A data-based approach for the prediction of stuck-pipe events in oil drilling operations

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***Abstract*—Stuck-pipe phenomena can have disastrous effects on drilling performance, with outcomes that may range from time delays to loss of expensive machinery. In this work, we develop three indicators based on the mudlog data, which aim to detect three different physical phenomena associated to the insurgence of a sticking. In particular, two indices target respectively the detection of translational and rotational motion issues, while the third index concerns the wellbore pressure. A statistical model that relates these features with the documented stuck-pipe events is then developed using machine learning. The resulting model takes the form of a depth-based map of the risk of incurring into a stuck-pipe, updated in real time. Preliminary experimental results on the available dataset indicate that the use of the proposed model and indicators can help mitigate the stuck-pipe issue.**

***Index Terms*—Oil&Gas, Drilling, Stuck-pipe, Detection, Prediction, Rare events.**

I. Introduction

DRILLING is a costly and complex process that may be slowed down or jeopardized by various adverse events, due to well problems (such as circulation losses, stickings, fluid influx, etc.), rig failures, downhole or surface equipment failures, etc. In particular, the occurrence of sticking (or stuck-pipe) phenomena may ultimately result in catastrophic outcomes entailing pipe breakage, the loss of expensive downhole equipment, and a considerable delay in the drilling operations. A sticking can be caused by various different physical phenomena and occurs when the vertical motion or the rotation of the drilling pipe is impeded. Various actions can be exerted by the operator in an attempt to unblock the Bottom Hole Assembly (BHA), at the cost of a delay in the drilling. In the most unfortunate cases, the BHA cannot be freed and must be abandoned, and the drilling is later resumed along a different trajectory.

The prediction of such events is therefore considered a primary necessity to aid the drilling team in the decision making process, so that appropriate countermeasures can be put in effect before the situation slips out of hand. The problem is very challenging due to the hybrid nature of the drilling process (which consists of different activities), the variability of geological conditions, the combined occurrence of adverse events, and the availability of indirect sources of information regarding the occurrence of stickings in the form of measurements associated to the functioning of surface equipment.

Numerous works have appeared in the recent scientific literature concerning the application of data analysis to tasks related to the drilling process (see *e.g.* [1], [2], [3]). Many works focus on the prediction and optimization of the rate of penetration (ROP) using machine learning methods, see *e.g.* [4], [5], [6], [7]. Others consider the task of predicting the bottom hole pressure, see *e.g.* [8], [9], [10]. In [11] the task of detecting and recognizing a kick is addressed. In [12] a clustering method is employed to recognize anomalies in the mud log data. Finally, some works are concerned with the prediction of stick-slip phenomena, as [13].

In this work we first develop three indicators, associated to different physical phenomena, aimed at recognizing stickings and their precursor events. We then use these indicators (as well as other mudlog raw signals) to learn a statistical model that can anticipate the occurrence of stuck-pipe events. Various data are available for this task, namely timelog data annotated by the drilling operators and mudlog data collecting measurements from the surface equipment. Lithology data are typically available only *a posteriori*, and therefore cannot be exploited for prediction purposes.

Timelog data are crucial in that they contain the operators' assessments regarding all the issues encountered during drilling. The processing of these data provides the ground truth for the detection of the sticking events. Unfortunately, the consistency of these data is sometimes questionable, due to the subjectivity of the operators' evaluations. As a consequence minor or brief sticking problems may not be reported as such, and other well problems may be reported mistakenly as sticking events. Furthermore, the annotations are not precisely aligned in time with the data, as required for the data processing task.

The rest of this paper is organized as follows. Section II provides a brief description of the mudlog variables and analyzes the sticking condition in terms of them. Sections III-V introduce the three indicators, while Section VI provides a brief outline of the statistical model that exploits them to predict the sticking events. Some concluding remarks are given in Section VII.

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II. Data-based characterization of the stuck-pipe conditions

A. Mudlog data description and analysis

The mudlog reports the measurements of several variables related to the drilling process (some variables are actually not measured, but computed from other measurements), sampled every 5 seconds. Various variables related to the drilling depth are available. In this work we consider the following mudlog variables:

- $DBTM$ - bit depth along the drilling direction
- $BPOS$ - position (height) of the traveling block, which supports the drill pipe
- $HKLA$ - (average) tension on the cable from the draw-works (hook load)
- TQA - (average) rotary torque applied to the drill string (taken at the rotary table or at the top drive motor cable)
- $RPMA$ - (average) rotary speed
- $SPMT$ - total pump stroke rate
- $SPPA$ - (average) pressure of the mud on the stand pipe

B. The stuck-pipe condition

A sticking occurs when the drillstring cannot be neither rotated nor moved along the axis of the wellbore. A pipe is considered stuck if it cannot be freed from the hole without damaging the pipe, and without exceeding the drilling rig's maximum allowed hook load. Pipe sticking typically occurs either because of differential pressure issues or by mechanical blocking. In the first case, if the pressure in the annulus exceeds that in the formation being drilled, the drillstring is pulled against the wall and held against it. A relatively low differential pressure applied over a large working area can suffice to stick the pipe. In high-angle and horizontal wells, the gravitational force also plays a role in extending the contact between the drillstring and the formation.

Conversely, the notion of mechanical sticking describes the limiting or prevention of motion of the drillstring for other reasons, *e.g.* the presence of junk in the hole, wellbore geometry anomalies, keyseats[1], the formation of packoff from poor hole-cleaning (the cuttings settle and eventually pack around the drill string), unfavorable properties of the drilled formation.

Early signals of a poor hole-cleaning conditions can be found in an erratic torque (the string is repeatedly getting stuck in the cuttings, wound up and spun free), an unexplained increase in the bottom hole pressure (which may be associated to a tight spot with packings causing flow restrictions further up the annulus), or an unexpected hook load (if the drill string rests on a tight packing the hook load is lower than anticipated) [1]. Preventing stuck-pipes requires a close monitoring of early warning signs, such as increases in torque and drag, excessive cuttings loading, tight spots while tripping, loss of circulation while drilling.

[1] A keyseat is a small-diameter channel worn into the side of a larger diameter wellbore, in which the drillstring may fit too tightly and ultimately get stuck.

In terms of the signals available in the mudlog the following phenomena –though not necessarily all at the same time– are often observed in connection with a sticking event:

1) $BPOS$ presents anomalies with respect to its previous pattern.
2) $DBTM$ is either constant or displays high frequency oscillations of small amplitude (due to the operator's attempt to disengage the stuck drill string).
3) $HKLA$ increases and/or oscillates.
4) $RPMA$ decreases or goes to 0 (it displays downward spikes).
5) TQA increases (and displays upward spikes).
6) $SPPA$ increases (due to the formation of some obstacle to the mud flow).

Not all these phenomena appear together in sticking events, at least to the recollection of the authors, but at least three typical patterns are observed. The first pattern explains the physical phenomenon of the sticking regarding the impairment of motion along the well main axis and is therefore associated to the depth variables: $DBTM$ and $BPOS$ are either constant or have small oscillations, and $HKLA$ oscillates following $BPOS$ (since the pipe is stuck, acting on $BPOS$ reflects directly on the load sensed on the hook). The second pattern is associated with difficulties in the rotational motion of the drill string and is found in drilling/reaming/backreaming operations (rotation must be on): TQA increases abnormally (possibly with spikes) while $RPMA$ falls. Notice that $RPMA$ can also be zero for legitimate reasons (simply because the rotation is set off). At the same time TQA spikes associated to the mounting of stands should be discarded. A third important phenomenon related to sticking regards the pressure balance in the wellbore and involves the pressure and pump flow variables. In particular, unexpected surges in $SPPA$, that are not justified by variations of the mud flow, may indicate the formation of a pack off due to poor hole cleaning, a condition which may degenerate to a sticking.

III. D_{lin}: a sticking indicator based on the $BPOS$ and $HKLA$ signals

During sticking events there are large time portions where the $BPOS$ and $HKLA$ dynamics are extremely well correlated in high frequency (see Figures 1-2). Indeed, if the motion along the borehole axis is impaired and the drillstring is blocked, every pull exerted by moving up the block produces a corresponding increase of the load measured at the hook, and viceversa. On the other hand, when the drillstring is free, the upwards and downwards motions of the block do not significantly affect the hook load.

This behavior of the $BPOS$ and $HKLA$ signals motivates the use of a correlation index for sticking detection and possibly for sticking anticipation, denoted D_{lin} in the following. Indeed, in difficult spots the string may get near to blocking conditions, with analogous results on $BPOS$ and $HKLA$, though to a smaller extent. The intensity and frequency of these events may be used as an anticipatory signal of the sticking.

The high frequency behavior of the $BPOS$ and $HKLA$ signals is captured by taking the differences with respect to

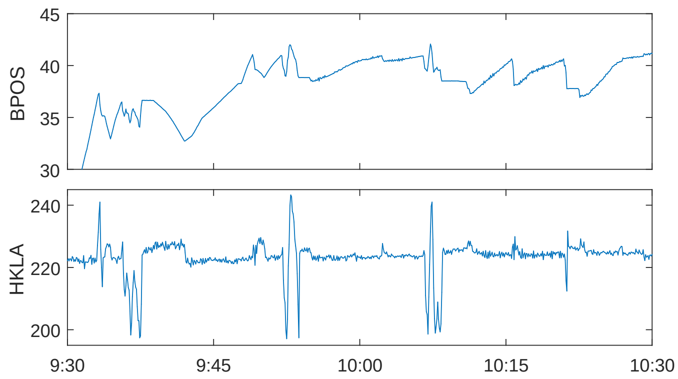

Figure 1. Sticking example 1: detail of the $BPOS$ and $HKLA$ signals.

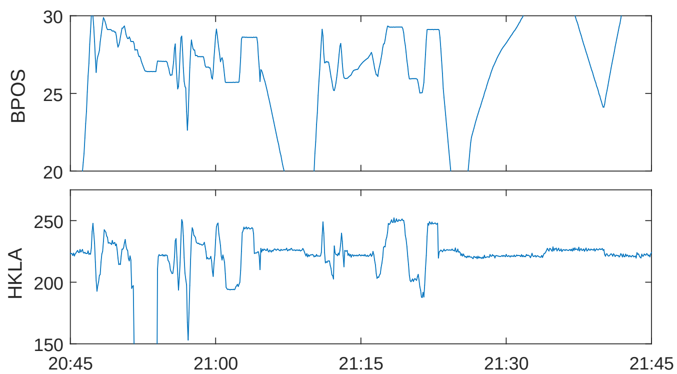

Figure 2. Sticking example 2: detail of the $BPOS$ and $HKLA$ signals.

smoothed version of the same signals obtained by a classical rolling median approach. More precisely, a baseline of each signal is computed with a rolling median with a window of 35 seconds, resulting in $BPOS_{median}$ and $HKLA_{median}$. Then, the high frequency components are computed as the differences between each signal and the respective baseline, yielding $BPOS_{diff} = BPOS_{raw} - BPOS_{median}$ and $HKLA_{diff} = HKLA_{raw} - HKLA_{median}$. Then, the correlation between these two signals is computed with a rolling window approach, *e.g.* over rolling windows of 60 samples (5 minutes). Prior to calculating the correlation, the $HKLA_{diff}$ signal is linearly detrended in the 5 minute window to avoid capturing unwanted low frequency correlations in the correlation index.

The raw correlation signal takes a relatively high value in correspondence to sticking events, but also generates a significant number of spurious events (see Figure 3, bottom). These false alarms are mostly connected with stand change operations (especially during tripping). Various data-based rules can be employed to detect stand changes. Since the drillstring is clamped during a stand change, with a significant reduction of the load perceived at the hook, a conservative simple rule consists in removing the samples associated to a $HKLA$ value less than a given threshold (depending on the length and weight of the drillstring). This removes the data corresponding to stand changes as well as some data portions corresponding to tripping operations, when only a small portion of the drillstring is inserted in the hole. This is not necessarily a problem, given that the initial part of the borehole is cased and no sticking problem is expected to occur inside the casing. For example, in the considered dataset the $HKLA$ is generally over 200 tons, and using a threshold of *e.g.* $HKLA \leq 150$ results in an effective elimination of all the problematic data. A good rule of thumb for the sizing of this threshold would be to use the $HKLA$ value corresponding to the drillstring covering the cased portion of the borehole.

Finally, for ease of interpretation, the correlation values (which range up to 1) can be discretized in various levels of alarm. In the following, we simply discarded all index values lower than 0.25 and issued an alarm otherwise.

In summary, the following steps are required to calculate the D_{lin} index:

1) Filter out stand change operations.
2) Take a rolling median of $BPOS$ and $HKLA$ with a window of 35 seconds.
3) Calculate $BPOS_{diff} = BPOS_{raw} - BPOS_{median}$ and $HKLA_{diff} = HKLA_{raw} - HKLA_{median}$.
4) For each time step k, consider the window from $k-L+1$ to k, where $L = 60$ is the length of the rolling window, and compute the correlation between $BPOS_{diff}$ and a linearly detrended version of $HKLA_{diff}$ over the said window.
5) Set $D_{lin}(k) = 1$ if the previous value is greater than or equal to 0.25, and 0 otherwise.

Figure 3 displays the performance of the D_{lin} on the data of a drilling process with 4 sticking episodes. The pre-filtering operation indeed removes many false alarms, that can be mostly ascribed to stand change operations. The remaining alarms are associated to the documented stickings, and to other minor non-catastrophic events. The latter are often associated with difficult spots encountered during the process, and deemed not sufficiently severe to be reported officially as stickings in the timelog. This indicates that the information provided by D_{lin} could be possibly used as an anticipation for problems in drilling. Notice in particular the frequency of such events just before the fourth sticking, which may be employed to anticipate it.

IV. D_{rot}: A STICKING INDICATOR BASED ON THE TQA AND $RPMA$ SIGNALS

The second physical phenomenon we considered is related to the rotational movement of the drill string. Intuitively, when resistance to rotation is encountered the $RPMA$ signal is expected to drop and at the same time a large value of TQA will be experienced. This phenomenon is emphasized during stickings where rotation can be completely blocked. As done in the previous section, let's take a closer look at the TQA and $RPMA$ signals during sticking events (see Figures 4-5).

As expected in both cases there are various time intervals in which the $RPMA$ signal drops and at the same time there is a surge in TQA, which is otherwise at a relatively low value. Notice that the duration of such time intervals can vary quite a lot: in the first sticking the events are relatively short, while a larger period is observed in the second case around 21:00. Apparently, in this case, the operator applied a sustained rotation to the drillstring to wear out the resistance (indeed,

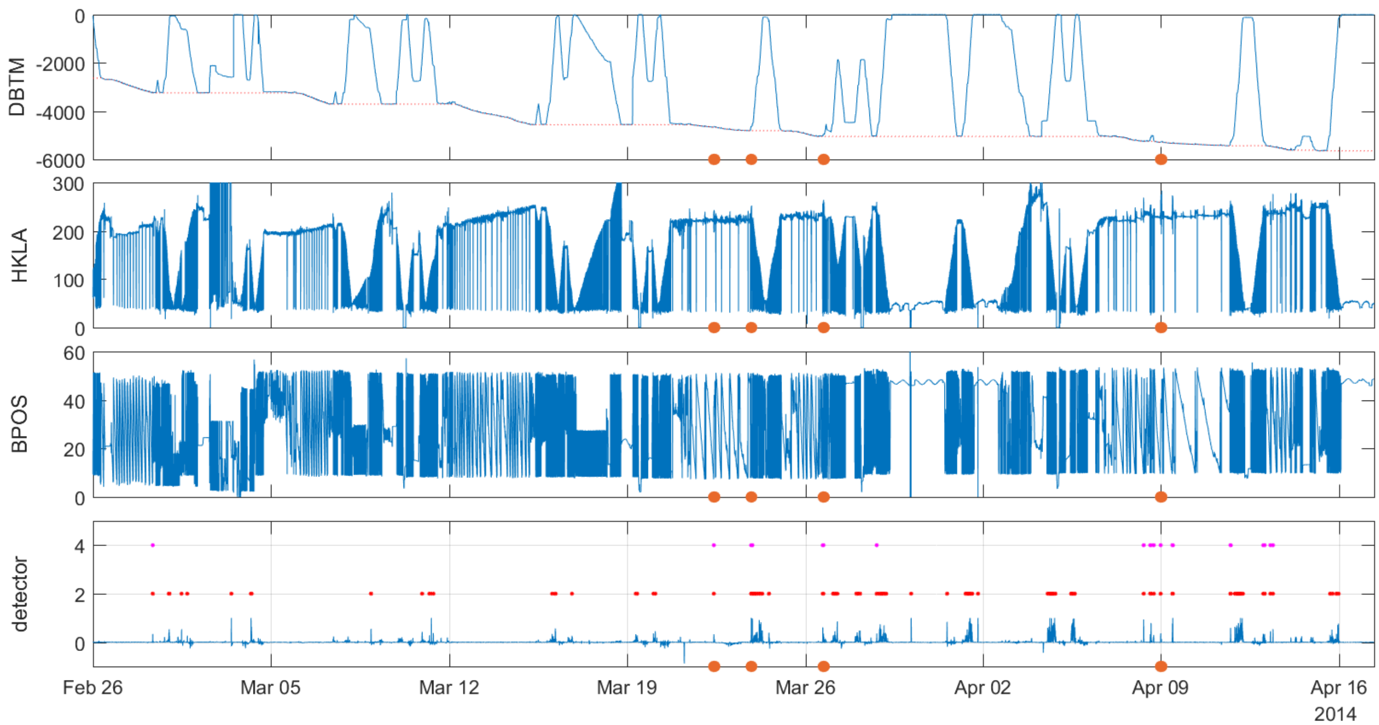

Figure 3. Detector D_{lin} as a function of time. From top to bottom: $DBTM$, $HKLA$, $BPOS$, detector (raw correlation in blue, correlation values higher than 0.25 in red, D_{lin} in magenta). The orange circles identify the locations of the documented stickings.

the TQA slowly drops to lower values). Notice that afterwards (slightly after 21:00) the operator has inserted a delimiter to the maximum torque (see the saturations at 1000).

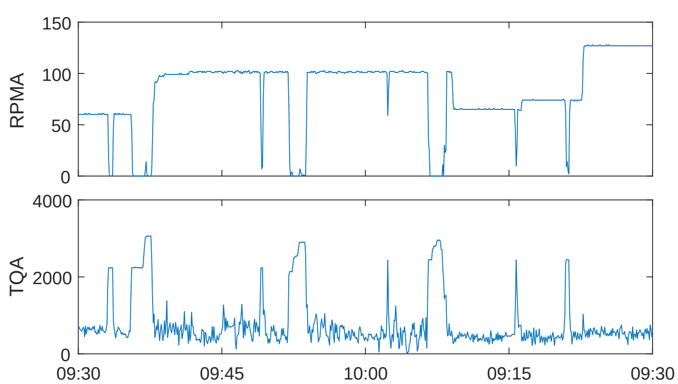

Figure 4. Sticking example 1: detail of the TQA and $RPMA$ signals.

The proposed index, denoted D_{rot} in the sequel, is based on the ratio between TQA and RPMA, which takes large values when the former variable is large while $RPMA$ is small, a typically observed condition in tight spots and stickings[2]. To avoid a division by zero, $RPMA$ is saturated from below by a small positive value. Notice that $RPMA$ can be zero for legitimate reasons as well (when the operator switches off the rotation), but in this case TQA is zero as well (and consequently also D_{rot}). Conversely, the TQA can have large spikes without this representing a problem, as happens during stand changes. For these reasons, as done for D_{lin}, the stand

[2]For appropriate generalization of this index to other well datasets, a normalization is in order for both variables.

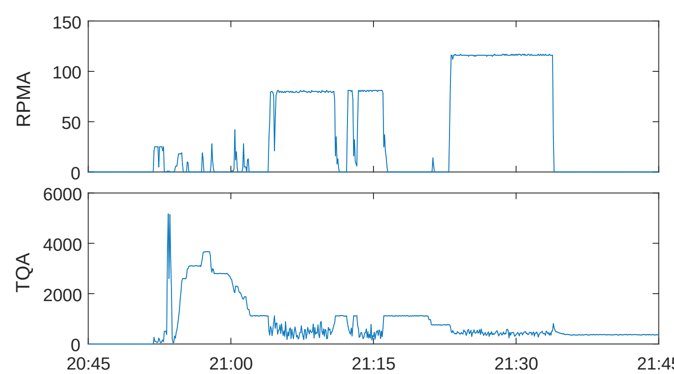

Figure 5. Sticking example 2: detail of the TQA and $RPMA$ signals.

change operations must be removed prior to the calculation of the index. In summary, the processing steps required to calculate the D_{rot} index are listed below:

1) Filter out stand change operations.
2) Calculate the ratio $\frac{TQA(k)}{\max(RPMA(k),1)}$.
3) Count the number samples of the ratio exceeding 1000 over a window of 20 samples (from $k-20+1$ to k) .
4) Set $D_{rot}(k) = 1$ if at the previous count reaches a value of 18 (*i.e.*, 90% of the samples in the previous window exceed the given threshold), and 0 otherwise.

Figure 6 reports the results obtained with the D_{rot} detector. All the documented stickings are captured by the index and a very small number of false positives is generated. Notice that most of the added alarms are in the deepest portion of the borehole (where several problems related to circulation losses are noted as well), well in agreement with the D_{lin} detector.

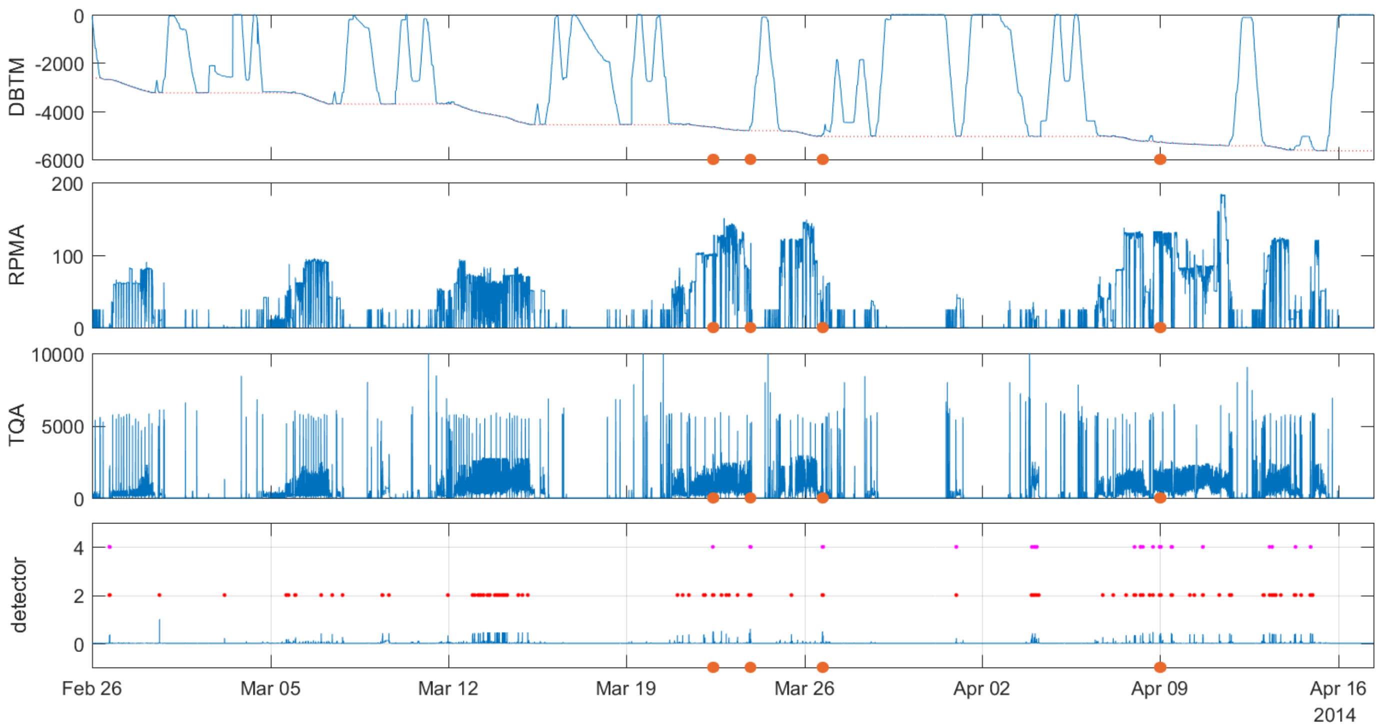

Figure 6. Detector D_{rot} as a function of time. From top to bottom: $DBTM$, $RPMA$, TQA, detector (normalized raw ratio in blue, rolling window count of over-threshold samples in red, D_{rot} in magenta). The orange circles identify the locations of the documented stickings.

V. D_{press}: A STICKING INDICATOR BASED ON THE $SPMT$ AND $SPPA$ SIGNALS

The role of the drilling mud in maintaining the borehole stability (by balancing the pore pressure with its hydrostatic pressure) is crucial in the drilling process. If the hydrostatic pressure of the mud is insufficient a blow out can occur, whereas if it is excessively large it may cause fractures in the formation, with consequent mud losses. Direct monitoring of the mud flow is not practicable in our case, due to the unreliability of the sensors employed for this purpose. Therefore, only the $SPPA$ signal can be used for pressure monitoring.

In this respect, observe that unexpected surges of the standpipe pressure can also be connected to poor cleaning conditions, leading to a formation of a pack off of the cuttings, causing in turn an obstacle to the BHA motion. To establish if an increase in $SPPA$ is instead associated to a deliberate action of the operator, one can check if the total pump stroke rate $SPMT$ is varied throughout the surge.

Accordingly, we define a third index, denoted D_{press}, that evaluates the variability of the $SPPA$ on a rolling window, if $SPMT$ is non zero and practically constant. The index is calculated as follows:

1) Filter out stand change operations.
2) For each sample time k consider the L-sample window from $k-L+1$ to k (*e.g.*, $L = 100$). If the standard deviation of $SPMT$ in the window is sufficiently small (*e.g.*, not greater than 1), and $SPMT$ is not equal to zero (*e.g.*, its mean in the window is greater than 10), then calculate the value of the raw index at k as the standard deviation of $SPPA$ in the window from $k-L+1$ to k. Otherwise, set its value to 0.
3) Calculate the rolling median $SPPA_{rm}$ of $SPPA$ with a window of length L.
4) Issue an alarm ($D_{press}(k) = 1$) if the raw index at k is greater than or equal to 10 and $SPPA(k) > SPPA_{rm}(k)+5$ (*i.e.*, if there is a positive peak of SPPA). Otherwise, $D_{press}(k) = 0$.

Figure 7 shows the performances of the proposed detector D_{press}. Apparently, alarms are issued at the locations of the documented stickings, as well as at other few locations, mostly in the deepest section of the borehole.

VI. PREDICTION MODEL

The three proposed detectors can be used in the post-processing of the drilling data to check the locations of well-bore problems, but –more importantly– can also be employed during drilling to point out both minor and major drilling problems (with an attached direct physical interpretation), the former representing also possible precursors for stickings. In this section we preliminarily discuss the construction of a prediction model based on these detectors.

The basic idea is to use the available drilling data to correlate the detectors (as well as raw mudlog signals) to an alarm signal which is constructed artificially by assigning the largest value in correspondence of each documented sticking, and a progressively lower value going backwards in time and upwards in depth. Indeed, we would like an alarm to be issued (and its level increased) as a sticking is approached, either in time or depth.

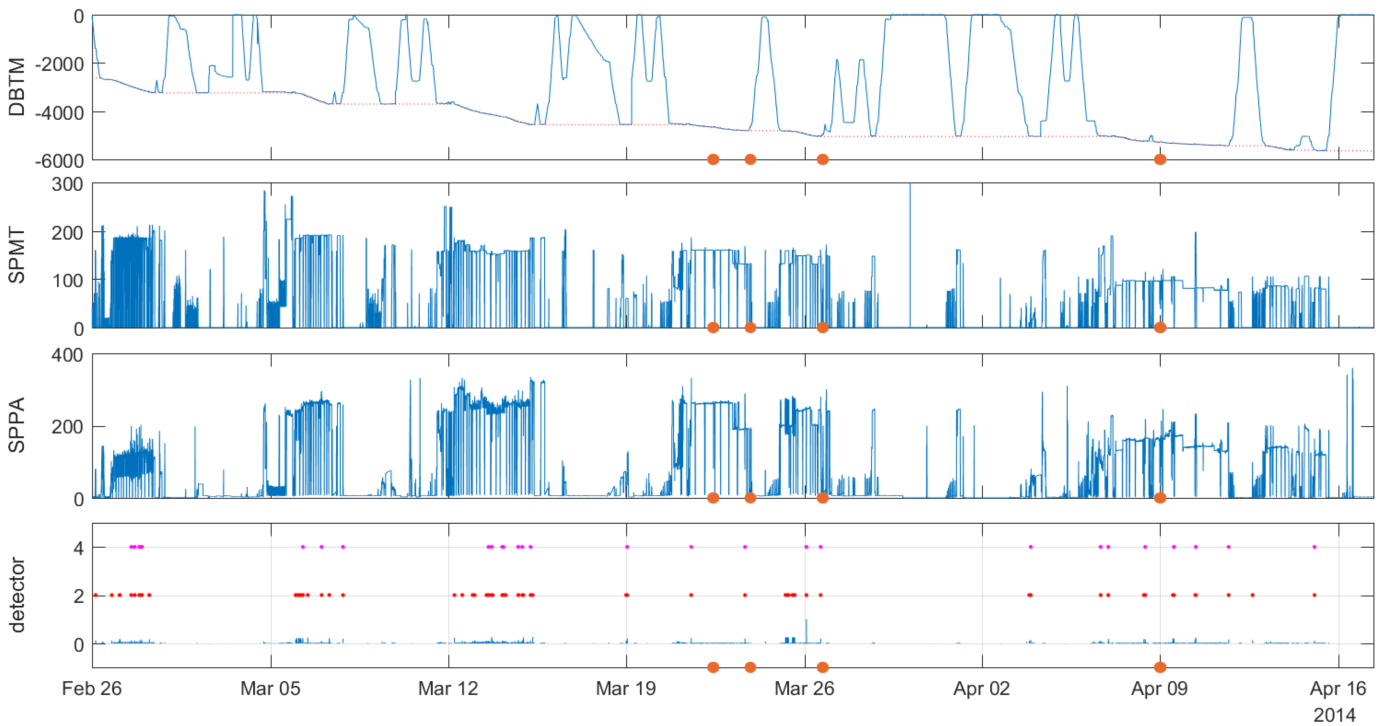

Figure 7. Detector D_{press} as a function of time. From top to bottom: $DBTM$, $SPMT$, $SPPA$, detector (normalized raw ratio in blue, over-threshold samples in red, D_{press} in magenta). The orange circles identify the locations of the documented stickings.

Both input and output data are aggregated in depth-based 4 m bins and averaged, prior to training, to reduce the variability and noise in the data. Then, at each time an input/output variable is characterized by a vector of values (one value for each depth bin), resulting in a tabular structure of the dataset. The data are divided into a training and a test set, the former to be used to train the model, and the second to assess its performance. The model can be trained by employing any standard regression algorithm on the training set. In this study we illustrate the results obtained with the Extra Trees method. Finally, one can obtain the predictions for the test set by applying the obtained model on the set of features at the current depth/time location.

In particular, to test the model performance along a specific phase of the drilling process (between two consecutive casing operations) of a well, we can use as training set all the data pertaining to the other available wells, as well as the data of the previous drilling phases of the same well (obtained before the last casing operation). The results take the form of an alarm vector, which has a value for each depth bin, indicating the alarm level for that depth. Over time the input features at a specific depth change as new data are collected in the same depth bin. Correspondingly, the level of alarm associated to a specific depth bin can increase, because more critical conditions are encountered, or decrease because of the operator's recovery actions (*e.g.*, reaming and backreaming). By monitoring the alarm vector, the operator can ultimately anticipate an impending sticking, and take appropriate action to try and avoid it.

Figure 8 shows a pictorial representation of the outcome of the prediction model taken at three subsequent moments during a drilling phase that ended in a particularly severe stuck-pipe event. As the drilling proceeds, the model (trained on other wells and on the previous phase of the same well) indicates initially a relatively healthy status of the wellbore (left picture), until the 200th bin is reached. Several depth bins are marked with a high level of risk (middle picture). Although the subsequent actions were able to modify only slightly the level of risk of the depth bins in this area, the drilling was resumed (the bit goes further down to the 240th bin) leaving behind a high risk area. This turned out to be a bad choice, as a stuck pipe incident occurred when passing again through that area in tripping out. Specifically, the sticking occurs when the bit is a few bins below the critical region, which is compatible with the position of the largest elements of the drillstring with respect to the bit. By appropriately reworking and consolidating the critical area before resuming the drilling, the sticking could have possibly been avoided.

VII. Conclusion

Three different indicators were designed based on the mud-log data, with the aim of capturing three different physical phenomena associated to the insurgence of a sticking. The first is designed to spot difficulties in the linear motion of the drillstring, whereas the second aims at recognizing rotational issues. The third indicator detects unexpected standpipe pressure surges.

All three indicators provide valuable information both during and after drilling, in the data assessment phase. During drilling operations a careful monitoring of these indicators can emphasize both minor and major drilling issues, and allow the drilling operator to take appropriate actions. An *a posteriori*

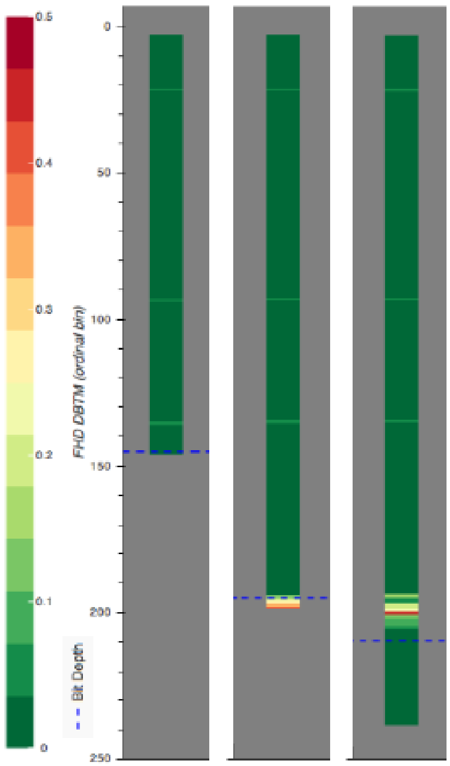

Figure 8. Screenshots of the web application showing the predicted well status of the wellbore at three subsequent timesteps.

inspection can help correct and integrate the manual timelog filled by the drilling crew. This post-processing is particularly useful to provide a reliable ground truth for machine learning models aiming to predict the mentioned drilling problems.

A model was also developed that correlates the three indicators as well as other features extracted from the mudlog data with an artificial target signal, that reproduces an increasing alarm level as a sticking event is approached. The preliminary results indicate that this model can provide useful information to the drilling crew, based on which timely actions can be taken to mitigate and sometimes avoid drilling issues.

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