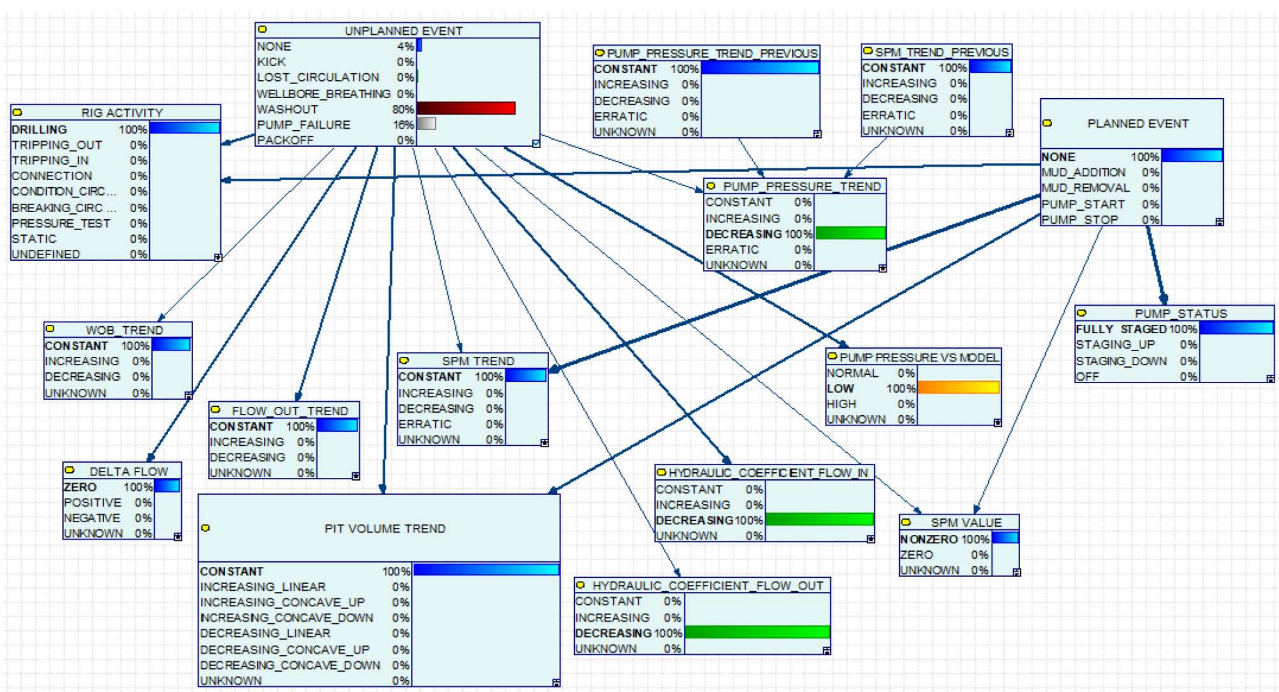

Figure 2—Bayesian Network outputs during a washout event. The key distinctive features are constant SPM trend, sudden decrease in pump pressure, low pump pressure compared to modeled value, constant flow out, and decreasing hydraulic coefficient for both flow in and out. The thickness of the arrows denotes the relative importance of each node in the Bayesian inference process.

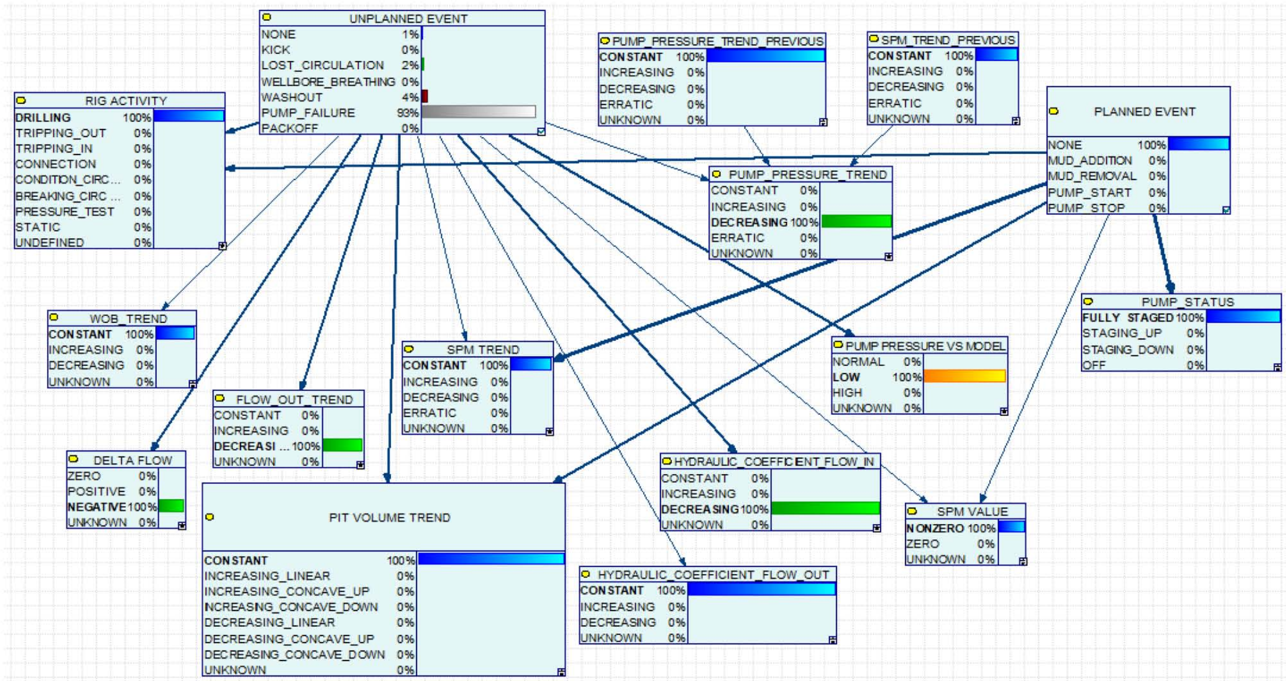

Figure 3—Bayesian Network outputs during a pump failure event. The key distinctive features are constant SPM trend, sudden decrease in pump pressure, low pump pressure compared to modeled value, decreasing flow out, constant hydraulic coefficient for flow out, and decreasing hydraulic coefficient for flow in.

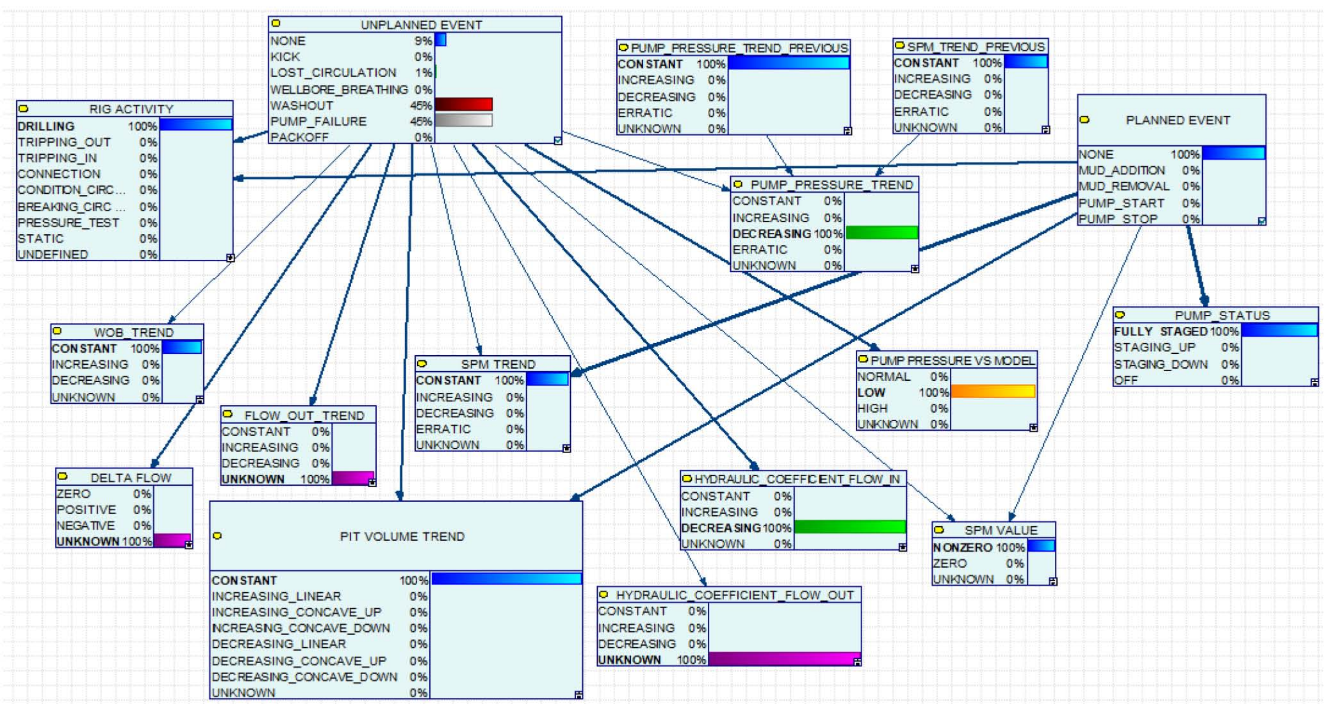

Figure 4—Scenario where the flow out sensor is unavailable, resulting in an Unknown state in the Flow Out Trend, Delta Flow and Hydraulic Coefficient Flow Out nodes. This leads to an inability to distinguish between washout and pump failure events, as both outcomes return the same probability.

Learning of Bayesian Network CPTs

Once the Bayesian Network structure has been defined, it is possible to learn the CPTs associated with one or multiple variables and their parent nodes. Several techniques can be used to accomplish the learning task, such as maximum likelihood estimation, Bayesian parameter estimation or maximum a posteriori estimation

(Koller and Friedman, 2009). Learning the CPTs requires a training data set consisting of labeled events and the corresponding detection features. If some fields in the training data set are incomplete, an optimization algorithm such as Expectation Maximization can be used.

Figure 5 illustrates a data set for learning the CPTs associated with washout detection. This data can be provided to the learning engine either on-line or off-line, as soon as the events can be labeled, e.g. by a human operator or by a third party detection software. It is possible to fix some of the node CPTs during the learning process in order to keep previously learned parameters. The learning process can be stopped after a number of samples are collected, and re-started when the drilling conditions or measurements have significantly changed, for instance a different mud is used or the flow sensor was re-calibrated. Figure 6 shows the Bayesian network with the same evidence assigned as in Figure 2 after the CPTs have been learned from the labeled training data set. This results in an improved washout detection probability, from 80% (as shown in Figure 2) to 100%. It should be noted that the strength of influence has increased for certain nodes, as indicated by the change in the arrow thickness. For instance, the Pump Pressure vs. Model node is given a lower weight than previously, which accounts for inconsistencies in the modeled pressure due to the quality of the model inputs.

PUMP_PRESSURE_TREND	PUMP_PRESSURE_TREND_PREVIOUS	SPM_TREND_PREVIOUS	HYDRAULIC_COEFFICIENT_FLOW_IN	HYDRAULIC_COEFFICIENT_FLOW_OUT	PLANNED_EVENT	UNPLANNED_EVENT
INCREASING	UNKNOWN	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
CONSTANT	DECREASING	CONSTANT	DECREASING	DECREASING	NONE	WASHOUT
CONSTANT	DECREASING	CONSTANT	DECREASING	DECREASING	NONE	WASHOUT
DECREASING	CONSTANT	DECREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	CONSTANT	ERRATIC	CONSTANT	CONSTANT	NONE	NONE
DECREASING	CONSTANT	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
DECREASING	INCREASING	CONSTANT	CONSTANT	CONSTANT	NONE	NONE
DECREASING	INCREASING	INCREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	INCREASING	DECREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	INCREASING	ERRATIC	CONSTANT	CONSTANT	NONE	NONE
DECREASING	INCREASING	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
CONSTANT	DECREASING	CONSTANT	DECREASING	DECREASING	NONE	WASHOUT
CONSTANT	DECREASING	CONSTANT	DECREASING	DECREASING	NONE	WASHOUT
DECREASING	DECREASING	DECREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	DECREASING	ERRATIC	CONSTANT	CONSTANT	NONE	NONE
DECREASING	DECREASING	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
CONSTANT	DECREASING	CONSTANT	DECREASING	DECREASING	NONE	WASHOUT
DECREASING	ERRATIC	INCREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	ERRATIC	DECREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	ERRATIC	ERRATIC	CONSTANT	CONSTANT	NONE	NONE
DECREASING	ERRATIC	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
DECREASING	UNKNOWN	CONSTANT	CONSTANT	CONSTANT	NONE	NONE
DECREASING	UNKNOWN	INCREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	UNKNOWN	DECREASING	CONSTANT	CONSTANT	NONE	NONE
DECREASING	UNKNOWN	ERRATIC	CONSTANT	CONSTANT	NONE	NONE
DECREASING	UNKNOWN	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
ERRATIC	CONSTANT	CONSTANT	CONSTANT	CONSTANT	NONE	NONE
ERRATIC	CONSTANT	INCREASING	CONSTANT	CONSTANT	NONE	NONE
ERRATIC	CONSTANT	DECREASING	CONSTANT	CONSTANT	NONE	NONE
ERRATIC	CONSTANT	ERRATIC	CONSTANT	CONSTANT	NONE	NONE
ERRATIC	CONSTANT	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
CONSTANT	INCREASING	CONSTANT	DECREASING	CONSTANT	NONE	PUMP_FAILURE
ERRATIC	INCREASING	INCREASING	CONSTANT	CONSTANT	NONE	NONE
CONSTANT	INCREASING	CONSTANT	DECREASING	CONSTANT	NONE	PUMP_FAILURE
ERRATIC	INCREASING	ERRATIC	CONSTANT	CONSTANT	NONE	NONE
ERRATIC	INCREASING	UNKNOWN	CONSTANT	CONSTANT	NONE	NONE
CONSTANT	DECREASING	CONSTANT	DECREASING	DECREASING	NONE	WASHOUT
ERRATIC	DECREASING	INCREASING	CONSTANT	CONSTANT	NONE	NONE

Figure 5—A sample training data set for learning CPTs for washout and pump failure detection. The labeled events are in the rightmost column, while the detection feature states are in the other columns.

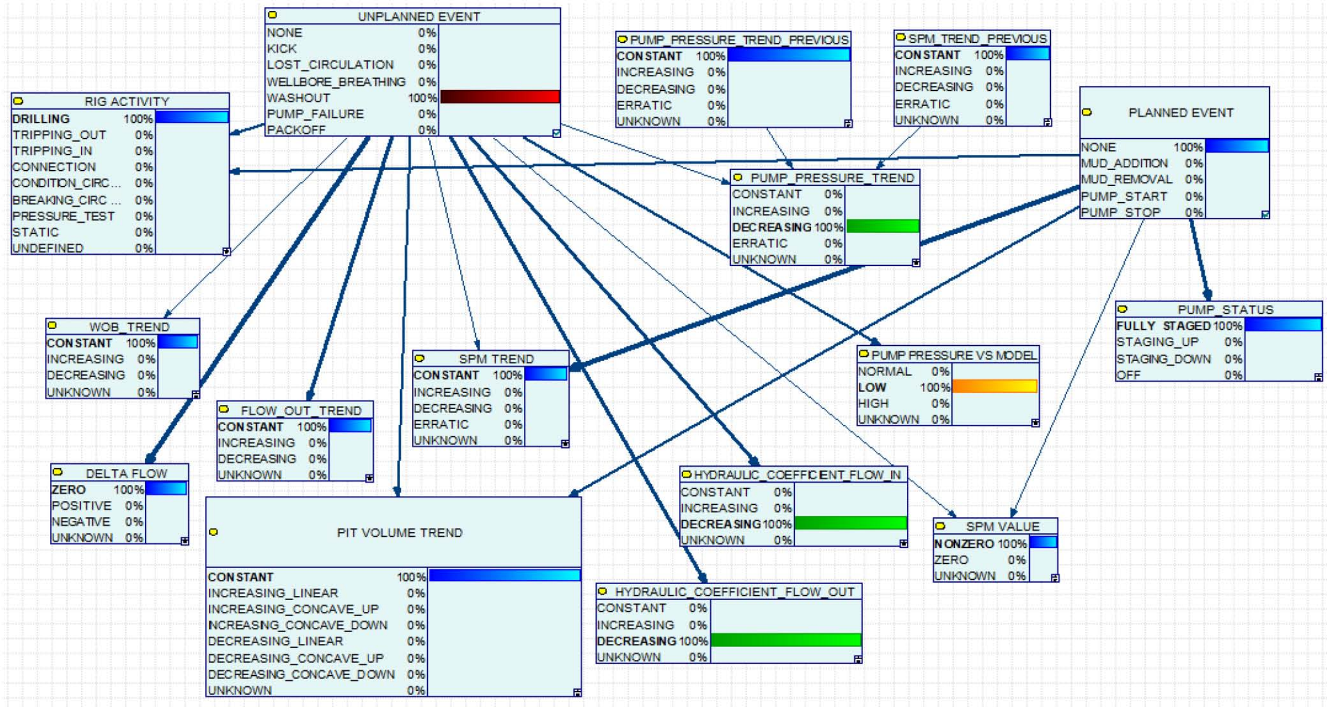

Figure 6—Bayesian Network outputs for a washout scenario after learning the CPTs from labeled event data. The washout probability now reaches 100% for this particular feature combination. Note the increased strength of influence for the Delta Flow, Flow Out and Hydraulic Coefficient Flow Out nodes.

Alerting Procedure

Alerting operators to potential washouts or pump failures happens in two phases. The first phase, which happens automatically, involves tracking a moving average of the summed washout and pump failure beliefs. If the moving average of this belief sum crosses a threshold, it is assumed that a washout or pump failure is likely to be taking place and an alert is automatically generated and sent to the office to be evaluated by a drilling engineer. This alert in the form of a PDF report will contain the event beliefs, pressure trends, and flow trends plotted over the hours leading up to the alert time. Once the engineer receives the alert, phase two of the alerting process begins in which he/she analyzes the flow trends in the alert to determine whether a washout or a pump failure is more likely to be taking place.

The goal of the first phase is to establish that *either* a washout *or* a pump failure has likely occurred or is about to occur. These two modes of failure are lumped together initially as they share most of the same signatures to the point where it can be somewhat difficult to tell them apart. One symptom of this similarity is that washout and pump failure beliefs almost always accompany each other. This means that it is much easier at a glance to determine that either one or the other is taking place than it is to declare exactly which one is happening. Thus, when washout and pump failure beliefs are constantly streaming in, it makes sense on a real time basis to track them as a whole rather than individually as doing so roughly halves the potential false alarms that may arise.

From a procedural standpoint, the sum of the washout and pump failure beliefs is constantly tracked and averaged over a 2 minute window 10 minutes behind real time. The 10 minute delay is added to provide some buffer to account for data connection issues that may arise with individual rigs. The 2 minute moving average window serves to filter out any errant belief spikes that could lead to false alarms. The window size started as an arbitrary time period as was pinpointed through trial and error. If the average value of the summed belief over this 2 minute window goes above 0.5 a washout or pump failure is deemed likely and an alert is automatically generated. As with the 2 minute moving average window, the 0.5 average summed belief cutoff value was determined through trial and error to maximize failure detection while minimizing false alarms. Given that this alerting threshold was intuitive to users, all further refinements are being made on the belief generation system itself, rather than continuing to adjust the threshold. Once the average summed belief reaches this cutoff, a PDF with relevant data trends over the 4 hours leading up to the alert is generated and sent to the office to be evaluated. So as not to overwhelm the office personnel with alerts, only 1 alert per rig may be sent out every 2 hours. An example of an automatically generated PDF report is shown in Figure 7.

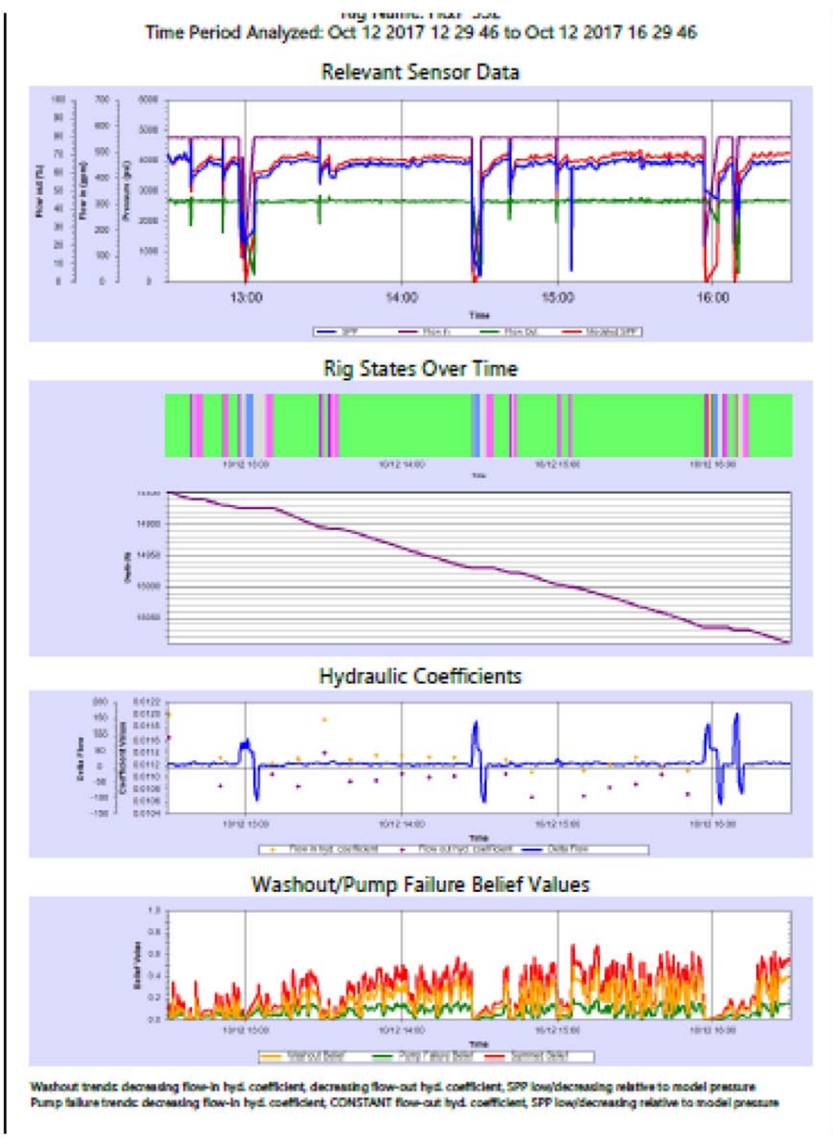

Figure 7—Sample of automated washout/pump failure alert sent out as a PDF.

Due to the nature of the first phase of alerting, the second phase serves to identify exactly which type of failure the automatically generated alert is most likely representative of. As previously stated, washout and pump failures exhibit similar data signatures so there are but a few key trends to consider when trying to differentiate between the two modes of failure. Once the alert reaches the office, it is the engineer's job to look for these trends in the context of the alert PDF to determine whether a washout or pump failure is more likely to be taking place.

The main trend that the engineer will use to separate washouts and pump failures is flow out. Pump failures will generally show decreased flow out while washouts will not. Because of this pump failures should in theory exhibit decreasing flow out, decreasing delta flow, and a more or less constant flow-out hydraulic coefficient. On the contrary, washouts are characterized by constant flow out, constant delta flow, and a decreasing flow-out hydraulic coefficient. While these three trends all stem from the behavior of flow out, due to the particulars of the data set analyzed one may be more evident to the naked eye than the others so all are included on the automated PDF report.

If based on the pressure trends a washout or pump failure seems evident yet the flow trends identified above are not clear enough for the engineer to definitively discern which mode of failure is likely taking place, he/she may declare as a last resort that either may be happening and instruct the rig operator to find out by process of elimination.

While it is the engineer's job to evaluate the validity of the washout PDF reports, all triggered alerts are catalogued on the rig as well and may be viewed at any time by rig personnel. In contrast to the PDF alerting system that goes through the engineer at the office, the rig alerting system is passive and the catalogued alerts are available in the form of a dashboard that may be accessed at any time (Figure 8).

The passive configuration of the rig alerting system is set up to find a compromise between distracting drillers with any false alarms that could arise with an active alerting system and keeping them completely out of the loop with no rig alerting system. The way it is now, the driller has the option to stay focused and wait to be notified by the engineer that a certain alert is valid and should be investigated. However, if the drillers themselves suspect something is wrong they still have the alerts catalogued and available to help confirm or deny their suspicions.

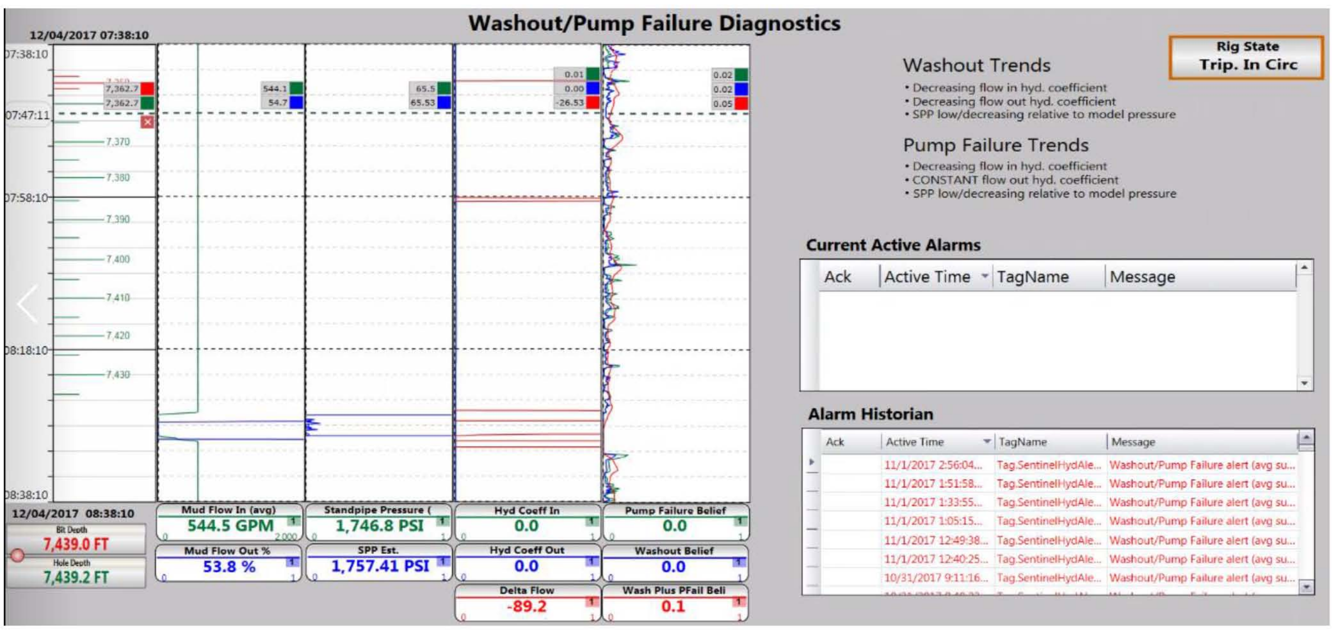

Figure 8—An alert diagnosis screen at the rig site helps the drilling supervisor/driller at the rig troubleshoot the event.

Case Studies

The real-time event detection engine and alerting system were implemented across 20 onshore rigs in North America, and they were continuously monitored and validated over a period of six months. Several case studies of washouts and pump failures were selected from the 100+ wells on which the system was active. A false alert scenario is also presented to highlight some of the challenges that may arise in the development of a robust event detection system.

Case 1: Washout Example

A certain washout on 10/12/2017 on Well A had three automated alerts generated prior to the event being caught at the rig site. The details for this are highlighted in Table 1. For context, this is the same washout described above in the washout alerting system example (Figure 7). Figure 9 shows relevant data plotted during this washout.

Table 1—Time history of alerts for Well A.

Event	Time
Alert generated	10/12/2017 16:49
Alert generated	10/12/2017 18:39
Alert generated	10/12/2017 20:29
Trip out due to pressure loss as stated in morning report	10/12/2017 23:00

In this particular case, the washout was detected by the automated alerting system over 6 hours prior to the rig crew tripping out due to washout and as such this event is a good example of the usefulness of the alerting system. These types of events usually develop over hours which make detecting them and alerting rig personnel both feasible and worthwhile. This particular event was caught by rig personnel before a twist-off event took place. However this is not always the case. Furthermore, the risk of catastrophic failure aside, identifying washouts or pump failures as quickly as possible means that rig personnel can address the problem proactively and get back to normal operation as efficiently as possible, minimizing the associated non-productive time.

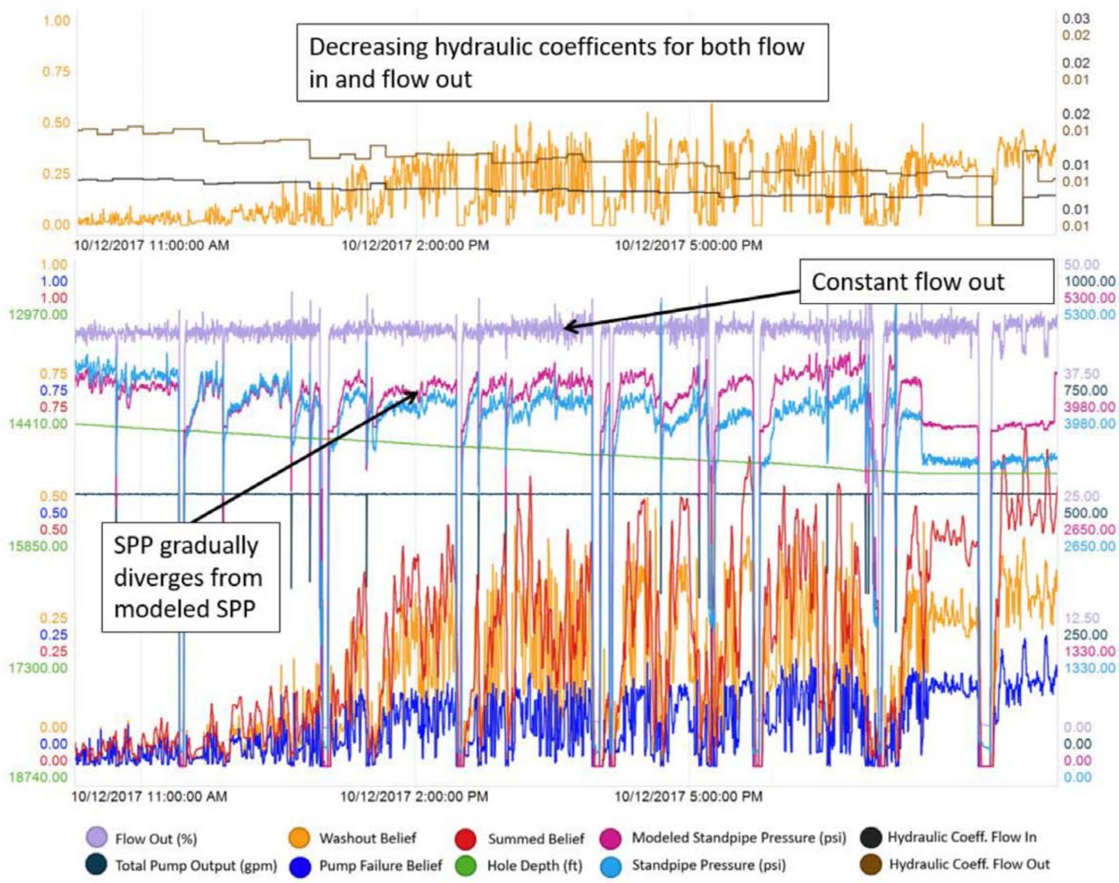

Figure 9—Data recorded during Well A washout on 10/12/2017.

Based on the pressure trend shown here it is very evident that a washout or pump failure took place; over time the measured standpipe pressure diverts farther and farther from the modeled standpipe pressure.

Because this divergence happens during a period of constant pump output it is a clear indication that washout or pump failure has occurred. While the pressure trends during this time assuredly point towards either a washout or pump failure, it is the flow out trend that makes it possible to differentiate between the two. Here, the flow out stays constant with the exception of some small fluctuations. If pump failure were taking place, one would expect to see this flow out diminished over time as the functionality of the pump(s) decreased. Since this is not the case, one can look at this data and be certain that it is indicative of a washout. The hydraulic coefficients for both flow in and flow out are decreasing, and this increases the belief in washout more than the pump failure belief.

Case 2: Twist-Off Example

This is an example of a twist-off in the rotary steerable system (RSS) that happened in Well B, with multiple alerts sent as early as 6.5 hours prior to the twist-off (Table 2). At the time of the alert generation, the system was still in the trial phase, and the alerts were not distributed to the rig personnel. The relevant data trends in the hours preceding the twist-off are shown in Figure 10.

Table 2—Time history of alerts for Well B.

Event	Time
Alert generated	6/27/2017 06:30
Alert generated	6/27/2017 08:20
Alert generated	6/27/2017 13:35
Trip out as communication to RSS was lost	6/27/2017 13:00

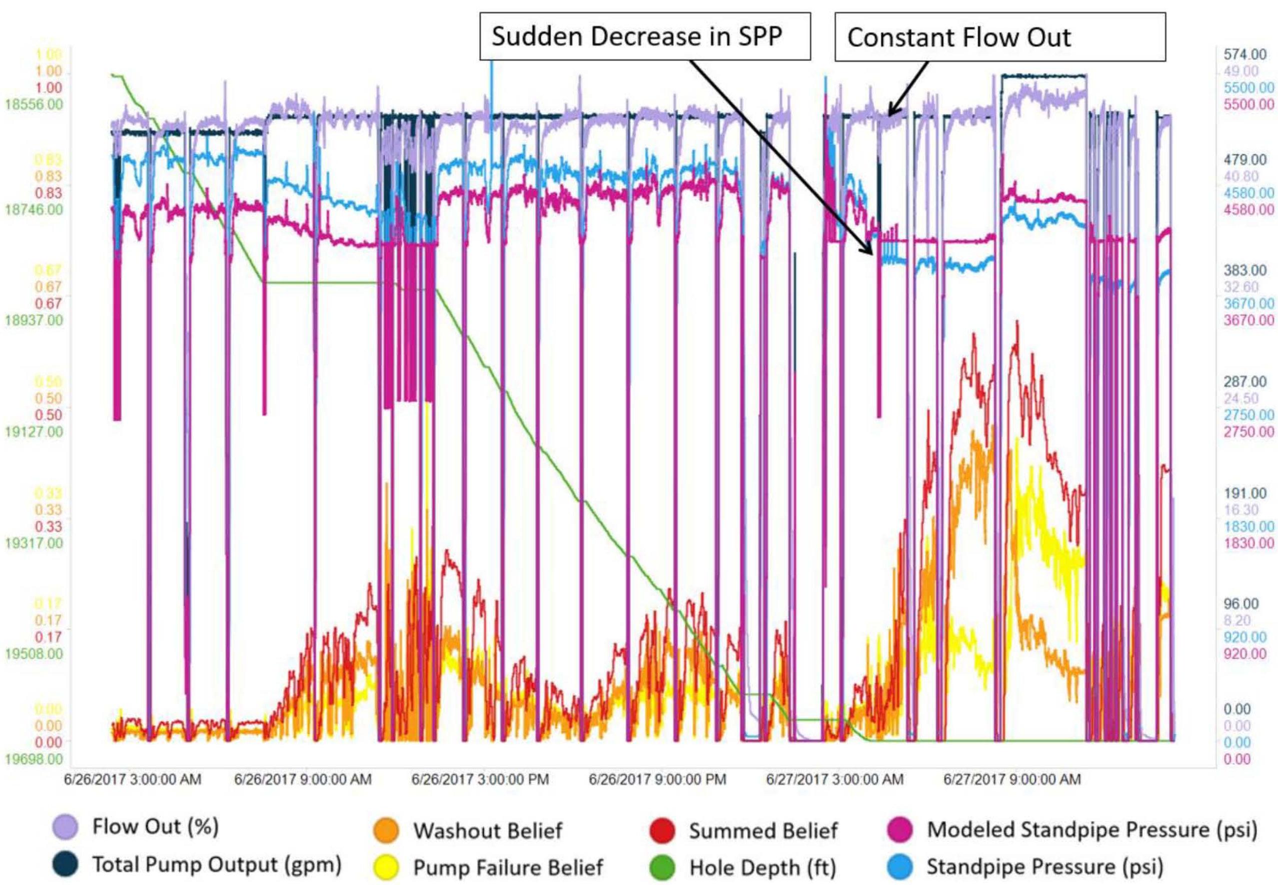

Figure 10—Data recorded prior to Well B twist-off event on 6/27/2017.

Here, a sudden decrease in standpipe pressure with constant flow was automatically detected by the system, generating an alert. This twist-off and the resulting fishing job (4.6 days) resulted in an estimated cost of $300,000. Figure 11 shows the condition of the RSS upon its recovery from the hole.

Figure 11—Twisted-off rotary steerable system from Well B after being recovered from the hole.

Case 3: Pump Failure Example

This case serves to illustrate how the system distinguishes a washout from a pump failure. On this particular well (Well C), there were a mixture of washout and pump related issues as can be seen in Figure 12. Here again the primary indicator is the stand pipe pressure which drops suddenly and unexpectedly. The change in the flow out is very subtle here and shifts from the flow out trend being constant for some time and then decreasing later on. After the washout problem was fixed at 4:30 PM on 07/03, they drilled for the rest of the day. During this time, there are clear indications that the flow out measurement is decreasing in comparison to the flow in (which is based on the calculations of pump strokes per minute), as shown in Figure 13. Note also that the hydraulic coefficient for flow out is constant while the hydraulic coefficient for flow in is decreasing. This results in the pump failure belief going up. Eventually maintenance was required to be performed on the swivel and all three mud pumps as all of them were failing, as indicated by the notes from the daily reporting system.

07/03/2017

00:00	06:00	6.00	Inter 1, Drill, Drill	TIH	PP		5,753	5,753	TIH F/170' T/4200'. Breaking circulation 2 stands out of shoe on the way in. Started seeing drag @ 3700' and continued working pipe down to 4200'. Decision was made that washing down would be fastest way to proceed with least risk of damaging wellbore or string tools.
06:00	11:30	5.50	Inter 1, Drill, Drill	Wash-Ream	PP		5,753	5,753	Wash and Ream F/4200' T/5753'. 765 gpm / 65 rpm.
11:30	13:30	2.00	Inter 1, Drill, Drill	Drilling	PP		5,753	5,875	Drlg. Rotate F/5753' T/5875' made 122' @ 61 fph.
13:30	15:00	1.50	Inter 1, Drill, Drill	Circulating	PN	FP	5,875	5,875	Air out mud pumps due to pressure loss
15:00	16:00	1.00	Inter 1, Drill, Drill	Drilling	PP		5,875	5,969	Drlg. Rotate F/5875' T/5969' made 94' @ 94 fph.
16:00	16:30	0.50	Inter 1, Drill, Drill	PU/LD Pipe	PN	DS	5,969	5,969	Wash out in drill pipe. L/D 2 joints of DP and replace.
16:30	00:00	7.50	Inter 1, Drill, Drill	Drilling	PP		5,969	6,481	Drlg. Rotate F/5969' T/6481' made 512' @ 68.2 fph.

07/04/2017

00:00	02:00	2.00	Inter 1, Drill, Drill	Drilling	PP		6,481	6,543	Drlg. Rotate F/6,481' T/6543' made 62' @ 31 fph.
02:00	04:00	2.00	Inter 1, Drill, Drill	Rig Repair	PN	SWV	6,543	6,543	Swivel packing went out pulled out of hole from 6543' to 6439' and changed out the packing.
04:00	05:00	1.00	Inter 1, Drill, Drill	Rig Repair	PN	FP	6,543	6,543	Pumps aired up. Mix diesel and stearate.
05:00	14:00	9.00	Inter 1, Drill, Drill	Drilling	PP		6,543	7,030	Drlg. Rotate F/6543' T/7030 made 487' @ 54 fph.
14:00	14:30	0.50	Inter 1, Drill, Drill	Rig Repair	PN	MP	7,030	7,030	Work on pulsation dampner on #1 mud pump. Change out gasket and valve on pump #2
14:30	15:30	1.00	Inter 1, Drill, Drill	Drilling	PP		7,030	7,070	Drlg. Rotate F/ 7030 T/ 7070 made 40' @ 40 fph
15:30	19:00	3.50	Inter 1, Drill, Drill	Rig Repair	PN	MP	7,070	7,070	Change out module on pump #3, and pulsation dampner on pump #1
19:00	00:00	5.00	Inter 1, Drill, Drill	Drilling	PP		7,070	7,285	Drlg. Rotate F/ 7070' T / 7285 made 215' @ 43 fph

Figure 12—Notes from the daily reporting system for Well C.

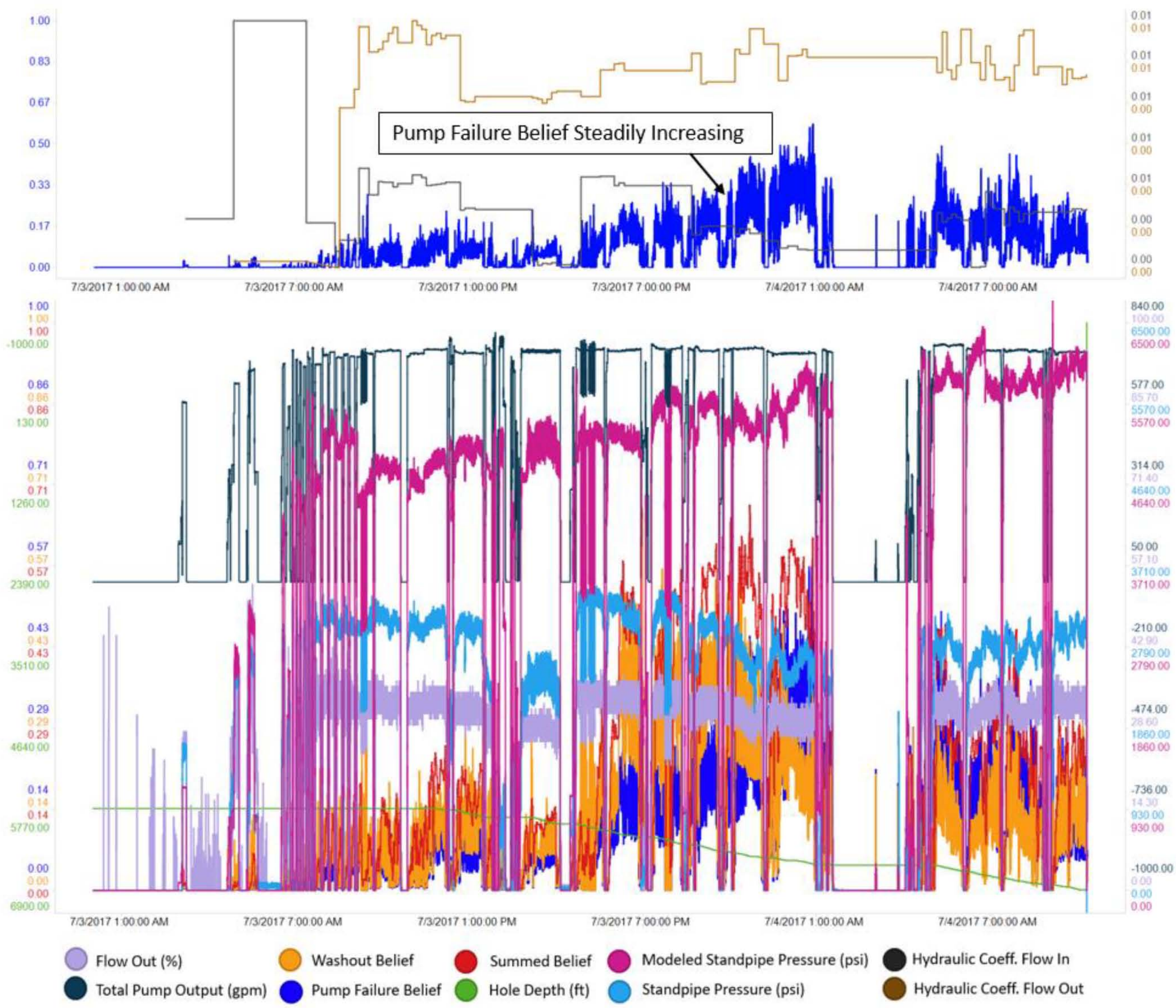

Figure 13—Well C: Example of pump failure detection.

Case 4: Swivel Leakage Example

The system was not particularly built to detect swivel leakage but just as in Case 3, swivel failure is detected here as well. In this particular case (Well D), the sum of the pump failure and washout beliefs hovered around the 0.5 threshold at many instances throughout the day, but missed the criteria for alerting. An alert was sent out at 6:28 PM, which coincided with the pump failure belief increasing significantly (Figure 14). From the notes on the rig, it is observed that the swivel leakage was also detected on the rig around that time (Figure 15).

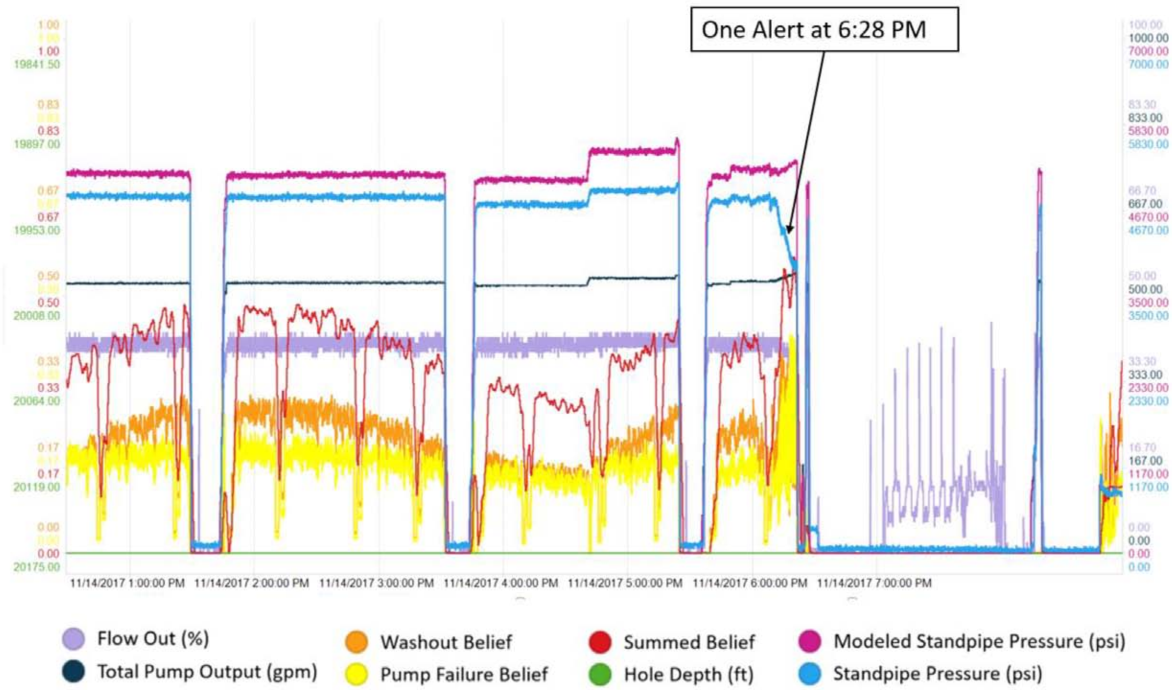

Figure 14—Swivel failure detection on Well D.

00:00	09:30	9.50	Prod 1, Drill, Lateral	Drilling	PP		19,831	20,175	Drill / Slide F/19,831' T/20175', 344' Avg. 36.2 fph. TD well at 09:30 am on 11-14-17 Call OCC office At 14:00 11-14-17 Notified OCC of Plans to Run 5 1/2" pipe & CMT
09:30	10:00	0.50	Prod 1, Drill, Csg Prep	Circulating	PP		20,175	20,175	Cycle Pumps & Take Final Survey.
10:00	19:00	9.00	Prod 1, Drill, Csg Prep	Circulating	PP		20,175	20,175	Circulate Five CUC Pulling Drill String at .8 fpm T/ 19,760'. Swivel Packing Started Leaking.
19:00	20:00	1.00	Prod 1, Drill, Csg Prep	TOOH	PP		20,175	20,175	TOOH on Elevators Wet f/ 19,760' to 18,850'. Tight f/ 18,950' to 18,850'.
20:00	20:30	0.50	Prod 1, Drill, Csg Prep	TIH	PP		20,175	20,175	RIH to 19,040'.
20:30	22:00	1.50	Prod 1, Drill, Csg Prep	Rig Repair	PN	SWV	20,175	20,175	Attempt to Tighten Swivel Packing (no success), R/U Circulating Hose, Change out Swivel Packing.
22:00	00:00	2.00	Prod 1, Drill, Csg Prep	Wash-Ream	PP		20,175	20,175	Backream f/ 19,040' to 18,760'.

Figure 15—Notes from the daily reporting system for Well D.

Case 5: Casing Run False Alert Example

Due to the variety of operating conditions encountered during the drilling process and limited sensor input available, the system is still prone to false alerts. One set of false alarm scenarios correspond to when casing strings are run. The frictional pressure drop in a casing string is significantly reduced compared to what is experienced when a drill string and bit are present. As a result, the hydraulic coefficients and modeled standpipe pressure are more sensitive to changes in flow rate, which may result in signatures similar to those that occur during washout or pump failure events. These alerts can be suppressed, if casing runs can be detected automatically. One potential to reduce these false alerts is to monitor the absolute value of the standpipe pressure in relation to the hole depth and use this additional information to suppress these alerts.

An example of a false alarm generated during a casing run is illustrated in Figure 16. The notes from the daily reporting system (Figure 17) do not mention any unexpected behavior during this time period. Note that washout / pump failure beliefs are also high during the clean-up cycle (06:00 to 08:30 in Figure 16) and as such clean-up cycles can also lead to some false alerts. Automatic detection of clean-up cycles, wash-downs and sweeps can be used to limit the generation of alerts during these times.

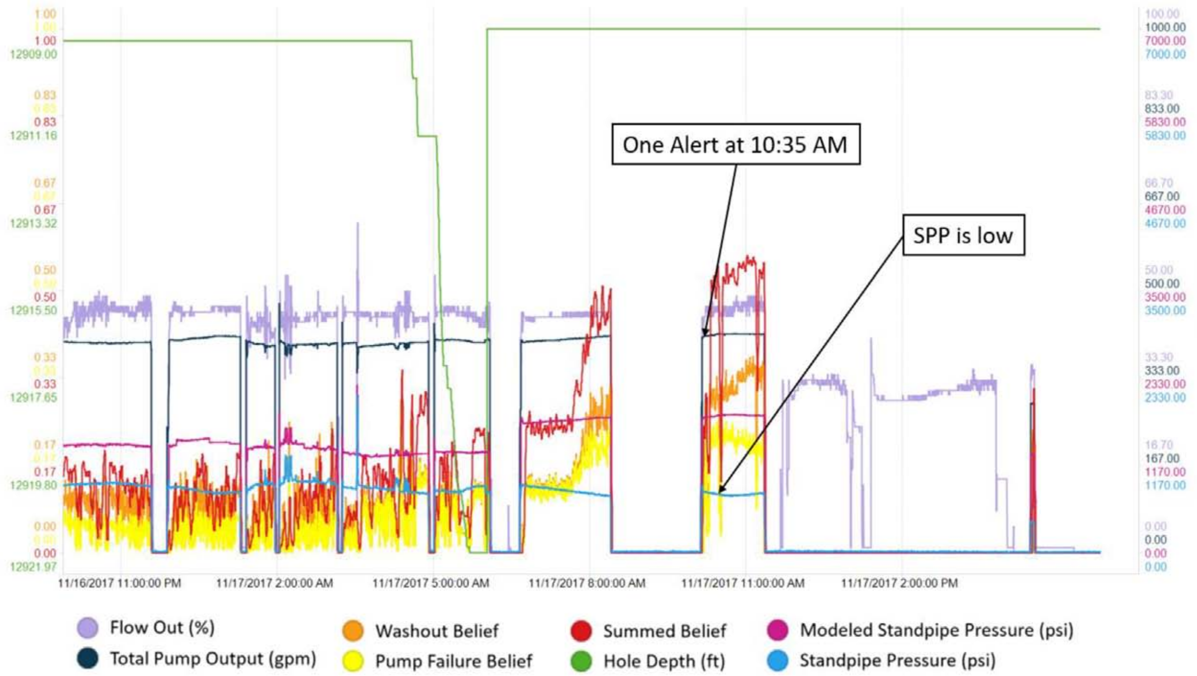

Figure 16—False alert generated during a casing run.

00:00	06:00	6.00	Inter 1, Case, Case	Casing	PP		12,909	12,909	Wash & Ream T/12,909' @ 400 gpm & 10 rpm
06:00	08:30	2.50	Inter 1, Cement, Cement	Circulating	PP		12,909	12,909	Circulate one casing capacity cleanup cycle
08:30	11:00	2.50	Inter 1, Cement, Cement	RU/RD	PP		12,909	12,909	R/D CRT and casing crew
11:00	11:30	0.50	Inter 1, Cement, Cement	Safety Mtg	PP		12,909	12,909	PJSM w/ O-Tex Cement crew and rig crew over R/U procedures and cement job
11:30	12:00	0.50	Inter 1, Cement, Cement	RU/RD	PP		12,909	12,909	R/U O-Tex Cement Crew

Figure 17—Notes from the daily reporting system during the casing run example.

Conclusions and Future Work

The main contributions and learnings from this work are as follows:

- A real-time washout / pump failure detection was developed and implemented across 20 rigs in North America. The system combines a physics based model with machine learning techniques to detect the faults.
- The physics based model used to determine stand pipe pressure, and compare it to actual stand pipe pressure, requires contextual data as input. Due to the fact that there may be inconsistencies in the input to the model, this feature is given a lower weightage in the alert generation process.
- A real-time alerting system was developed. This system sent emails to appropriate personnel with detailed information on the reason the alert was generated. This enabled the user to understand why the alert was generated, and subsequently served as a mechanism to improve the algorithm.

- Since a Bayesian network is at the core of the methodology, learning is enabled by this approach. While some of the parameters in the model may be learned online, currently the detection model is refined through offline learning.
- The detection of pump failure could be strengthened by addition of a reliable flow sensor at the input to the well.
- False alerts get generated during casing runs, wash-downs and sweeps due to the fact the pressure and flow signatures are similar to those that may happen during and prior to washouts and pump failures.

Future work involves reducing false alerts through the automatic identification of casing runs, wash-downs and sweeps. Some possibilities include:

- Using the relatively low stand pipe pressure in relation to hole depth to automatically suppress alerts generated during casing runs.
- Monitoring the transients caused by pump output changes that happen during clean-up cycles to further reduce false alerts.

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