Leveraging Targeted Machine Learning for Early Warning and Prevention of Stuck Pipe, Tight Holes, Pack Offs, Hole Cleaning Issues and Other Potential Drilling Hazards

Tim S. Robinson, Vlad K. Payrazyan

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Abstract

Stuck pipe and other related drilling hazards are major causes of non-productive time while drilling. Being able to spot early indications of potential drilling risks manually by analyzing drilling parameters in real-time has been a significant challenge for engineers. However, this task can be successfully executed by modern data analytics tools based on machine learning (ML) technologies. The objective of the presented study is to prove and demonstrate the ability of such machine learning algorithms to process and analyze simultaneously a variety of surface drilling data in real-time in order to: a) detect anomalies, that are in most cases invisible to a human eye; and b) provide early warnings of possible upcoming drilling risks with sufficient time in advance, so that the rig crew can execute the appropriate mitigation actions.

The algorithms developed have favorable characteristics, such as adaptiveness to real-time data and agnosticism to well types, BHAs, mud types, lithologies or any other specific well characteristics. This supports out-of-the-box usage, which enables scalability to large numbers of wells. Targeted sub-systems detect the current operation type (tripping, drilling, reaming, etc), and detect symptoms related to differential sticking, hole cleaning issues, mechanical sticking, pack offs, tight holes, obstructions and other risks by analyzing standard surface drilling time logs in real-time, such as hookload, WOB, RPM, bit depth, mud pressure, etc. The ML models and wider risk detection system have been demonstrated to generalize to new wells, and consistently produce high performance across those tested, without any need to pre-train the models on historical data from offset wells.

The system connects to WITSML data stores and outputs warnings with specific information regarding the identified symptom of the potential drilling incident, leaving it up to the rig crew or drilling supervisor to decide how to act on those warnings. The system provides drilling engineers with live warnings on average 1.5-4 hours prior to incidents, giving rig crews enough time to react. This also allows drilling engineers to know in advance a specific source of potential risk, which assists in selecting the right strategy for implementing corrective actions.

The technology's performance was successfully verified in live operations and post-drill studies on historical data on over 300 wells worldwide during the past 2.5 years, with mean recall and precision metrics of 0.986 ± 0.050 and 0.712 ± 0.181 respectively across historical test wells, and significantly reduced occurrence rates of stuck pipe incidents in both onshore and offshore operations. Real case studies for onshore, offshore, conventional and unconventional assets will be presented and discussed.

Introduction

Stuck pipe is a major cause of Non-Productive Time (NPT), with an estimated cost exceeding \$580MM per year for the industry; as reported by Muqeem et al. (2012), stuck pipe can be responsible for 25% of the total cost related to NPT annually. A more recent study showed stuck pipe incidents accounting for approximately 15% of NPT (Alshaikh et al., 2019). Stuck pipe incidents occur in all types of well operations, from tripping/reaming (56%) to drilling steady (14%) and while the drill string is stationary (30%). The main causes of stuck pipe incidents are differential sticking (25%), packed hole (42%) and jammed pipe (20%). In addition to high cost, stuck pipe incidents may also pose risks to health and safety or result in environmental damage. Reducing risks of stuck pipe is a critical cost and safety driver in any well operation.

Since the early 2000s, and especially during the past 10 years, numerous data analytics methodologies, including those labeled as Machine Learning and Artificial Intelligence (ML/AI) have been researched and developed, with varying levels of success. Typically, in most of the published case studies the technology is demonstrated to bring value when it is targeting specific well types, drilled in specific plays, with specific BHA types, etc., with many of these only tested on historical datasets (Al Dushaishi 2021, Alsahaiti 2021, Alzahrani 2022, Brankovic 2021, Elahifar 2022, Elmousalami 2020, Khanh Do 2021, Mopuri 2022, Nautiyal 2022, Singh Saini 2020, Zhu 2022), and very few works reporting on field-tested applications (Bahlany 2021, Salehi 2022). A good analogy would be if doctors had to invent new antibiotics for each and every patient who have the same bacterial infection. The "holy grail' of drilling ML/AI is a technology that can be applied on any well, at any moment, regardless of the well specifications and without needing any preparation work. There are three main challenges that could be immediately addressed by such high-efficiency and versatile technology:

1) Operators/contractors have accumulated an enormous amount of time/depth drilling data and digital well reports, the majority of which is not being used for any data analysis. Lessons learned are not incorporated on a regular basis. The stuck pipe incident occurrence rate for some operators has remained consistent year after year. However, drilling parameters in most cases exhibit symptoms which could be used to address this issue.
2) With a strong growth of drilling activity around the world, companies are facing challenges of hiring experienced and well trained personnel at the rig, resulting in human factors becoming a prominent source of NPT and Invisible Lost Time (ILT). Automated solutions, using Machine Learning, can significantly reduce errors due to human factors and improve reliability and consistency across all wells drilled.
3) Drilling engineers of operators or oilfield services companies lack the time to prepare data, pre-train ML/AI on offset wells or study the underlying techniques/methodologies to properly configure an automated risk detection system. The associated costs may also discourage them from pursuing such initiatives themselves.

The industry is ready for a "mass scale" deployment of ML/AI technology, with the following building blocks already being in place:

1) Data quality is now becoming much better and more standardized. Data pre-processing, clean-up and preparation is still required, however these processes can be automated within the software.
2) Internet connectivity and rig-office real-time communications have been significantly improved, allowing ML to be easily added on top of existing data streaming, monitoring and visualization infrastructure.
3) Sparse but successful ML/AI case studies (as part of general digital transformation initiatives) have demonstrated value and triggered strong interest in the industry, opening the path for full scale development and deployment of ML/AI applications
4) Some companies already have highly suitable (for ML/AI deployment) infrastructure in place, consisting of real-time operations centers (RTOCs) and established decision making and communication processes between RTOC and the rig. Other operators, that don't have RTOCs, have established procedures and work closely with drilling contractors to improve drilling performance. In any case, whether ML/AI is deployed on the operator or contractor side or both, it is ultimately bringing value to operations.

This paper provides case studies and analysis of a stuck pipe risk detection system (SPDS) tested across various geographical regions, fields, well types, drill specs etc., in both historical and live operations, in order to (a) test the generalizability of the methodology; b) verify that the system could detect early risk symptoms and pre-warn engineers of potential hazards with a maximum "heads up" time and minimal of false alarms; and c) automatically analyze and identify the possible cause of detected stuck pipe hazard, such as differential sticking, dynamic friction or hole cleaning, and notify the engineers accordingly, thus allowing them to take appropriate risk-mitigating actions.

Methodology

The risk detection system discussed in this work is made up of sub-components targeted at a variety of common causes of Stuck Pipe, and their associated risk symptoms. These include Differential Sticking, Mechanical Sticking, poor Hole Cleaning, tight spots and restrictions, as well as transient risk symptoms such as unexpected pressure or torque spikes. All the main operations carrying stuck pipe risks are within scope of the system, such as drilling, tripping in or out, circulation, (back)reaming and hole opening. For more information about the functionality of the software, the reader is directed to previously published works, which provide further details on the Differential Sticking (Meor Hashim 2021a), Mechanical Sticking (Bin Othman 2022) and Hole Cleaning (Robinson 2022) risk detection modules, as well as techniques developed to identify rig states and events which contribute to false warnings if undetected, and eliminate them (Robinson 2023). Furthermore, operators have also published articles on their experience of running the software on live operations (Meor Hashim 2020, Meor Hashim 2021b, Meor Hashim 2021c, Rosli 2021, Yusoff 2021).

To develop the system, the authors used data from offshore (deep and shallow water) and onshore wells, located in variety of regions, such as Central and South America, Northern Europe, West Africa, Central Asia and South East Asia. These included a mixture of vertical and deviated wells, different section sizes and downhole drive types, such as Positive Displacement Motors and Rotary Steerable Systems. Wells used in the training datasets were not included in the validation datasets, which used a set of independent wells. This more closely replicates the difference between using a system in production compared to historical benchmarking, and is a better test for generalizability than using a different training/validation data splitting scheme. Strong performance at this stage was a prerequisite for progressing to the testing and case studies explored in this work. A new and distinct set of wells, many located in North America, South America, Southeast Asia and the Middle East, was analyzed for the case studies presented in this article, which again had not been used for training the SPDS's underlying models at the time of testing. Hence, this work is only concerned with cases that can indicate whether or not the software is well-suited to generalization and out-of-the-box usage.

Several types of test were used for performance validation, each fulfilling a particular purpose for demonstrating the system's effectiveness at identifying stuck pipe risks and assisting operators to mitigate these, resulting in fewer incidents and less non-productive time. These testing methods were

(1) tests on data from historical wells to verify whether the SPDS generates valid early warnings prior to known stuck pipe incidents;
(2) *blind* tests on historical data where information on whether an incident occurred or not was unknown to the tester;
(3) live field tests to verify risks are detected in real-time, communicable to monitoring engineers and compatible with operational workflows and practices;
(4) analysis of larger samples of wells, with and without the SPDS running, for evidence of a change in the occurrence rate of stuck pipe incidents between the sample groups.

General historical tests with known incidents

Testing on historical data was used to demonstrate that stuck pipe risk symptoms could be detected ahead of recorded restrictions or incidents in the test wells. Efforts were made to conduct these tests by running the SPDS with its standard configuration, without repeat runs using tuned configurations to suit the now-known stuck pipe scenarios. As a result, a few of the test wells were analyzed using an older version of the software, which lacked certain upgrades designed to reduce false warnings and detect transient (short-timescale) Mechanical Sticking risk symptoms.

Contrary to in live-testing, software-generated warnings based on historical data obviously have no operational impact, allowing risk detection capabilities to be assessed without warnings having any causal effects on observed outcomes, which would complicate analysis. In live-tests, rig crews can take action based on warnings raised and mitigate potential issues; indeed, in the ideal case, all risks would be detected and mitigated, making it difficult to estimate statistics such as recall, precision, or other commonly used metrics for classification problems, which are useful for historical tests. Recall is defined as the proportion of the total "positive" (stuck pipe risk) events correctly identified by a classifier, whereas precision is defined as the proportion of "positive" classifications which actually correspond to "positive" values in the dataset.

Note that in some cases risks may also have been identified and mitigated by monitoring specialists and/or rig-based staff; these are also useful to consider, as they provide insight into how early symptoms can be detected by software compared to trained humans. In cases where incidents did occur with no sign of interventions in the historical well data, the working assumption is that operational teams were not able to identify the risk symptoms. Hence, for performance analysis purposes, warnings coinciding with or prior to an intervention by operational teams, or prior to an observed stuck pipe incident or restriction regardless of interventions, are considered valid. While one cannot conclude with certainty that a given historical incident would have been prevented had warnings been raised, the system's capability to provide early warnings for as many incidents as possible (high recall) can be confirmed, and that false warnings are within an acceptable limit (high precision, low false positive rates). In real operations, there is a time and attention cost to monitoring engineers associated with false warnings, hence these should be minimized as much as possible for practicality, while maintaining high recall values. Typically, multiple warnings are raised prior to a particular stuck pipe risk or incident. Recall was thus calculated based on whether or not a specific risk or incident was identified by the software, whereas precision was calculated in the usual way based on all warnings raised, following validation of alerts by a drilling engineer. Calculating recall on an incident basis is preferred, as counting all valid warnings prior to incidents can distort the values (particularly if many warnings are raised in a few cases), possibly resulting in overestimated performance.

In certain historical test wells, there may have been no stuck pipe-related incidents or symptoms, and very small numbers of warnings raised. In these cases, recall cannot be calculated (zero divided by zero) and precision is also misleading; for example, if just one false warning is raised over a 10 day period with no incidents, the system's precision at stuck pipe risk identification as evaluated on that dataset would still be zero, which would distort precision statistics averaged across wells. Hence, a more intuitive way to assess the prevalence of false warnings is to calculate an average daily rate of false warnings over the full span of the well, which better reflects the potential time cost to monitoring engineers; this is presented alongside other metrics in the next section.

Blind tests on historical data

An improved method for using historical data to test the efficacy of the SPDS, and its ability to generalize to new scenarios, is to conduct *blind tests* on wells not included in the datasets originally used to develop and validate the system. For blind tests, an operator would provide data from several wells, where the data intervals provided would be cut-off at a time before the end of the well. In some cases, but not all, a stuck pipe incident had occurred on the wells some time shortly after the cut-off point, usually within 2 hours. While the authors were conducting the test, the operators withheld this information, and only confirmed which wells had incidents after completing the analysis and presenting the results. This is a superior testing method compared to generic tests on historical data, as it removes the ability of the tester to repeatedly run the test with slightly different configuration parameters until some notionally "correct" outcome is obtained. Hence, blind tests provide more objective insights into how well the SPDS performs on new wells, and more closely replicate how such software systems would be used in real operations, compared to generic tests on historic data. Many of the blind test wells were located in fields and regions from which no data had been used to develop the risk detection system at the time of testing. However, the exact number of wells in this category cannot be confirmed, as the companies providing the data did not always provide information on well locations.

Live field tests

Field tests on multiple live operations were also conducted as part of the system validation and performance benchmarking exercise. The field tests presented in this work included two key components. Firstly, analysis of specific interesting stuck pipe risk scenarios from the live wells was conducted; these were intended to illustrate in more detail how monitoring engineers were able to consume the notifications generated by the software, and act accordingly to mitigate an identified risk. In the cases presented, additional information not captured in the rea-time data feeds was obtained from discussions with the operators which helped to confirm the validity of warnings raised, such as the presence of excessive cuttings at the shakers, or a particular depth range in the well which had been previously (and separately) linked to higher risk of stuck pipe.

Analysis of effects of running live risk detection software on larger groups of wells

While specific cases from live operations where monitoring engineers were able to use the software's outputs to make interventions are noteworthy, they are not sufficient on their own to demonstrate the software's efficacy for stuck pipe prevention when integrated with an operator's wider portfolio of assets. Given that an intervention was made, and it is not possible to assess what would have happened had monitoring staff not intervened, experience obtained from a selected few wells is not a sufficiently strong indicator of the system's performance. Therefore, a larger sample of wells drilled with and without the software was considered to assess whether it had a measurable effect on the occurrence rates of stuck pipe incidents encountered by the operator, as observed in the treatment (software used) and control (software not used) groups.

In live operations, the SPDS was deployed to cloud servers, and integrated with operators' remote WITSML data stores. An operational overview is provided in Figure 1. Data was read from the remote stores, processed by the SPDS, and outputs written back to the data stores in the form of dedicated WITSML logs and curves linked to specific wellbores, which could be displayed using standard commercial WITSML viewers used by the operators. Monitoring specialists based in remote offices or RTOCs were then able to consume the outputs of the SPDS in the form of risk notifications and other quantitative information concerning the drilling parameters. Upon being notified of stuck pipe risks, monitoring engineers were responsible for notifying the rig-site crew, according to the operators' communication protocols, which typically vary from company to company.

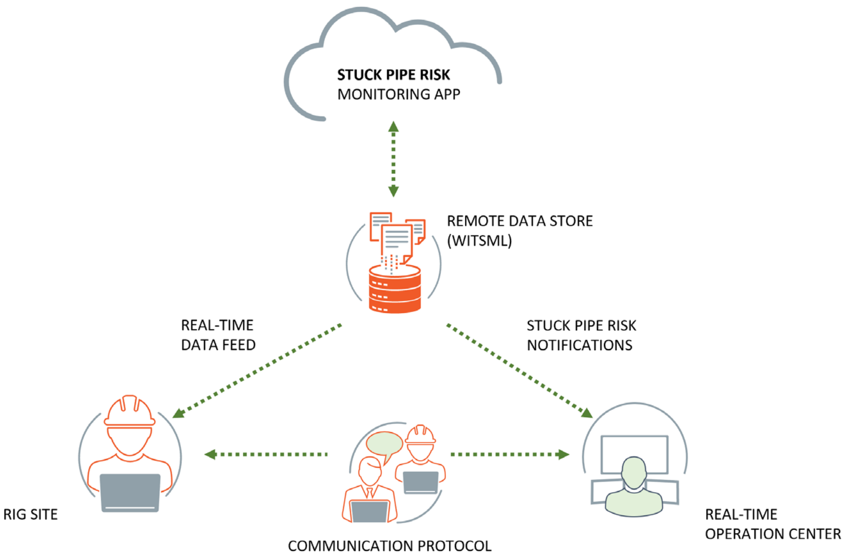

Figure 1: Simplified overview of how the software is deployed and used by monitoring engineers in operations.

Results and Discussion

Tests on historical datasets

The performance of the SPDS evaluated on 26 historical wells is summarized in Table 1. A high proportion of the 64 stuck pipe-related issues (95%) present in the dataset had relevant early warnings generated based on identified risk symptoms, resulting a mean recall of 0.986 ± 0.050, averaging the individual recall values from all wells. To the best of the authors' knowledge, the majority of these wells were located in fields from which no data was used to initially develop, configure and validate the detection system's underlying models and algorithmic detectors, although not all well locations were known. Four wells were not included in the calculations of mean recall and mean precision (averaged across the wells), as these had no incidents recorded within their data.

Table 1: Summary statistics from general tests on historical data from wells not included in the datasets used for developing and validating the stuck pipe risk detection system. Averages were calculated across all wells in the dataset, and standard deviations or interquartile ranges are provided as dispersion metrics for mean or median values respectively.

Number of test wells	26
Number of incidents in dataset	64
Number of incidents detected	61 (95% of all incidents)
Mean warning time horizon (hours)	3.86 ± 3.22
Mean Recall	0.986 ± 0.050
Mean Precision	0.712 ± 0.181
Median warning count per day (all warnings)	3.5
Interquartile range, warning count per day (all warnings)	5.2
Median false warning count per day	1.0
Interquartile range, false warning count per day	0.8

To complement the summary statistics in Table 1, the distributions of precision, average warnings issued per day (total and false-only) are shown in Figure 2 for the set of historical test wells. The precision distribution in Figure 2(a) is skewed, with a majority of wells with precision values greater than 0.7, and a tail containing a small number of well with lower precisions, and higher false warning rates; some of these correspond to wells with small numbers of warnings in total. In all but two of the wells, fewer than two false warnings were issued per day of data, on average across the full time interval of the well, as can be seen in Figure 2(c). These two outliers correspond to tests conducted using an older version of the stuck pipe risk detection software that did not include the modules for suppressing false warnings described by Robinson et al. (2023), hence higher false warning rates were recorded in these cases (lower precisions), as well as more warnings in general. The distribution of total warnings issued from tests on each well is also provided in Figure 2(b) for comparison. At an average rate of fewer than 2 false warnings per 24 hour period, the number of false warnings that would be issued to monitoring specialists was within manageable limits, although attempts should be made to reduce this rate as much as possible via system upgrades.

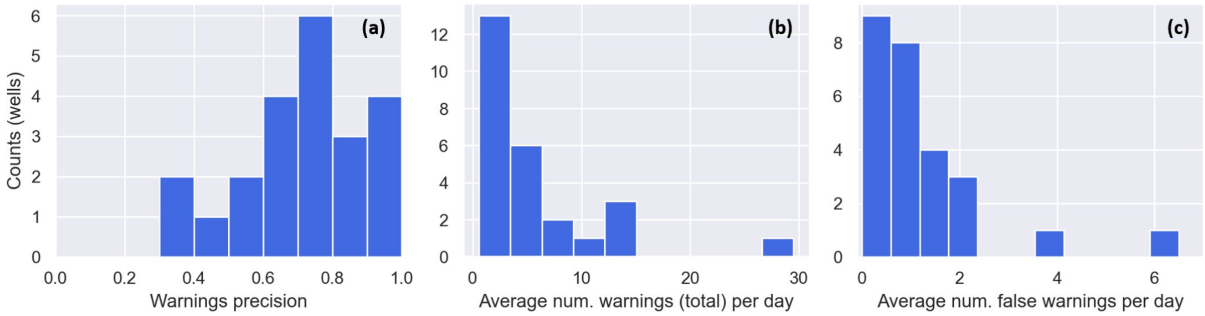

Figure 2: Distributions of key summary metrics provided in Table 1, demonstrating how (a) precision, (b) average count of warnings per day, and (c) average count of false warnings per day, vary across the test wells.

The aforementioned historical test results collectively provide an indication that the risk detection system is suitable for general, out-of-the-box usage on new wells. However, it should be noted that not every stuck pipe incident can prevented, which highlights the importance of the role of human factors, rig-site to RTOC communications and organizational practices in acting on the stuck pipe risk warnings when notified. Also, certain incident types cannot be detected ahead of time due to their sudden nature, such as severe collapses of material into wellbore from wellbore walls, however these types of incidents are typically rare, and tend to occur within particular formation types, namely fractured and unconsolidated with poor structural integrity.

Two example cases from the historical wells analyzed which faced stuck pipe issues are provided in Figure 3 and Figure 4. The first scenario, from a well in the Eagle Ford formation, encountered mechanical sticking issues while pulling out of hole, shown in Figure 3, visualized using a commercial WITSML viewer. In this case, the pipe was stuck for approximately 5 hours after the time interval displayed, with the beginning of the stuck issue shown at the end of the sample interval. A static friction warning and two mechanical sticking symptoms were flagged in the early part (~08:00), prior to a restriction around 08:40, from which further mechanical sticking symptoms were highlighted. After working the drillstring free and pulling out further (without rotation or circulation), more mechanical sticking warnings were issued approximately 20 minutes before getting stuck at around 09:50.

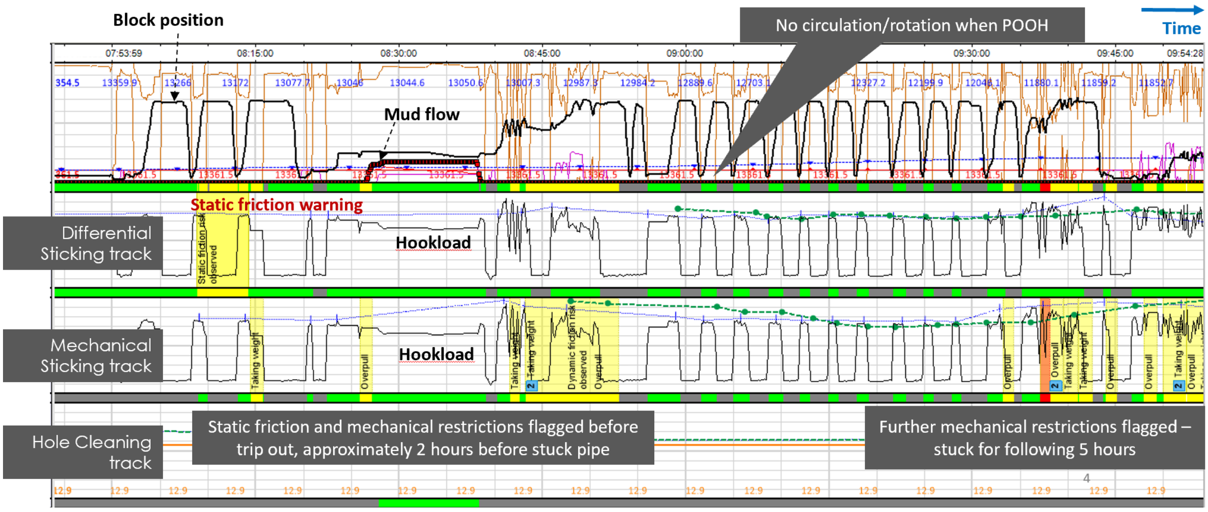

Figure 3: Example test scenario from historical data with mechanical restrictions visible in the hookload measurements while tripping. Historical surface data from the operation and the stuck pipe risk outputs are visualized in a commercial WITSML viewer. Several warnings were raised by the software in advance of the stuck pipe event occurring at the end of this interval.

The second scenario was observed in data from an unconventional well in the Middle East, with possible Differential Sticking and mechanical issues while running in casing shown in Figure 4. Here, several symptoms of drag were identified by the Differential Sticking agent prior to the area where the casing needed to be worked down, starting approximately two hours before. Two mechanical sticking warnings were also flagged when the restriction was encountered.

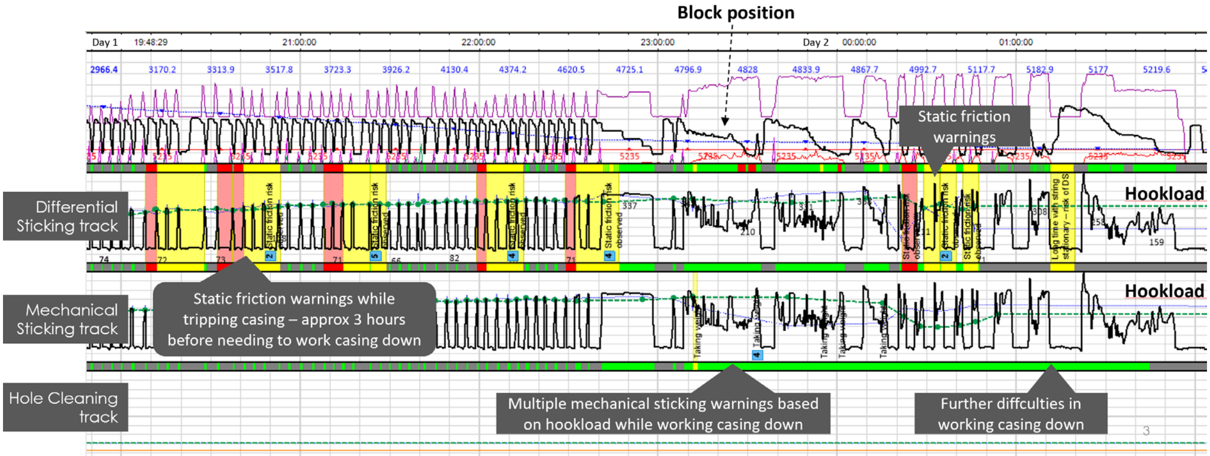

Figure 4: Example test scenario from historical data with static friction warnings (differential sticking risk) and mechanical restriction symptoms visible in the hookload measurements while running in casing prior to a period with restrictions. Historical surface data from the operation and the stuck pipe risk outputs are visualized in a commercial WITSML viewer.

Blind tests on historical data

The stuck pipe detection software's performance in historical blind testing is summarized in Table 2. All 10 wells where warnings were raised prior to the end of the well data intervals were confirmed by the relevant operators to have experienced a stuck pipe incident a short time after the cut-off point. Furthermore, warnings were not observed before the data cut-offs in the 4 wells which were not followed by incidents. By definition, the software had not been exposed to any of the 14 blind test wells prior to this analysis, and in the majority of cases (the locations of some test wells were unknown), nor had it been exposed to wells from the specific regions or formations the test wells were drilled in. Warnings were analyzed by a drilling engineer to either validate them or label as "false".

Table 2: Summary statistics relating to the software's performance on historical blind tests. Warning time horizons were defined relative to the ends of blind test data intervals provided by operators.

Number of wells blind-tested	14
Number of wells followed by stuck pipe incidents	10
Number of incidents pre-warned at least 1 hour before data cut-off	10
Mean false warning count per 24 h	< 2

These positive summary metrics demonstrate the software's capability to generalize to new wells, fields, and regions while maintaining high performance at detecting symptoms and risks pertaining to Stuck Pipe. An example screenshot of data from the latter part of a blind test well, visualized in a commercial WITSML viewer, is shown in Figure 5. In this well, an unconventional well drilled in the Haynesville formation (East Texas), the software generated mechanical sticking risk warnings with increasing frequency and severity (yellow vs orange) while tripping out, and approaching the cut-off point in the data provided by the operator. This indicated increasing drag during dynamic conditions, and is a good example of risk symptoms starting to appear several hours in advance of an incident. The operator confirmed that a stuck pipe incident occurred after the data's cut-off point.

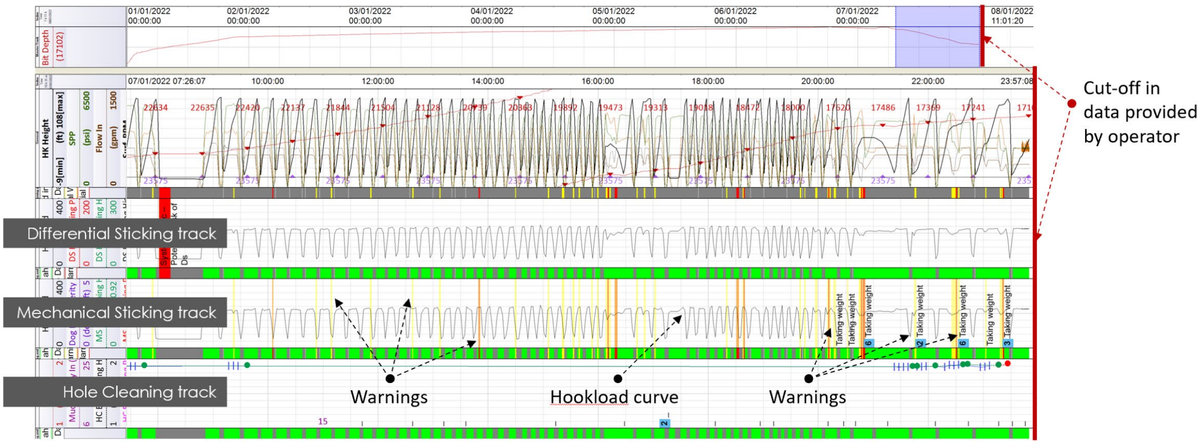

Figure 5: A blind test data interval visualized using a commercial WITSML viewer. Mechanical sticking warnings are raised with increasing frequency and severity over the displayed interval. Orange warnings indicate a higher risk severity than yellow warnings. After the cut-off in the data at the end of the interval, a stuck pipe incident occurred.

A second example from a blind-test well, with a stuck pipe incident confirmed to have taken place by the operator after the cut-off in data, is shown in Figure 6. Several Differential Sticking warnings, based on monitoring and forecasting static friction characteristics over several stands, were raised during the approximately ten hour interval before the end of the available data, and can be seen in track 2 of 4. Furthermore, multiple Mechanical Sticking alerts were issued in the last two hours while tripping out, indicating restrictions to linear motion. Finally, two hole cleaning warnings, based on downhole Equivalent Circulation Density (ECD) estimates, were issued while reaming. This combination of hole cleaning warnings, and both high dynamic and static drag, was consistent with a pack-off scenario.

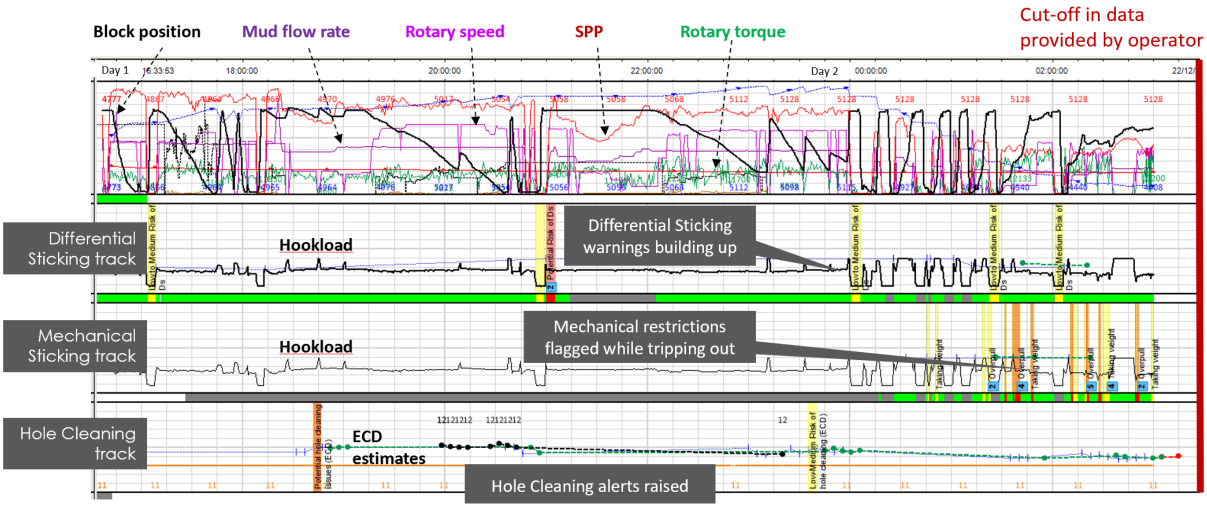

Figure 6: Screenshot from the final time interval of a blind test well, where the operator confirmed that a stuck pipe incident occurred within an hour of the cut-off in the data.

Field testing on live operations

The following section reviews field test cases where the stuck pipe risk detection software was actively used in live operations, with three example scenarios discussed. In all cases, the tests were conducted with operators with wells located in fields which the risk detection system had not been previously exposed to via training or validation datasets. The objectives of these tests were to verify the system's efficacy on live operations, in terms of identifying risk symptoms, testing capability to generalize to new wells and fields, as well as verifying that it could be integrated with, and complement, the operators' existing processes and IT infrastructure.

A live field test scenario from a well drilled in South America is shown in Figure 7. While tripping in hole, the operator's remote monitoring engineers observed Differential Sticking risk warnings on approaching a depth range where some restrictions had previously been encountered in offset wells; note that this information was unknown to the software. This is consistent with Differential Sticking risks usually being closely linked to formation types. Approximately 30 minutes after the first warning, some resistance to translational motion was encountered, prompting the monitoring engineers to intervene and advise corrective actions to the rig crew. After following the recommendations to ream and then move through with pipe rotation and circulation, the risk area was passed without incident.

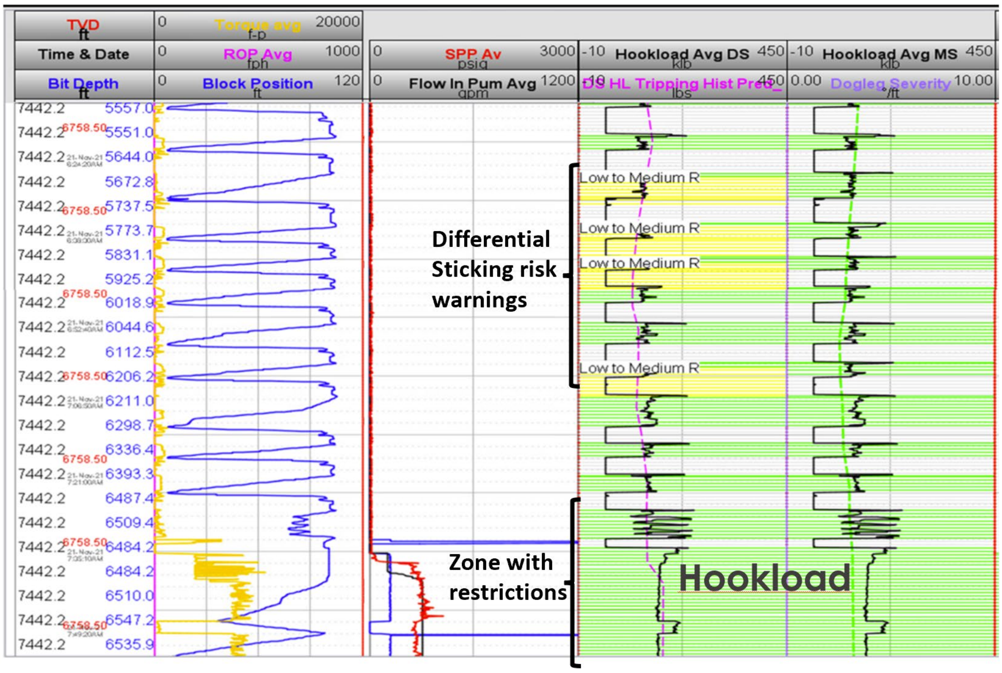

Figure 7: Example annotated screenshot taken from a live operation in South America where the operator's monitoring engineers observed stuck pipe risk warnings (Differential Sticking) while tripping prior to a risk zone, and advised corrective actions to the rig. After following recommendations to ream and move through with pipe rotation, the risk zone was passed without incident. Data is visualized in a 3rd party commercial WITSML viewer.

Another example from a live operation, where software-generated alerts prompted an intervention to be made successfully, is presented in Figure 8, which visualizes the observed well data in a different commercial WITSML viewer. This scenario was observed during field tests on a conventional offshore well located in Southeast Asia. While reaming, several Hole Cleaning warnings were raised based on the estimated downhole ECD and its forecasted values in the near-future; these alerts are indicated by the shaded area and message texts in the figure.

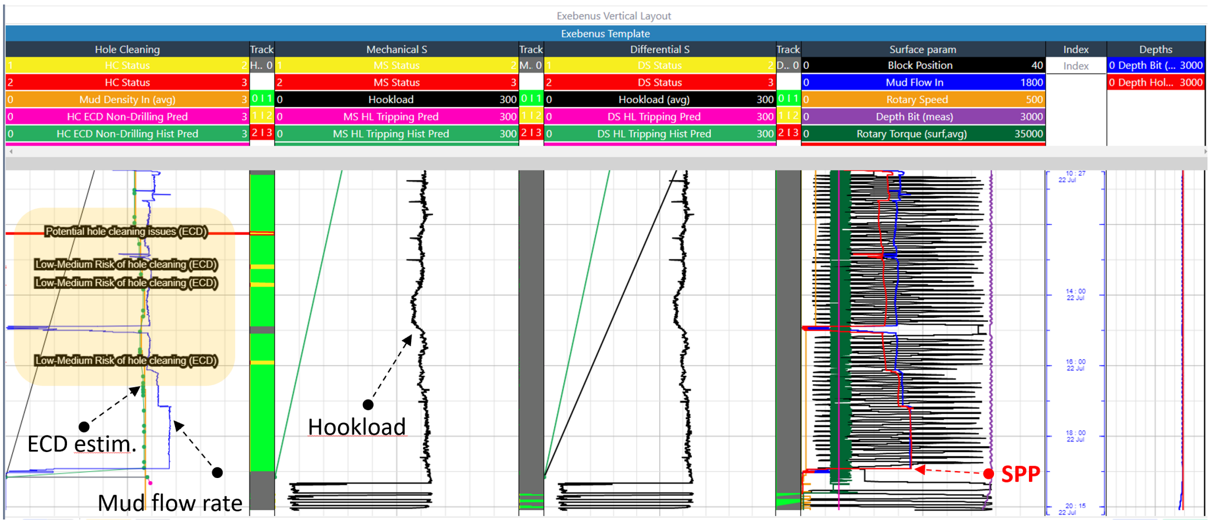

Figure 8: Example case from a live field test on a conventional offshore well, where Hole Cleaning risk warnings were raised (leftmost track, in shaded area) The vertical position of the alert text corresponds to the notification time. Curves for estimated ECD, mud flow rate, standpipe pressure and hookload have been annotated. The drilling data is visualized in a third party commercial WITSML viewer. Upon notifying the rig site, the shakers were checked and excessive cuttings were observed in the returns, which prompted remedial actions to be taken.

Upon receiving these alerts, the monitoring engineer notified the Drilling Supervisor of the potential hole cleaning risk. This prompted the rig-based crew to check the shakers, where they observed excessive cuttings in the returns; based on this, it was decided that actions would be taken to mitigate the risk identified by the software. After circulating bottoms-up and increasing the mud weight, the downhole ECD estimates were observed to stabilize, and no further hole cleaning warnings were raised during this interval, as well as no pack-off incident.

A final live field-test scenario, from an offshore well in the North Sea, is presented in Figure 9. Here, hole cleaning warnings were raised based on an increasing trend in the system's estimated ECD values, shown by the green dotted line in the lower track. These estimates were independently confirmed by the downhole ECD measurements, which are not used by the SPDS, but can provide a useful reference for assessing the detection system's ML model for estimating ECD. Of note, pack-off tendencies were recorded by the mud loggers during this time interval, which adds further evidence validating the software's outputs. Some spikes in rotary torque were also observed during this time period, suggesting increased resistance to rotation, consistent with a pack-off. Warnings were generated by the Hole Cleaning module approximately 1 hour before the first observation of pack-off tendencies by the mud loggers, with a second warning raised approximately 30 minutes later. Following this, the ECD stabilized, as can be seen in the central time interval of Figure 9, before the third visible warning was raised, coinciding with observation of some ECD fluctuations and additional notes regarding a pack-off situation.

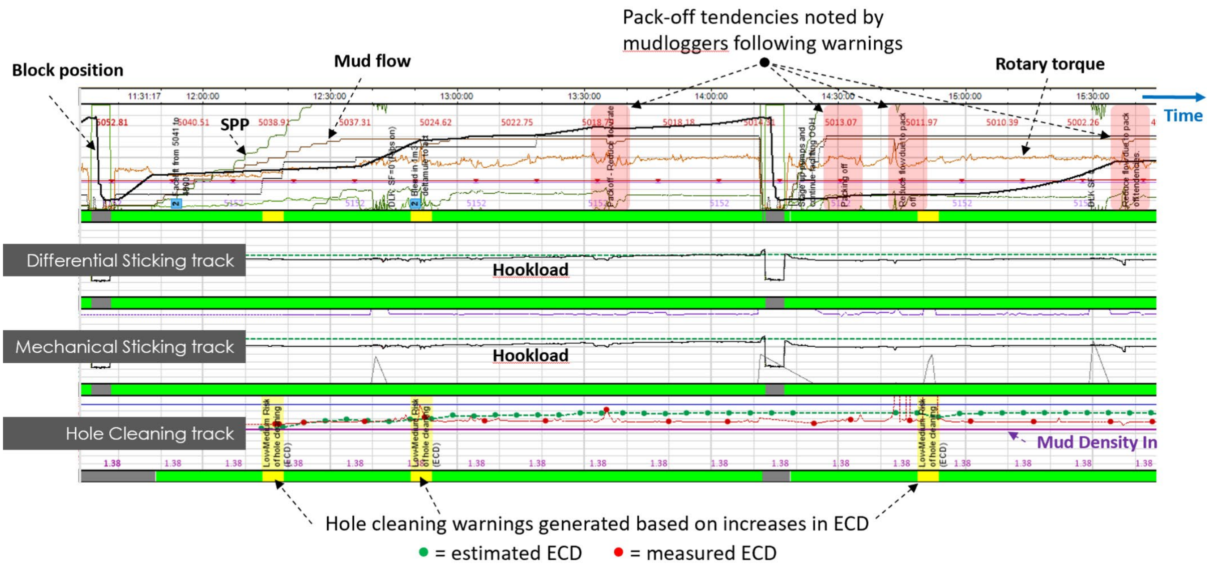

Figure 9: Example scenario from a live operation where hole cleaning warnings were raised prior to pack-off tendencies reported by the mud loggers.

Analysis of stuck pipe incident rates on a portfolio of wells

Results from a study considering stuck pipe incidents before and after the software was used in live drilling operations (from 2020 onwards) are shown in Figure 10. In this case, the statistics specifically refer to stuck pipe incidents related to hole cleaning issues, due to the availability of data on historical hole cleaning incidents prior to 2020, which made up approximately half of the stuck pipe cases recorded during that time period (Liang 2017, Meor Hashim 2021b, Robinson 2022) allowing a comparison to be made. From 2020 onwards, the drilling software solution used in 2017-2019 was either replaced by the stuck pipe risk detection system developed by the authors, or used in conjunction with it in certain cases. The sharp reduction in occurrence rates of hole cleaning-related incidents (per 100 wells) demonstrates that the SPDS has been effective as a preventative tool, even relative to the more challenging baseline case rate from 2017-2019. This also provides further evidence that the system's underlying methodology and algorithms generalize to new wells. Compared to the sample wells where no real-time drilling software solutions were used, an approximately tenfold reduction in stuck pipe cases was observed, while comparison to wells drilled during the 2017-2019 time period yielded an approximately halved incident rate.

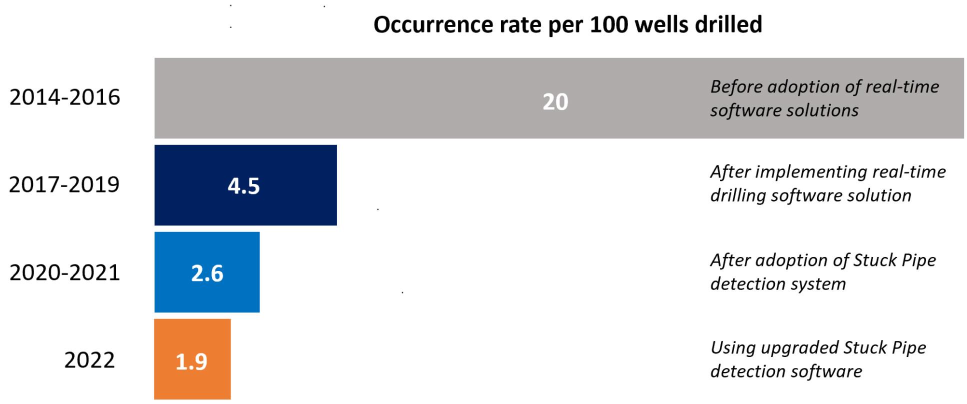

Figure 10: Observed occurrence rates of stuck pipe incidents related to hole cleaning issues, per 100 wells drilled, from several time periods before and after adoption of the Stuck Pipe risk detection software into live operations.

Wells drilled in 2022 used an upgraded version of the software. The values for 2014-2021 are reproduced from previously published work (Robinson 2022).

Note that although the authors have attempted to perform a like-for-like comparison, there remains the possibility of an issue with sample selection bias, as the operator's policy was to primarily use the software on wells which had been identified to be at greater risk of stuck pipe during the planning stages. Hence, the higher risk wells are expected to be over-represented among the sample analyzed during the study from 2020 onwards, the period in which the software was used. If only a sample of high risk wells had been considered up until 2019, the observed stuck pipe incident occurrence rates may have been higher. Similarly, had both low and high risk wells been included in the sample where the software was deployed, lower observed occurrence rate would be expected. Unfortunately, the information required to quantify this was not available to the authors, hence only a general caveat can be provided regarding this expected sampling bias based on knowledge of operational practices. Regardless of this, the observed stuck pipe incident occurrence rates from years where the software was used indicate that the risk detection system can be deployed effectively on real operations, with strong performance not limited to tests on historical data.

Conclusions

Several types of historical and live field tests were presented in this work, and have demonstrated that stuck pipe risk detection software can identify risk symptoms and leading indicators, and provide early warning notifications to monitoring engineers. Tests on historical data, particularly the blind test cases, provide evidence that the software can detect risks, without the possibility of interfering with occurrences at the rig, while live field tests augment this by verifying the system is compatible with operators' existing workflows and practices and can provide value in the oilfield. The system has been tested on previously unseen data from wide variety of geographies (continents, regions, fields, wells etc), with strong performance across the board. This shows the system's broad utility and ability to generalize to new wells, supporting out-of-the-box usage, which greatly simplifies utilization of such a tool due to minimal configuration requirements. Evidence from a wider study on an operator's portfolio of drilling operations, which compared wells drilled with and without the stuck pipe risk detection system in use, indicated that the occurrence rate of stuck pipe incidents can be greatly reduced through use of the real-time monitoring software.

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References

Al Dushaishi, M. F., Abbas, A. K., Alsaba, M. et al. 2021. "Data-driven stuck pipe prediction and remedies", Upstream Oil and Gas Technology, Vol. 6, 2021, 100024, ISSN 2666-2604, DOI: https://doi.org/10.1016/j.upstre.2020.100024.

Alsaihati, A., Elkatatny, S., Mahmoud, A. A., Abdulraheem, A. 2021. “Use of Machine Learning and Data Analytics to Detect Downhole Abnormalities While Drilling Horizontal Wells, With Real Case Study”, *J. Energy Resour. Technol*. Apr 2021, 143(4): 043201. DOI: https://doi.org/10.1115/1.4048070

Alshaikh, A., Magana-Mora, A., Gharbi, S. A., et al., 2019. “Machine Learning for Detecting Stuck Pipe Incidents: Data Analytics and Models Evaluation”. Presented at the International Petroleum Technology Conference (IPTC), 26-28 March, Beijing, China. IPTC-19394-MS. DOI: https://doi.org/10.2523/IPTC-19394-MS.

Alzahrani, M., Alotaibi, B., Aman, B. 2022. “Novel Stuck Pipe Troubles Prediction Model Using Reinforcement Learning”. Paper presented at the International Petroleum Technology Conference, Riyadh, Saudi Arabia, February 2022. IPTC-22151-MS. DOI: https://doi.org/10.2523/IPTC-22151-MS

Bahlany, S. Mohammed Maharbi, M., Zakwani, S. et al. 2021. “STEP Change in Preventing Stuck Pipe and Tight Hole Events Using Machine Learning”. Paper presented at the Abu Dhabi International Petroleum Exhibition & Conference, Abu Dhabi, UAE, November 2021. SPE-207823-MS. DOI: https://doi.org/10.2118/207823-MS

Bin Othman, E., Gomes, D., Ezharuddin Bin Tengku Bidin, T. et al. 2022. “Application of Machine Learning to Augment Wellbore Geometry-Related Stuck Pipe Risk Identification in Real Time”. Paper presented at the Offshore Technology Conference Asia, Virtual and Kuala Lumpur, Malaysia, March 2022. OTC-31695-MS. DOI: https://doi.org/10.4043/31695-MS

Brankovic, A., Matteucci, M., Restelli, M. et al. 2021. “Data-driven indicators for the detection and prediction of stuck-pipe events in oil&gas drilling operations”, *Upstream Oil and Gas Technology*, Vol. 7, 2021, 100043, ISSN 2666-2604, DOI: https://doi.org/10.1016/j.upstre.2021.100043

Elahifar, B. and Erfan Hosseini, E. 2022. “Machine learning algorithm for prediction of stuck pipe incidents using statistical data: case study in middle east oil fields”. Journal of Petroleum Exploration and Production Technology, Vol. 12, pages2019–2045 (2022). DOI: https://doi.org/10.1007/s13202-021-01436-3

Elmousalami, H.H., Elaskary, M. 2020. Drilling stuck pipe classification and mitigation in the Gulf of Suez oil fields using artificial intelligence. *J Petrol Explor Prod Technol* 10, 2055–2068 (2020). DOI: https://doi.org/10.1007/s13202-020-00857-w

Khanh Do, Q., Quang Hoang, T., Nguyen, T. and Khanh Phat Ong, V. 2021. “Predicting and avoiding hazardous occurrences of stuck pipe for the petroleum wells at offshore Vietnam using machine learning techniques*”. IOP Conf. Ser.: Earth Environ. Sci*. **1091** 012003. DOI: https://doi.org/10.1088/1755-1315/1091/1/012003

Liang, L. C. 2017. “Analysis of Stuck Pipe Incidents in PETRONAS Carigali Operations in Malaysia”. Perak. Universiti Teknologi PETRONAS

Meor Hashim, M. M. H. et al. 2020. “Wells Augmented Stuck Pipe (WASP) Indicator – Value Creation and Scalability of Artificial Neural Network for Real Time Drilling Operations to Identify Stuck Pipe Symptoms”. Perak. Universiti Teknologi PETRONAS.

Meor Hashim, M. M. H. et al. 2021 (a). “Utilizing Artificial Neural Network for Real-Time Prediction of Differential Sticking Symptoms”. Presented at the IPTC International Petroleum Technology Conference 2021. DOI: https://doi.org/10.2523/IPTC-21221-MS

Meor Hashim, M. M. H. et al., 2021 (b). “Case Studies for the Successful Deployment of Wells Augmented Stuck Pipe Indicator in Wells Real Time Centre”. Presented at the IPTC International Petroleum Technology Conference 2021. DOI: https://doi.org/10.2523/IPTC-21199-MS

Meor Hashim, M. M. H. et al. 2021 (c). “Performance Improvement of Wells Augmented Stuck Pipe Indicator via Model Evaluations”. Presented at the IPTC International Petroleum Technology Conference 2021. DOI: https://doi.org/10.2523/IPTC-21455-MS

Mopuri, K. R., Bilen, H., Tsuchihashi, N., et al. 2022. "Early sign detection for the stuck pipe scenarios using unsupervised deep learning". J. Petr. Sci and Eng. Vol. 208, Part C., January 2022, 109489. DOI: https://doi.org/10.1016/j.petrol.2021.109489

Muqeem, M.A., Weekse, A. E., and Al-Hajji, 2012. "Stuck Pipe Best Practices – A Challenging Approach to Reducing Stuck Pipe Costs". Presented at the SPE Saudi Arabia Section Technical Symposium and Exhibition, Saudi Arabia, 8-11 April. SPE-160845. DOI: https://doi.org/10.2118/160845-MS.

Nautiyal, A., Mishra, A.K. 2022. "Machine learning approach for intelligent prediction of petroleum upstream stuck pipe challenge in oil and gas industry". *Environ Dev Sustain* (2022). DOI: https://doi.org/10.1007/s10668-022-02387-3

Robinson, T. S., Gomes, D., Meor Hashim, M. M. H. et al. 2022. "Real-time Estimation Of Downhole Equivalent Circulating Density (ECD) Using Machine Learning And Applications". Paper presented at SPE/IADC International Drilling Conference and Exhibition, March 2022, Galveston, TX, USA. SPE-208675-MS. DOI: https://doi.org/10.2118/208675-MS

Robinson, T.S., Revheim, O. 2023. "Automated Detection of Rig Events From Real-time Surface Data Using Spectral Analysis and Machine Learning". Forthcoming paper at SPE/IADC International Drilling Conference and Exhibition, March 2023, Stavanger. SPE-212481-MS. DOI: https://doi.org/10.2118/212481-MS

Rosli, A., Jin Mak, W., Richard, B et al. 2021. "Closed-Loop Data Analytics for Wells Construction Management in Real Time Centre". Paper presented at the International Petroleum Technology Conference, Virtual, March 2021. IPTC-21175-MS. DOI: https://doi.org/10.2523/IPTC-21175-MS

Salehi, Y., Ziada, A., Rawahi, Z. 2022. "Significant Stuck Pipe Event Reduction Realized Through Structured Holistic Approach Machine Learning and Artificial Intelligence". Paper presented at the ADIPEC, Abu Dhabi, UAE, October 2022. SPE-211738-MS. DOI: https://doi.org/10.2118/211738-MS

Singh Saini, G., Pradeepkumar Ashok, P.; van Oort, E. 2020. "Predictive Action Planning for Hole Cleaning Optimization and Stuck Pipe Prevention Using Digital Twinning and Reinforcement Learning". Paper presented at the IADC/SPE International Drilling Conference and Exhibition, Galveston, Texas, USA, March 2020. SPE-199548-MS. DOI: https://doi.org/10.2118/199548-MS

Skalle, P., Aamodt, A., & Sveen, J. (1998, November). "Case-Based Reasoning, a method for gaining experience and giving advise on how to avoid and how to free stuck drill strings". IADC Middle East Drilling Conference, Dubai, Nov. 3-4, 1998. In proceedings of IADC middle east drilling conference (Vol. 1, p. 11).

Tsuchihashi, N., Wada, R.; Ozaki, M. 2021. "Early Stuck Pipe Sign Detection with Depth-Domain 3D Convolutional Neural Network Using Actual Drilling Data", *SPE J.* 26 (02): 551–562. SPE-204462-PA. DOI: https://doi.org/10.2118/204462-PA

Yusoff, M. H., Meor Hashim, M. M. H., Hamzah, M. H. et al. 2021. "Leveraging on Machine Learning Solution for Pioneering Wells Augmented Stuck Pipe Indicator in Real Time Centre". Paper presented at the IADC/SPE Asia Pacific Drilling Technology Conference, Virtual, June 2021. SPE-201037-MS. DOI: https://doi.org/10.2118/201037-MS

Zhu, S., Song, X., Zhu, Z. et al. 2022. "Intelligent Prediction of Stuck Pipe Using Combined Data-Driven and Knowledge-Driven Model". *Appl. Sci.* 2022, 12(10), 5282; DOI: https://doi.org/10.3390/app12105282