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Early Stuck Pipe Detection based on Real-Time Data Analysis

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Affidavit

I declare in lieu of oath that I wrote this thesis and performed the associated research myself using only literature cited in this volume.

Eidesstattliche Erklärung

Ich erkläre an Eides statt, dass ich diese Arbeit selbständig verfasst, andere als die angegebenen Quellen und Hilfsmittel nicht benutzt und mich auch sonst keiner unerlaubten Hilfsmittel bedient habe.

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Name, 27 September 2017

Abstract

This research looks at the work previously done by other scholars regarding pipe sticking prediction, especially the ones using real-time data, then goes on to prove it possible to predict impending sticking events using real-time and simulated data.

An algorithm is created based on case based reasoning and improved methods from previous work. This algorithm is then tested on historical real-time data to come to the conclusion that it can predict pipe sticking.

This work sheds the light on the potential developments in drilling towards full automation and better economical practices.

Acknowledgement

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Last but not least, I would like to thank my family, friends and close ones for being there for me and supporting me while I was working on this thesis.

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Introduction

The magnitude of pipe sticking among the problems occurring while drilling is well known to the oil and gas industry. This problem is costly time wise and economically.
Through the last decades this problem was understood and studied. Best practices were generated and methods of dealing with it were benchmarked. But despite all that the problem seem to be persistent and in the weak industry economy that we face today the issue need to be addressed more.

What was happening alongside that is an accumulation of data. This data is being stored and not taken advantage of. And if there was an answer for the question posed above, that answer must be in the data.
The industry is aging and there is so much experience to be let go and put to retirement. For that the urge to move forward technologically has grown.

A combination of technological advancement and years of experience can crack down the mountains of data accumulated and is being accumulated day to day. This will eventually lead to having a strong ground to understanding the data as it is generated in real-time. The crews will have the time to react, problems such as pipe sticking are going to be avoided and mitigated and better economy can be eventually achieved.

Literature review

Since the question of pipe sticking has been posed, many approaches have been taken to tackle the problem. In this literature review the concepts used through the history to deal with the pipe sticking issue and solve it are addressed and the most recent approaches that might lead to actual prediction of the phenomenon are analyzed in depth and assessed on the basis of the added value to this research.

In the early phase, the focus was to understand the pipe sticking physical phenomenon. Most relevant of these literature are studied in my Bachelor Thesis (Msahli, Pipe Sticking Causes & Preventions). Physically, total prevention was not possible. After understanding the physical reasons behind pipe sticking, literature was focused on reducing its occurrence and generating practices to mitigate it as well as to make freeing the pipe more feasible. Sticking back then had great impact economically, a study (Bradley et al. 1991) estimated the yearly cost of this problem to be $250 million in the late 80s.

The need for pipe sticking prediction was a necessity. The need for it was crucial to reduce the non-productive time (NPT) which some papers (such as Muqeem et al. 2012) related 25% to the sticking. (Joshua Hess 2016) summarized the history of most relevant attempts to predict pipe sticking. The paper mentioned that since the 80s studies have been conducted in order to predict the sticking occurrence. It started with statistical analysis to define the relationships between parameters (Hempkins et al. 1987). Later, more analytical methods were used with implementation of artificial intelligence tools such as artificial neural networks (ANN) and support vector machine (SVM). These methods allowed the prediction of the occurrence of a sticking event during the drilling operation quite accurate, but were not able to be definitive. Analytical methods lacked the physical aspect.

On the other hand the implementation of the previously mentioned technologies shed the light on the importance of data in order to understand the phenomenon and solve the problem as it occurs during drilling. This awareness of the importance of data came associated with the shift of the industry towards real-time.
For years companies have been accumulating data with less analysis and even more less applications that would be reflected on the everyday operations.

Recently, many researches targeted the issues above mentioned and many researches have been performed with the goal of solving drilling problems in real-time while allowing transfer of experience through automation. This all is seen to be achievable through case based reasoning (CBR).
The concept of CBR was best introduced in the early 90s by Kolodner, but is still a brand new concept in the drilling industry. This can be very reflective of the gap the industry has in technology and in updating methods.

CBR was defined (Kolodner 1992) as follows: "Case-based reasoning means using old experiences to understand and solve new problems. In case-based reasoning, a reasoned remembers a previous situation similar to the current one and uses that to solve the new problem". The core concept of CBR is simple to understand as it is the basic way humans learn from experience.

A worth mentioning introduction of CBR in drilling, (Aminul et al. 2008) focused on the importance of passing the experience attained by the organization and the individuals in it to those who need it when they do need it. This was described possible through computerized support for information handling in the purpose of prediction of potential unwanted events and decision support on a later stage. The first part of this support can be achieved through this thesis in the case of pipe sticking.

Then, the paper went on to suggest a four steps process to solve CBR problems (Aamodt and Plaza 94). The four steps are:

1. Retrieve: collect the similar and relevant cases
2. Reuse: use the knowledge in the retrieved case for solving the problem
3. Revise: revise the proposed solution
4. Retain: retain the experience that can be used in future problem solving

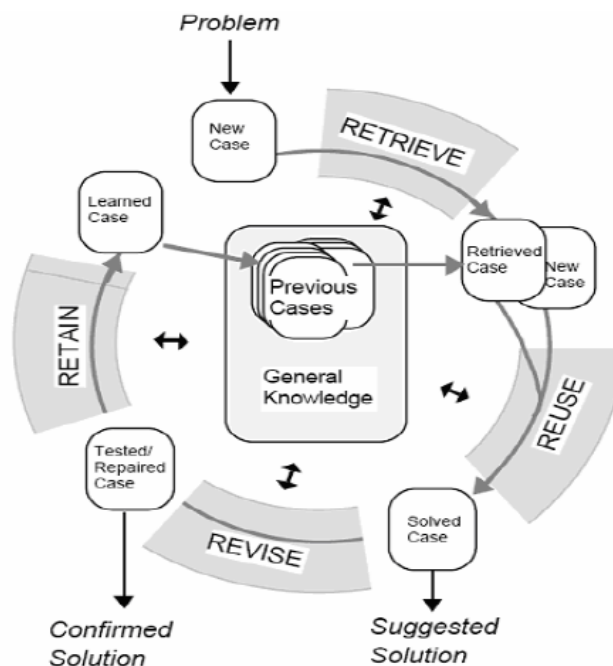The process is well illustrated in the CBR cycle below.

Figure 1 CBR cycle

The paper managed to put in the scope the key points to solve a drilling problem through previously available experiences, but failed to provide clear real case use and potential of use after the planning phase.

Where the previous paper failed, others were successful. After few years, (Dadlier 2013) presented an automated real-time solution for drilling problems. The solution reduces drilling risks through applying case-based reasoning to compare the current problem to historical ones. The main target was to detect and well identify the similar events that came and somehow led to the event.

The approach is straight forward and presented below.
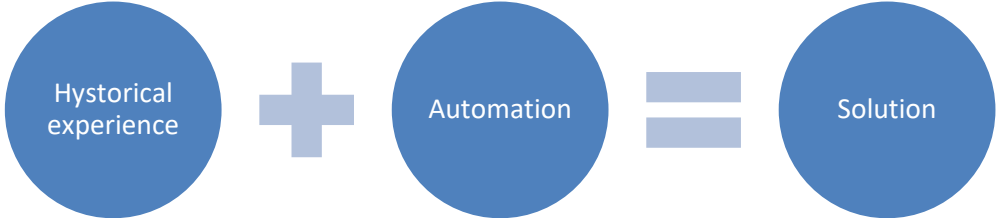
The solution would consist in the relevant historical cases and related workflows presented to the operator as soon as there is enough similarity in that case with the current situation. This is feasible through two forms of machine learning. First, there is pattern recognition where meaningful pattern are identified and classified into events. Second, display of historical cases in an order where similarity is measured through attributes and the most similar one is displayed.

This working principle is similar to what an experienced engineer would do. An experienced engineer would recall his personal experience or the cases he got exposure to and from there think of how to react based on what worked or not.

At this point, weather the solution suggested is proven or not, the logic behind it answers the question of how experience is transmitted from the older generation and their lessons learned to the younger ones hungrier for experience in an aging industry.

The display is in the radar figure below; where the side notes give recommendations from best practices and the dashed line represent a 75% matching case, the outer circle is a 50% case and the center is the current case. The historical case would show up at certain percentage and direction. This is analogue to submarine radar where the threats are marked with dots and the closer the higher the risk and where the direction gives away the origin of the threat.
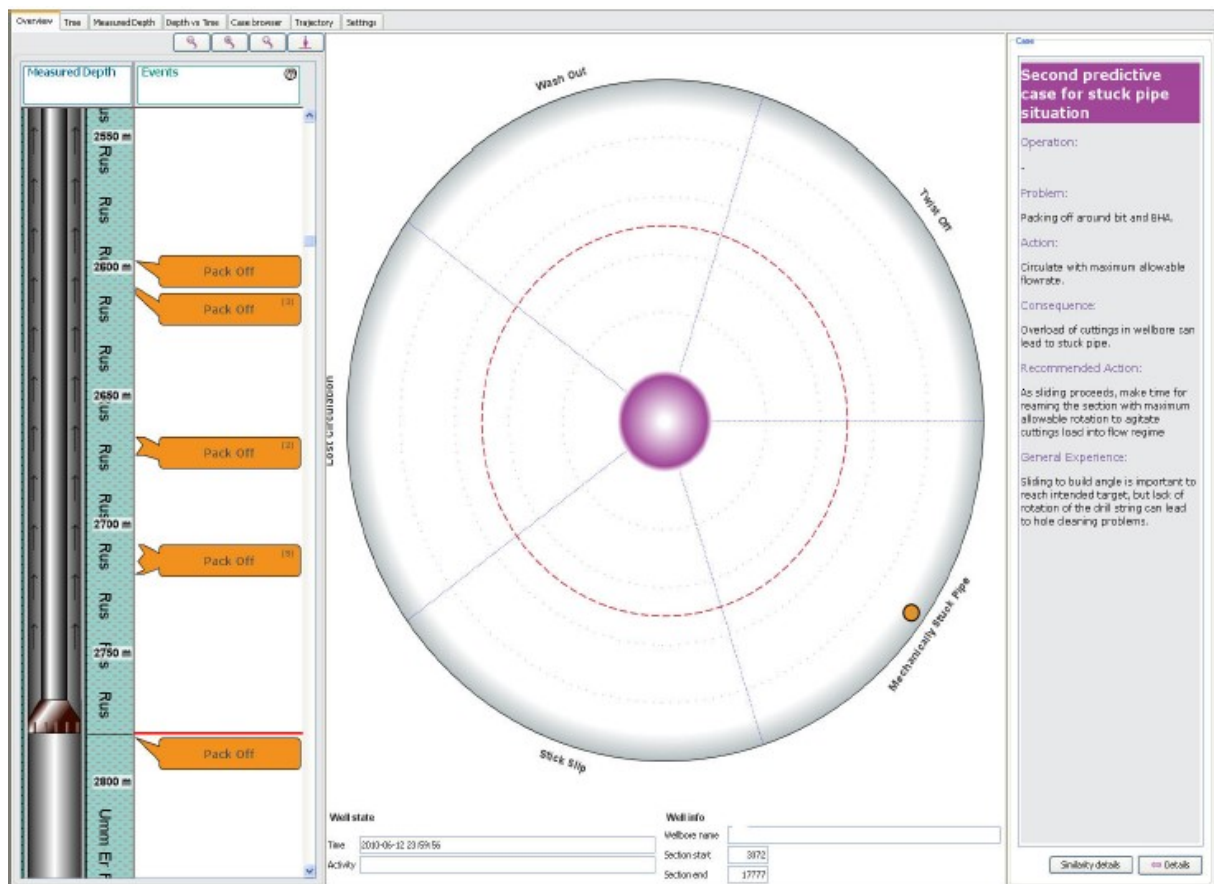
Figure 2 Pipe Sticking Radar

The paper suggested that the solution can be used for the planning phase as well. An example of that was the case where it allowed the operator to develop strategies prior to drilling as well as watching relevant cases in real-time. This is said to have saved $2mo per incident.

Even in case of success, there are lessons to be learnt. Meaning that, false positives can be used to improve the platform of the solution.

False positives can be reduced by diving operations. In case they still exist, that leads to the question of maturing and improving the platform.

Maturing can be tackled straight through analysis of more data and through collaboration between different involved parties to share experiences and generate protocols.

The suggested solution promises a variety of uses in drilling and surely goes in the direction of preserving the industry's knowledge.

After a couple of years, a new approach was published. This approach (Ferreira et al. 2015) goes in the same direction that the previous one, but focuses on pipe sticking which makes it more relevant for this thesis and a great encouragement for the chosen direction of research. In order to deliver a well on plan, the drilling team would need actionable information.

Symptoms of drilling problems needs to be identified prior and delivered in a simple straight forward way or else the information might just be lost in the huge amount of data streams and get sent to the data graveyard which is known as data storage.

There are three key elements to make this into a success. They are 24/7 real-time surveillance, case-based reasoning software and real-time solution to avoid NPT. The solution is provided when similarities are detected and need expert guidance to achieve less risk and less operational costs.

This goes as well in the direction of knowledge transfer to machine but do not dismiss the importance of expert collaboration to provide the final solution.

This is an important half-way step towards Automatisation, with such a solution experts become able to keep watch over different wells from a remote location and intervene when their intervention is really needed. This is presented from a management point of view.

Events in this paper were presented as prior symptoms to the actual problem. The software part will continuously identify the events and help engineers to focus where their focus is required. It is important to mention that single signal is not enough to mean a problem but it can be part of a pattern and still requires investigation.

The solution was as well presented as radar with a similar percentage assignment as the previous paper. This is as well associated with solution protocols and the paper highlights that it can be done remotely.

This literature presents a logical and effective way to solve the challenges in drilling but there is a need for practice to prove it working. The scope of it is a bit wide and assesses the situation from a management point of view, this resulted in a lack of details regarding the process and the method used to achieve the solution.

In the same direction, another relevant to this thesis approach was taken. The approach taken by (Kent Salmine et al. , SPE 178888-Ms) consisted of three main steps. First, studying wells with sticking incidents and gathering a defined type of data, then, patterns detection and finally alert generation.

- Data gathering:
  In order to make the solution work on most available rigs and through different types of operations some contingencies were used on the data selection. Data needs to be available on most rigs in real-time, informative about the wellbore, fluid and the drilling string and can be logically related to impending pipe sticking.
  This raises already an issue of data consistency between wells, even those drilled by the same operator. And in this case were only the basic data is used, would it be enough to be indicative.
  The paper suggests that at least one data point per 10 seconds (0.17 Hz) is required. The data used is divided as follows in the table.

Table 1 Inputs and Outputs used for Pipe Sticking Detection

Input	Output	Other
- Flow rate in - Surface rotary speed - Surface weight on bit	- Pump Pressure - Surface rotary torque - Hook load	Equivalent circulation density (ECD)

- Pattern Detection:

  To cover all the deviations in the data streams, two types of calculations are made. First one is the deviation of the data from the real-time predictions from software and the second is the rate of change in the real-time data.

  The indicators of sticking through this approach are either a significant deviation from the prediction or a rapid rate change or a combination of both.

  The issues with this approach are model flaws and measurement flaws. But they have been mitigated by using smoothing on small depth intervals and not taking into account alerts from single points. The paper claims this solution can help detect calibration errors.

  Once the data is received, an algorithm assigns an activity type to rows of data. This is very important since data that is depth-based is straight forward for drilling but not for off-bottom activities. Now that the data can be divided to depth-indexed subgroups based on rig activity and are time-based, all rig activities can be covered and this is one of the advantages of this approach.

  In order to quantify the changes in the data streams, thresholds have been defined in a way that data deviation should stay below in order to be considered within the acceptable.

  The issue with these thresholds is that their value shifts from well to well and also are based on the sticking cases noted in the studies cases for the paper and thus cannot be considered accurate.

  Below a system model is presented to illustrate the structure of this approach.
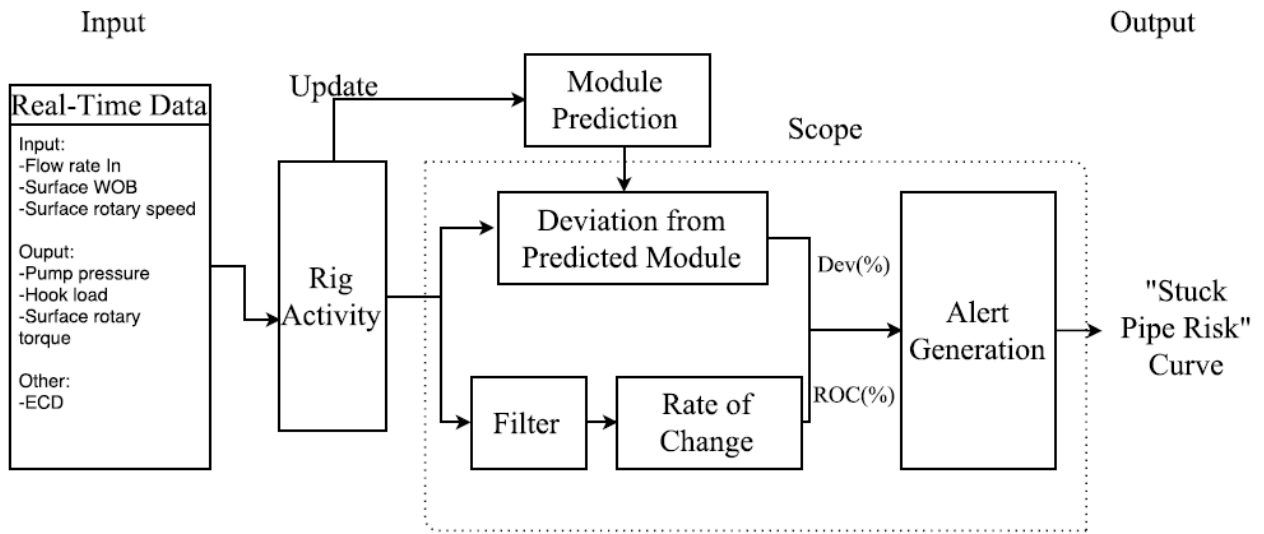
Figure 3 Method Illustration

> Deviation from predicted Module:

The deviation can be either positive or negative, depending in the rig activity. The equation used is as follows

$$Dev(\%) = \left(\frac{X\ actual - X\ predicted}{X\ predicted}\right) \times 100$$

> Rate of change:

If we consider a and b as interval or time or depth, depending on data type. The rate of change is measured as follows

$$ROC(\%) = \left(\frac{X\ avg[b] - X\ avg[a]}{X\ avg[a]}\right) \times 100$$

$X\ avg[y]$ represent the average value of data in the interval y.

> Filter:

This block deals with the issues of calibration and measurement errors.

- Alert generation:

After defining thresholds and calculating deviation, an alert level can be defined by a simple division.

$$Alert\ level = \frac{Calculated\ deviation}{Threshold}$$

This resulted in ranges of alert; [0..1] ,]1..3[and [3..∞[where the latter would be limited in the value of three. The reasons behind this specific value are not explained in the paper, but limiting the values would prevent one factor from dominated the other alerts.

This resulted in a maximum alert value as following

$$Max.\,alert = N \times 3 \times 2$$

Where N is the number of parameter used. And in this study, N is equal to three.

So the maximum alert level is 18.

For reasons of practicality and to allow operators an easier guidance through sticking risks, a concept of "Stuck Pipe Risk" curve was introduced. The curve ranges from 0 to 100% and is drawn simultaneously aside the data streams. The curve is drown from the following equation

$$Stuck\ Pipe\ Risk = \frac{\sum all\ alert}{Max.\ alert} \times 100$$

During normal operations while verification, the values were low and said to be increased as a known risk is approached. For this to be a success, the increase should be noticed before the event leaving enough time for the crew to react and prevent the occurrence of the sticking.

Even the paper presented success in real wells, the values were not consistent and the alert value did not seem representative of the risk magnitude.

This approach was well defined despite of the many assumptions made. There is clear evidence of the success of it in the practical world, but the success can be limited to a certain area and lack consistency.

In general, this paper represents a strong logical construction and would contribute greatly for the guidance of this thesis. The number of assumptions made allows a wide margin for improvement.

Research Methodology

The goal of this thesis is to prove it possible to predict pipe sticking using real-time measurement data. Through the studied literature, it was seen that using case based reasoning aligned with some analysis methods like used in (Ferreira et al. 2015) would allow reaching this goal.

The process chosen was to develop an algorithm that takes as input the real-time measured data as well as simulated data and certain related parameters. For this algorithm, two wells are going to be used for the development phase where the functions are going to be tested and improved. Those functions are mainly a deviation and rate of change (ROC) functions, inspired by the work in (Ferreira et al. 2015).

Once the algorithm is developed, it will be tested on two other wells to verify if the final goal is reached or not. The wells are chosen from a database of wells where sticking occurred. The choice of the wells is based on the type of operation in play when the event occurred. The first two are offshore wells where the sticking was in one while drilling and while pulling out of hole in the other.

The second two are similar.

Besides considering the operation in choosing the wells, the data is later going to be filtered based on the operation of interest. This will be done using the provided Rig States from ProNOVA. The rig states would allow easy access to each operation and the time span it took.

It was possible to filter the data otherwise, but this final product is more accurate and would allow reaching the goal of this filtering more accurately, which is to avoid having false alerts from drops or increases in the data streams that are caused by switching from one operation to the other.

At first, it was planned to filter the data and then use it as input. But doing that would not allow using the same data parameter for different operation of interest. And because the operation of interest is inputted in the first deviation function, it is simpler and more efficient to keep the data intact and just filter the deviation and rate of change after it was calculated for all. This decision would allow choosing a different operation to monitor without having to load the data again.

The real-time data chosen for study is the hook load, stand pipe pressure (SPP) and torque. This data is available in most wells that are equipped for basic real-time measurement. For the simulation of those streams ProNOVA is used as it provides enough accuracy and consider alternatives. This is beneficial to choose the right stream in case the friction factor is not available which the case is in this study.

Literature suggested that the equivalent circulation density (ECD) can be used for better results. But it defies the purpose of this thesis to use something that might not be available is some rigs.

The simulated data is simulated using the available information and some guesses or analogies in some cases. Certain companies, in their policies, do not provide full exposure regarding the type of equipment, mud or other drilling parameters. For that the simulated data is plotted against the measured streams and the best fitting one is chosen as an input. This is very important for the success of this thesis, because getting the wrong simulated stream could make it impossible to track deviation between simulated and real-time measured data.

It is important to keep in mind the difference in units between the simulated streams and the measured ones because those differences change from one company to another. In this case, there are only powers of ten to be multiplied with and consideration of the different time indexing.

The first step is to create the basic functions of deviation and rate of change, those functions included sub-functions that had the calculation point by point done and the operation type considered. This allowed higher flexibility and much more options in terms of possible future changes in the method used.

To add more flexibility, a window is added to the functions, where the averaged range in the ROC can be adjusted by changing this window input as well as allowing the deviation from simulation function to take average values and not just point by point. This has, as well, purposes of smoothing the curves and avoiding wrong measurement in bad real-time data streams.

After calculating the deviations, alerts are generated from these deviations and then those alerts are added up and used to generate a sticking risk percentage. First, those alerts need thresholds in order to be generated. The value of deviation is simply divided by the threshold and that gives an alert.

The literature suggested having thresholds from experience or similar cases but there was no hint on how to get those values. Thus, the used approach was to try a wide range of values to attempt limiting the threshold values into smaller ranges. Basically, throwing mud at the wall to see what sticks. Once a somehow smaller range is defined, it would be much easier to detect a patter or a logical way of getting the threshold.

In case of success, the second developing well would be used for the purpose of proving the threshold method right because the third and fourth well should be used with the same thresholds as the first ones and having those values non-tested would add ambiguity.

For the final sticking risk, the development wells would be matched intentionally with the historically noted event of the drilled well. As for the testing wells, the risk plots have to be explainable with those notes associated with the events.

Once the events are matching the obtained curve, the thesis goal in achieved and the question posed before are answered.

Findings/Results/Data Analysis

At first, two wells where a sticking incident occurred are investigated. The wells were chosen based on the type of operation and the sticking occurred during.
The first well, we call it well A, the sticking occurred while drilling.

Well A: Sticking while drilling

Well A is an offshore drilled well. The drilling operations in scope are from 350m to 835m of MD.
The major sticking problem occurred while drilling at 835m and is explained below in details.

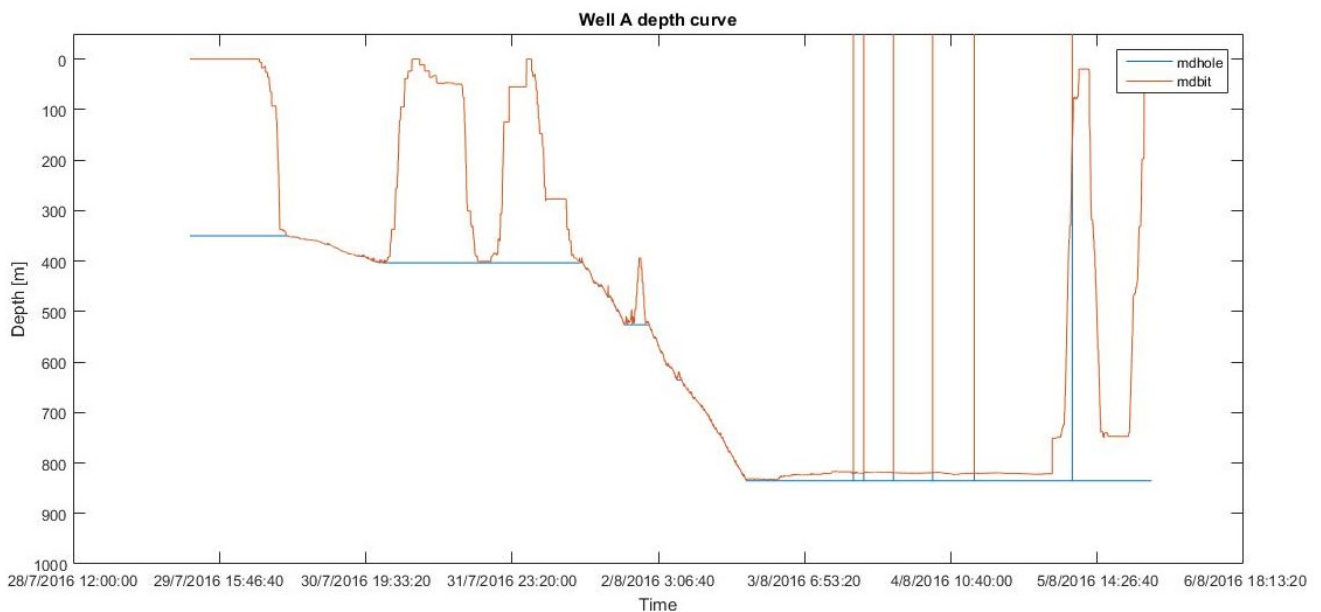The depth curve of well A is presented below.

Figure 4 Well A depth curve

The first sticking problem in this well appeared at the measured depth of 393m. Erratic torque was experienced when drilling 36" hole from 390m to 403m at 19:30 July 30, that resulted in the string becoming stuck at few depth points; 393m , 399m and 402m.
The string was pulled free using an overpull range of 5-25 tons and the reason of this sticking was reported as possible boulders.

The second sticking incident was reported at a depth of 831m around 20:00 2nd of August after pulling off bottom, stopping rotation and orienting toolface for sliding.
Packing off was observed and the MWD tool indicated an increase in ECD from 1.13 sg to

1.40 sg which meant that the pack off is above the tool.

Attempts to work the string down were not successful, the increase in torque was not able to rotate the string and reducing flow to minimize pump off effect and firing the jar down had no effect.

The team moved the ROV in position to observe the string above the wellhead for any buckling and reduced the flow with firing the jar but still no go.

While circulating for a while a reduction in string weight was observed which indicated increased pack off. The pumps were stopped and 19 bars of trapped pressure where observed.

At this point, overpull was increased gradually with jarring attempts and working the string upward and downward with some minor progresses at first but then no movements anymore.

The overpull was increased to max; 346 tons, flow was staged up and pressure increased to increase push force. The pipe moved 3m before stopping again. After applying these parameters and working the jar up and down the string was freed.

The increases in hook load and other changes of parameters can be observed below in the graphs representing the real-time parameters measured for this sticking while drilling event.

These parameters for well A are used to create the base algorithm using their rate of change and the deviation from the simulated data curves.

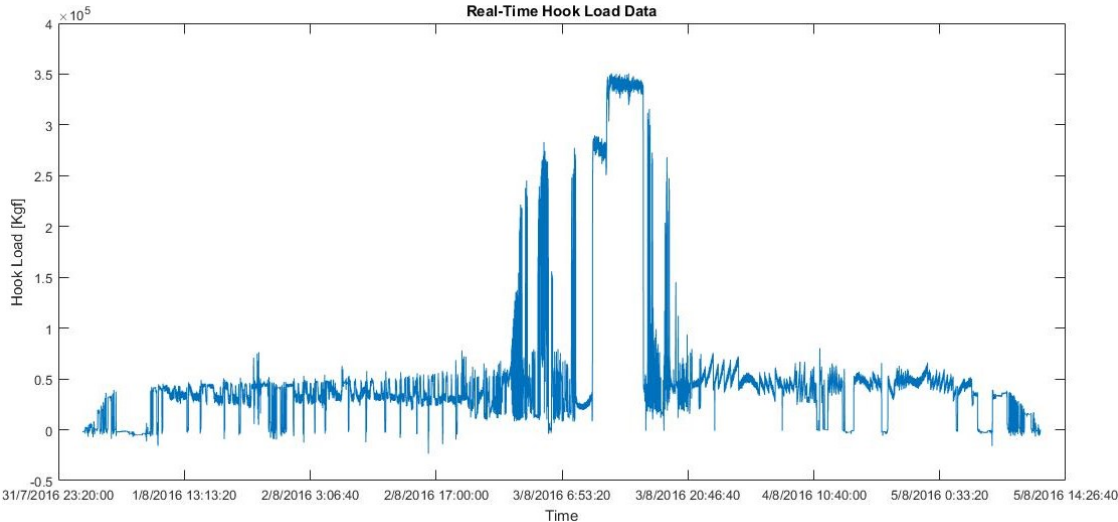Below is found the Real-Time Hook Load data curve.

Figure 5 Real-Time Hook Load Data - Well A

The Hook Load data curve show the shifts and disturbs in the Hook Load before the sticking happens and at some point the peak would start to represent the added loads in the attempts of freeing the pipe.

In the first period there is a slight increase of the value which is natural to drilling operation and addition of stands. Then, the gradual increase till reaching the flat max hook load tells about the teams approach to resolving the problem.

The second measurement considered is Stand Pipe Pressure which is the total friction induced pressure loss in the hydraulic circuit. It is measured in real-time for its importance in mud weight selection.

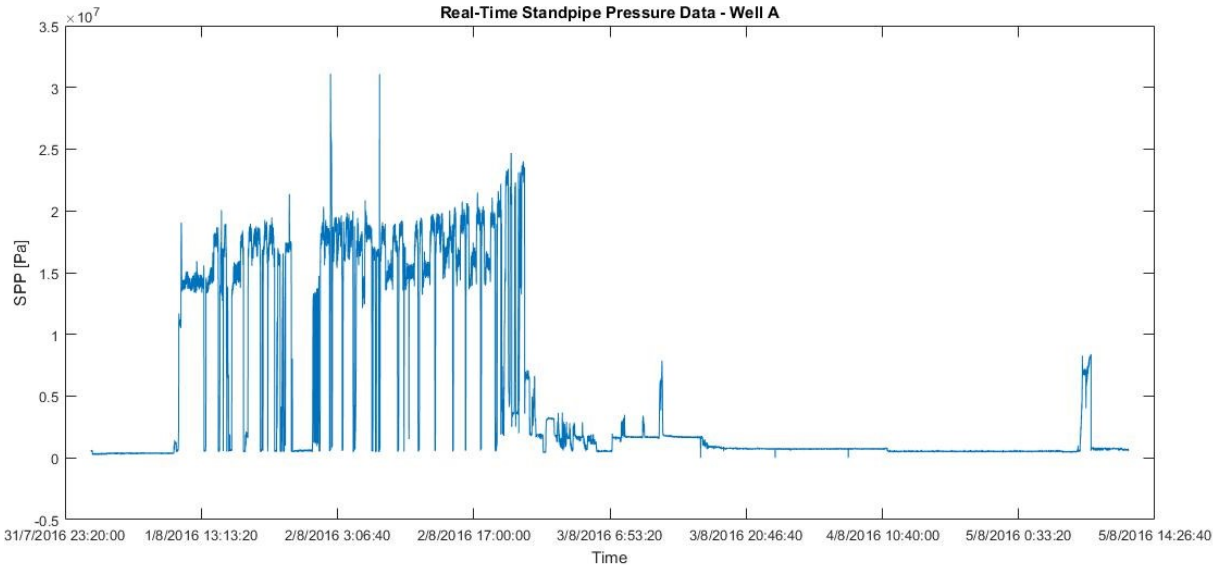Below, the real-time measurements of Stand Pipe Pressure are presented.

Figure 6 Real-Time Standpipe Pressure Data - Well A

The increase of the hydraulic circuit and thus the increase of the surface explain the slight and gradual increase in the value of SPP. Then the drop just happened when the sticking happened for the simple reason of circulation stopping.

The third measured data used is the Torque data. Knowing the torque is important primarily to avoid getting stuck and to have better borehole quality and longer equipment lifespan.

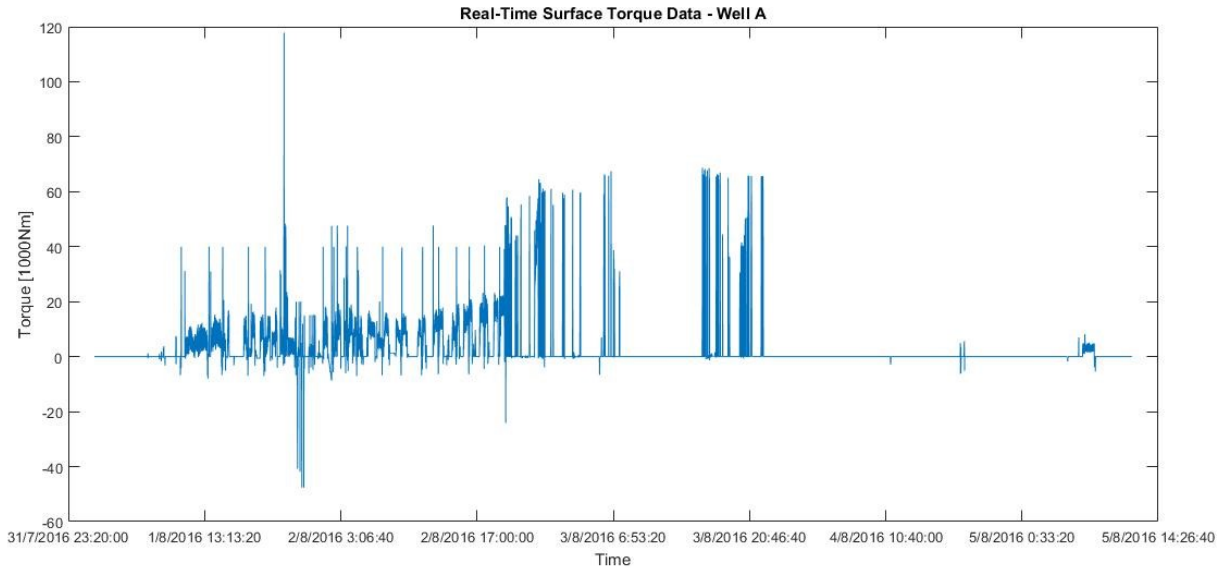The surface torque real time measurement for well A is presented in the figure below.

Figure 7 Real-Time Surface Torque Data - Well A

In order to be able to measure the deviation of real-time data from the predicted range of values, it is very important to have accurate simulated data streams.

The simulated data streams are provided using ProNova. The inputs needed were BHA assembly, bit position, casing depths, trajectory and mud rheology properties.

The challenge at this point was that certain information was not available because of non-disclosure policies for some companies. So in the inputs some numbers were used based on the closest similar tool size and weight and some approximated through common industry practices.

In some cases, the range of error was estimated with few tens of kilograms. It is quite irrelevant in a wellbore.

The simulation then proceeded and the results are presented below.

The first plot below represents the predicted hook load curves during the job performance. The simulation provided different sets of results; two groups referred to as down and up. The difference between both is that the hook load when POOH is higher than when RIH for friction-acting direction. And for each group of results there is five different curves based on different friction factors that are considered for the simulation.

The friction factors are as follows:

Table 2 Friction factors used for simulations

Friction factors				
#	#1	#2	#3	#4
0,1	0,2	0,3	0,4	0,5

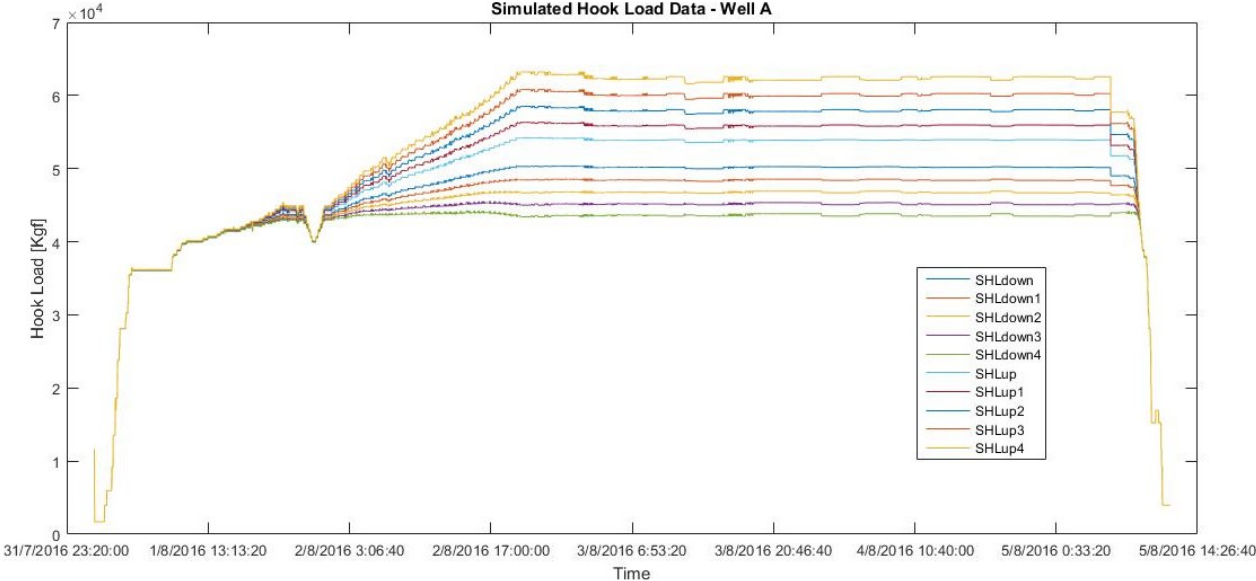The numbering in the table is matching to the graph below.

Figure 8 Simulated Hook Load Data - Well A

Among the simulated results one would be used. In the real case that one can be chosen by determining the properties of the rock or doing a real-time friction analysis. In this case, the data used would be the one closest in matching most of the Real-time measurement stream. Matching till the sticking happens is much more important and would be the criteria in choosing the simulated data for the following steps.

The chosen curve is represented below with the Real-time stream. It is referred to before as SHLup.

The simulated curve obviously do not account for connections. We can see the R-t value going to zero when the pipe is in the slips. This might disturb the resulting values of deviation with the chosen method but that is eliminated since only the drilling time values would be considered.
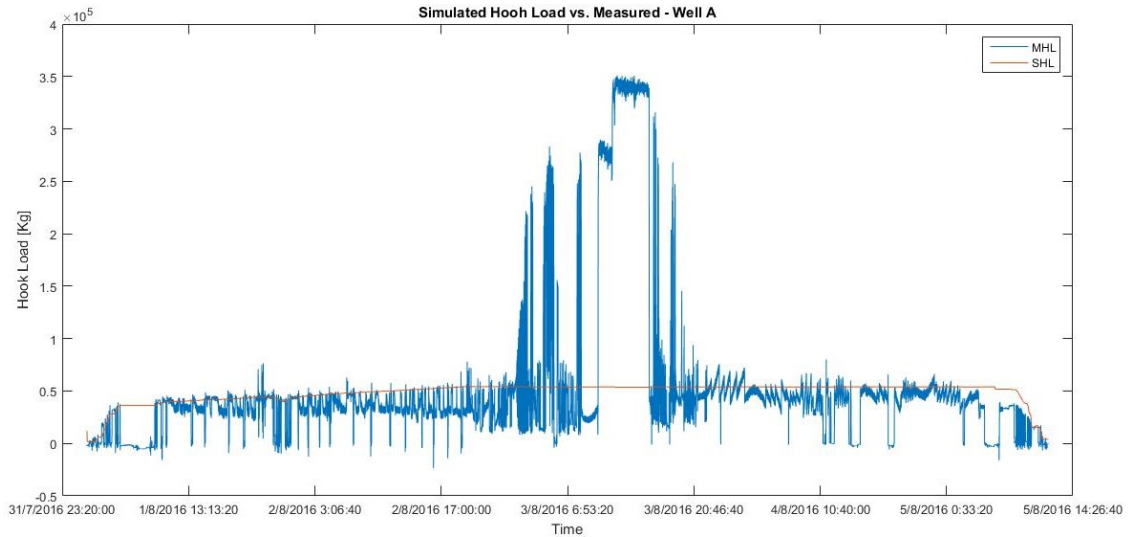
Figure 9 Hook Load Simulated vs R-T

The curve above shows how the simulated data follow the real-time trend till the point where the pipe got stuck and induced higher peaks of hook load where visualized. The matching quality is great and once the data is filtering based on the operation type then the results would be more promising.

The second plot is the Stand Pipe Pressure (SPP). It is plotted below versus the real-time measurement. The two curves match quite accurately in the trend but the simulated values are higher with a constant value. That is best explained by the fact that the rheology information was not available and had to be guessed in order to run the simulation. The shifting value is quite high but the graphs could be matched by simple subtraction of the extra value. But in this case, the difference would not make any difference in the final results.
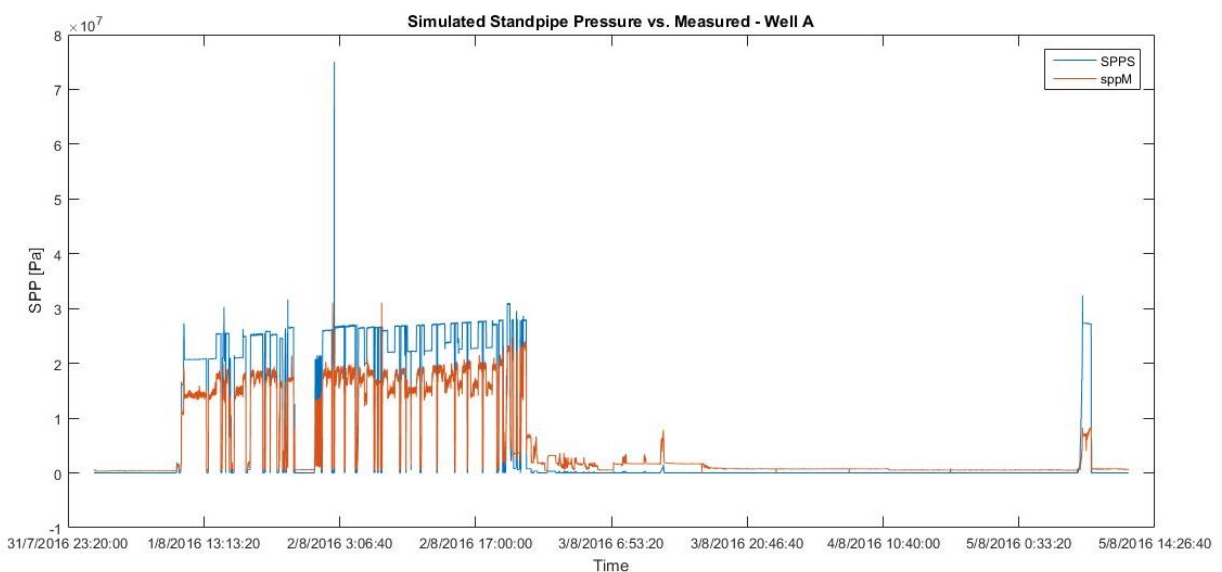

Figure 10 Simulated Standpipe Pressure vs Measured - Well A

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The time window to investigate is best represented in the graph above.
The graph shows again a pretty accurate prediction regardless of the small shift due to lack of knowledge in the inputs.

The last plot is for the Torque data. The simulation resulted in five different graphs associated with the same friction factors as before.
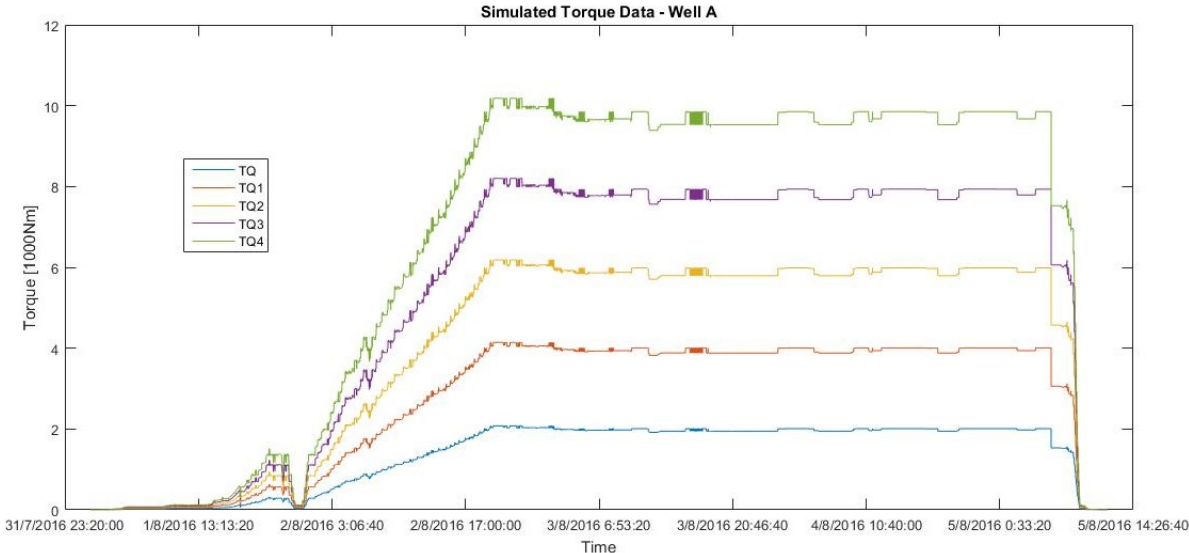

Figure 11 Simulated Torque Data- Well A

These curves are then plotted versus the real-time stream and it shows that the values are too low to match. This means that the friction factor is higher that is it in the input values. But that is not the case since the real-time measurement in this well was corrupt for the torque.
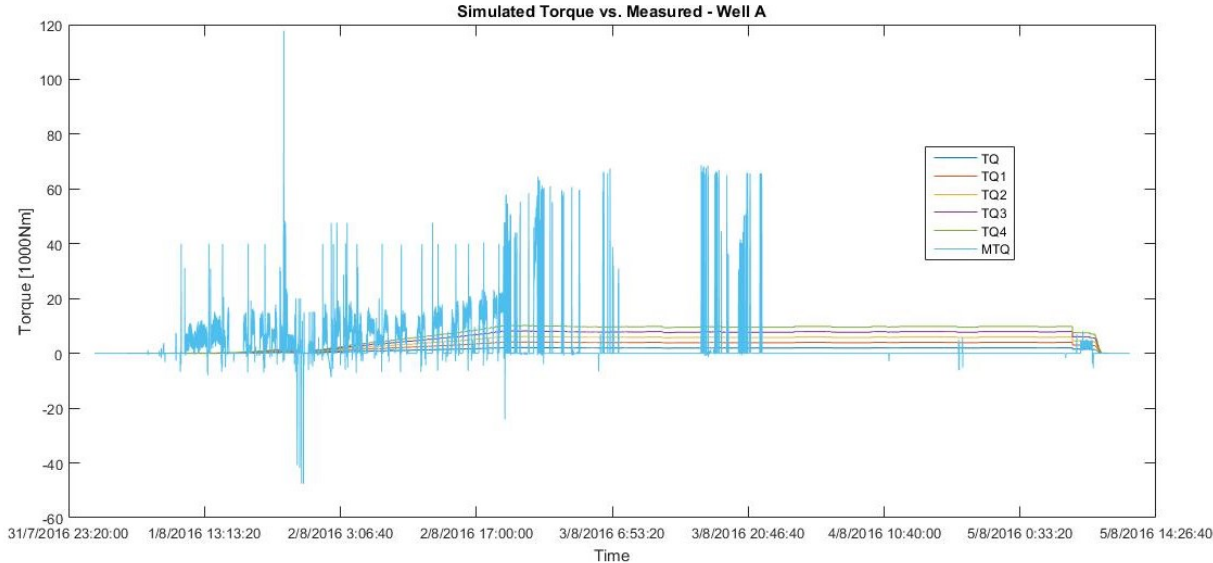

Figure 12 Simulated Torque vs Measured - Well A

With the available inputs these curves are accepted but with different considerations when it comes to the thresholds since that can cover the gap in the deviation between the two models.

This decision was based on the fact that this well is just for the purpose of creating the first algorithm used later to test the rest.

Regarding the algorithm, the first step was to determine the inputs and the desired outputs. Those parameters are listed in the table below.

Table 3 Algorithm Inputs and Outputs

Inputs	Outputs
• Operation time span (tlend, tlstart) • Types of operations (Opcode) • Operation in scope (330 ; drilling) • Time index (timeA) • R-T Measurement data (HLM , MTQ, SPPM) • Simulated data (HLS, TQ , SPP) • Window (10) • Threshold boundaries	• Deviation from simulation • Rate of Change • Alerts • Pipe Sticking Risk

Before moving to the structure of the algorithm, some of the inputs are to be explained. As for the operations, those parameters were already available and can be provided as a service by TDE in the rig activity report.

In order to save time and be more accurate and efficient those parameters were taken from the already prepared reports. The operation time span is in two parameters, one that signals the start and the other the end of the operation associated in the "types of operation" input referred to as Opcode. The last parameter is the numerical benchmark for operation and is the number associated with the operation of interest; like in this well drilling (330).

The other inputs are the data as it was detailed above and a window, the window is there to first allow more flexibility into the averaged intervals. It would have a direct effect on the rate of change and would allow surpassing measurement errors in deviations. Further effects of it are presented in the appendix. The last input is are the threshold boundaries and for the first algorithm the values are set at (+10% , -10%). On a later stage the values would be adjusted in order to find a logical method of determining better effective values. Using neural networks to determine the thresholds was brought to the table but then put away for believing that a more logical and realistic method exists.

The script for deviation and rate of change looks as follows.

```
HLdev=SDev(tlend,tlstart,Opcode,330,timeA,HLM,HLS,10);
HLROC=SROC(tlend,tlstart,Opcode,330,timeA,HLM,10);
```

The function of specific deviation "Sdev" which outputs the deviation is defined as follow.

```
function [ SDev ] = SDev( tle,tls,op,opt,time,Rt,sim,R )

SDev=Dev(Rt,sim,R);
s=opdet(tle,tls,op,opt,time);
k=length(s);
for i=1:k
   if s(i)==0
      SDev(i)=0;
   end
end
```

The first embedded function to explain is "opdet" which would determine the operation ranges. The function takes as input the operations inputs, all of them, and in addition the time of operation in scope. Later, the function would assign "1" to the time points where there is the scope operation in progress and "0" to where other operations are ongoing.

```
function [ s ] = opdet( tle,tlb,op,opt,time )
ts=Opstarts(tlb,op,opt);
te=oprange(tle,op,opt);
l=length(ts);
k=length(time);
s=time*0;
for i=1:l
   for j=1:k
   if ts(i)<=time(j)&& te(i)>=time(j)
      s(j)=1;
   end
   end
end
```

As shown above in the function SDev first calculates deviation for all time points but then eliminates the ones where there are different operations than of interest by assigning the value "0".

An alternative was into consideration and it consisted of calculating the deviation for where the "1" value is. This method would have meant less calculation for one example but actually is more time-consuming for changing operations and testing.

As for how the deviation is calculated, it is presented below in the function "Dev".

```
function [ Dev ] = Dev( RT,sim,R )
l=length(RT);
Dev=0;
for i=1:l
   s=DevM(i,R,RT,sim);
   Dev=[Dev;s];
end
Dev=Dev(2:l+1);

end
```

Each value added to the series of Deviation is calculated in the following function "DevM". The R value represents the window, where this value is used to determine the mean value before and after the point is calculation. The effect of R can be reduced or totally removed but it is as mentioned before important to experiment with the data and check how the quality affects the results of the foreseen prediction.

```
function [ DevM ] = DevM(i, R , x , y )
t=i+R;
l=i-R;
g=length(x);
if  t>g
   t=g;
end
if l<=0
l=i;
end
x1= mean(x(l:t));
y1= mean(y(l:t));
DevM=((x1-y1)/y1)*100;

end
```

As for the rate of change, the same approach was applied.

```
function [ SROC ] = SROC( tle,tls,op,opt,time,Rt,R )
SROC=ROC(Rt,R);
s=opdet(tle,tls,op,opt,time);
k=length(s);
for i=1:k
   if s(i)==0
      SROC(i)=0;
   end
end
```

The function ROC is the equivalent of function Dev. It takes the results from the next function ROCM that just calculates the rate of change on each point.

```
function [ ROC ] = ROC( Rtdata,size )
ROC=0;
l=length(Rtdata);
for i=1:l
   s=ROCM(Rtdata,i,size);
   ROC=[ROC;s];
end
ROC=ROC(2:l);

end
```

This function basically is the same; it just calculates the deviation of the curve within itself. And in this one the R in needed more to be precise as the results changes directly with the change of R.

```
function [ ROCM ] = ROCM( x,i,R )
t=i+R;
l=i-R;
g=length(x);
if  t>g
   t=g;
end
if l<=0
l=i;
end
x1= mean(x(l:i));
y1= mean(x(i:t));
ROCM=((y1-x1)/x1)*100;

end
```

The results for the deviation and rate of change are presented together in the following plot. The two graphs where of different signs. And for the deviation, the positive thresholds is irrelevant and the other way around for the rate of change.
There is noted symmetry and the two events show bells shapes of proportional sizes to the relevance of the sticking event. The increase already puts the light on the significance of the hook load for the sticking events.
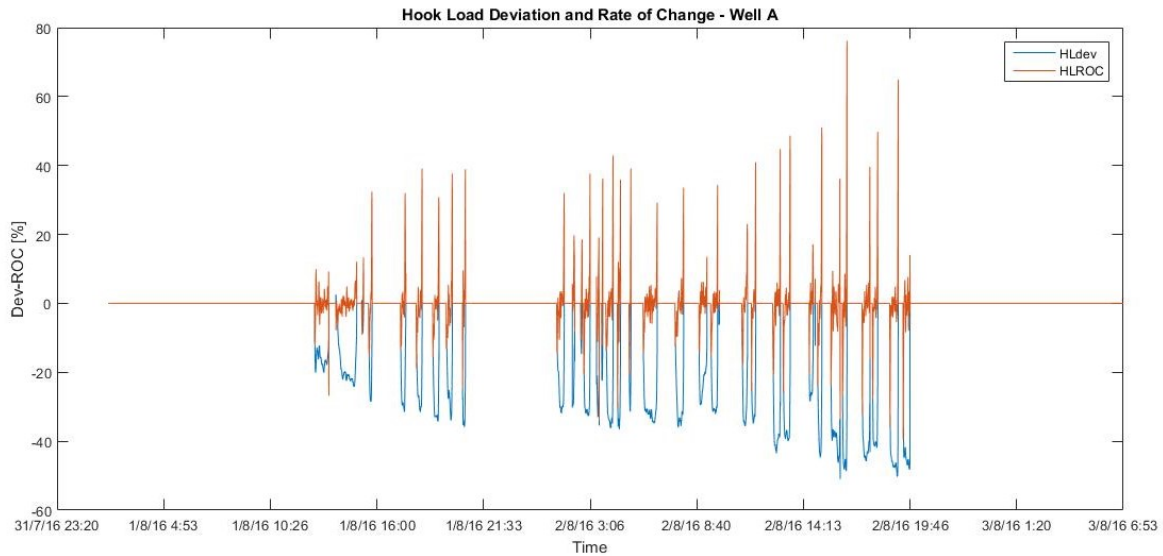
Figure 13 Hook Load Deviation and Rate of Change - Well A

The stand pipe pressure showed a uniform behavior for both deviations with few peeks.
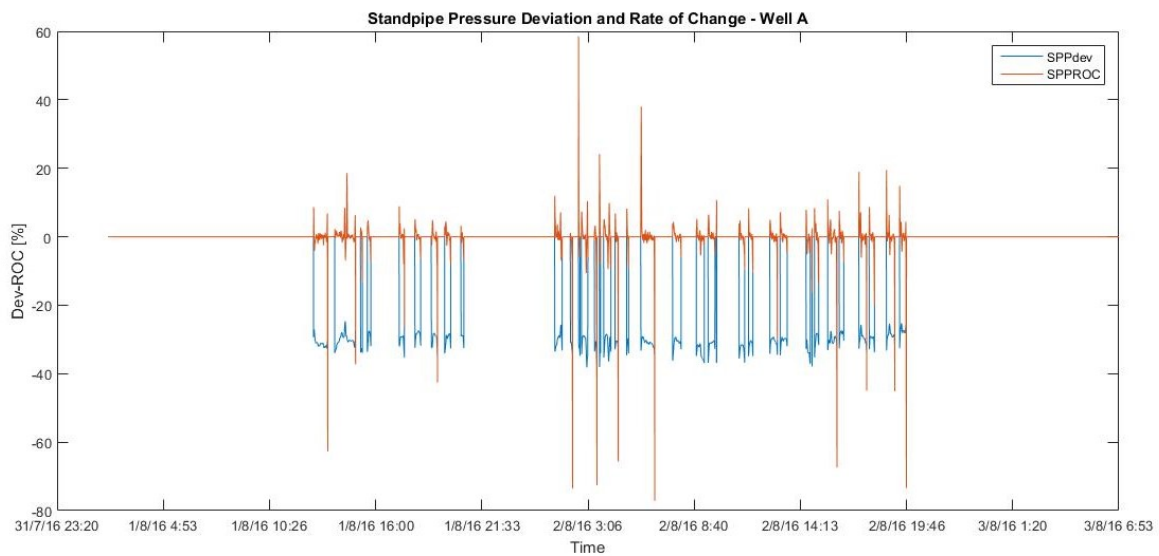

Figure 14 Standpipe Pressure Deviation and ROC - Well A

As for the torque, the Deviation and the rate of change values had far different range of values that they couldn't be properly plotted together. The resulting curve for the deviation has a hyperbolic trend.

The trend might be of significance and requires further investigation, but it is to leave aside since the actual simulated data do not fit with the measured one.
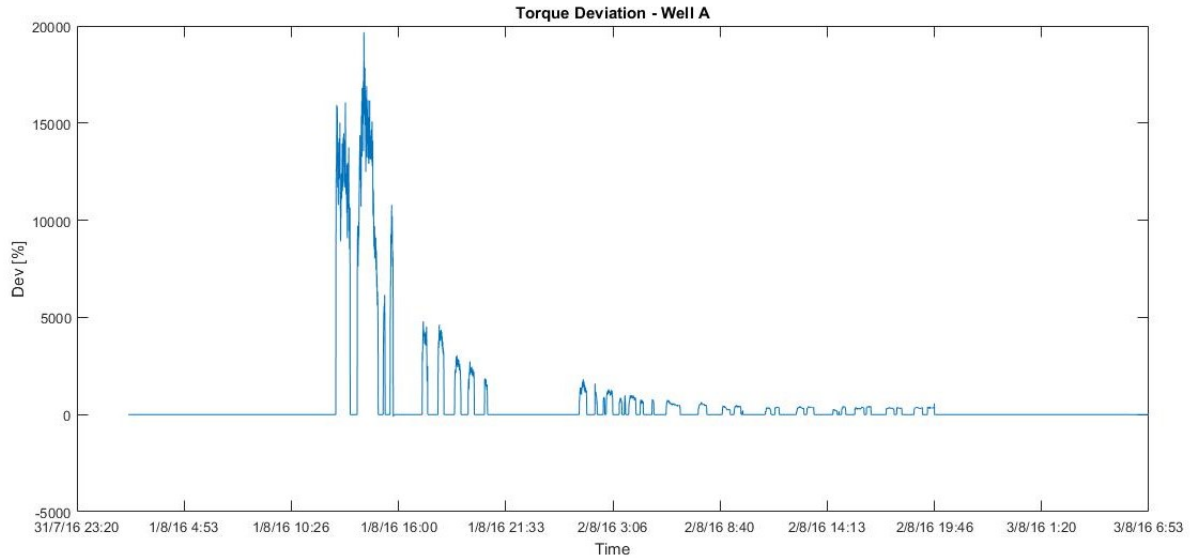
Figure 15 Torque Deviation - Well A

In the rate of change curve, the values were both positive and negative. It shows that every stand being drilled had increases and decreases in the torque. And peaks in all of them show disturbed torque values.
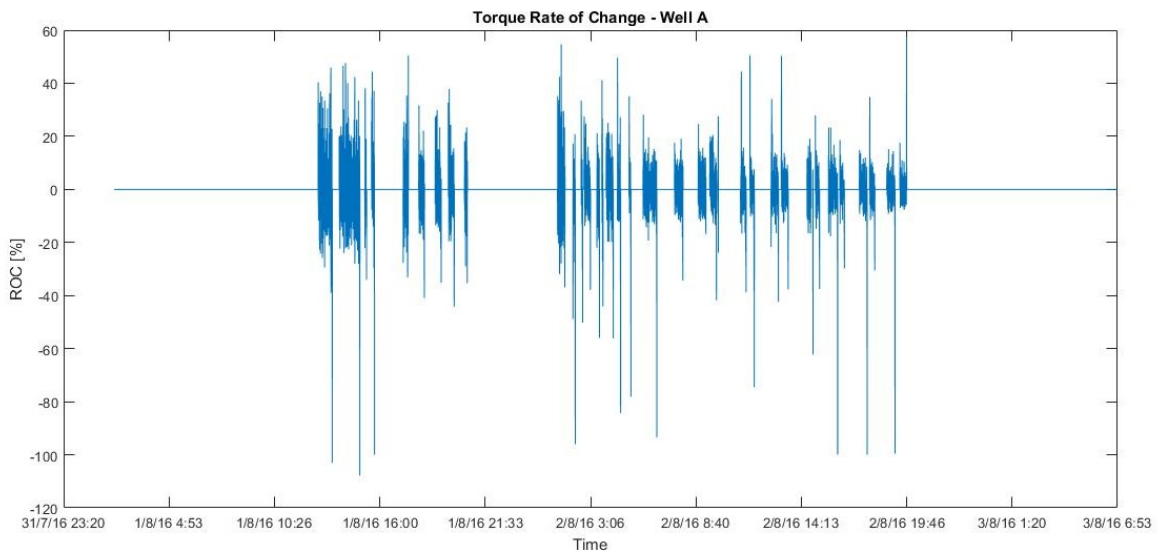

Figure 16 Torque ROC - Well A

After having the rate of change and deviation for data ready, alerts need to be generated. The alert is the ratio of the change whether it is deviation or ROC to the thresholds that are to be better defined later.

Since the change curves have both positive and negative values. There needs to be two thresholds for the sake of have a positive alert and to allow increases and decreases to be differentiated and weighted differently.

The script part for alerts is as follows.

AlertHLdev=Alert(ThHLdev,NThHLdev,HLdev);
AlertHLROC=Alert(ThHLROC,NThHLROC,HLROC);

The Alert function is defined as below. For this function, Alert was given a null value by being multiplied in the change. This was for the purpose of having the size of the series set in prior which is recommended on Matlab.

```
function [ Alert ] = Alert( Th,ThN,change )
l=length(change);
Alert=change*0;
for i=1:l
   if change(i)>=0
    Alert(i)=change(i)/Th;
   else Alert(i)=change(i)/ThN;
   end
end
end
```

The resulting alert curves are presented in the following graphs. At this point, there needs to be a decision on the value of the maximum alert.
It is prior to decide on a value that covers most of the alert points without being too high to avoid making lower alert levels irrelevant.

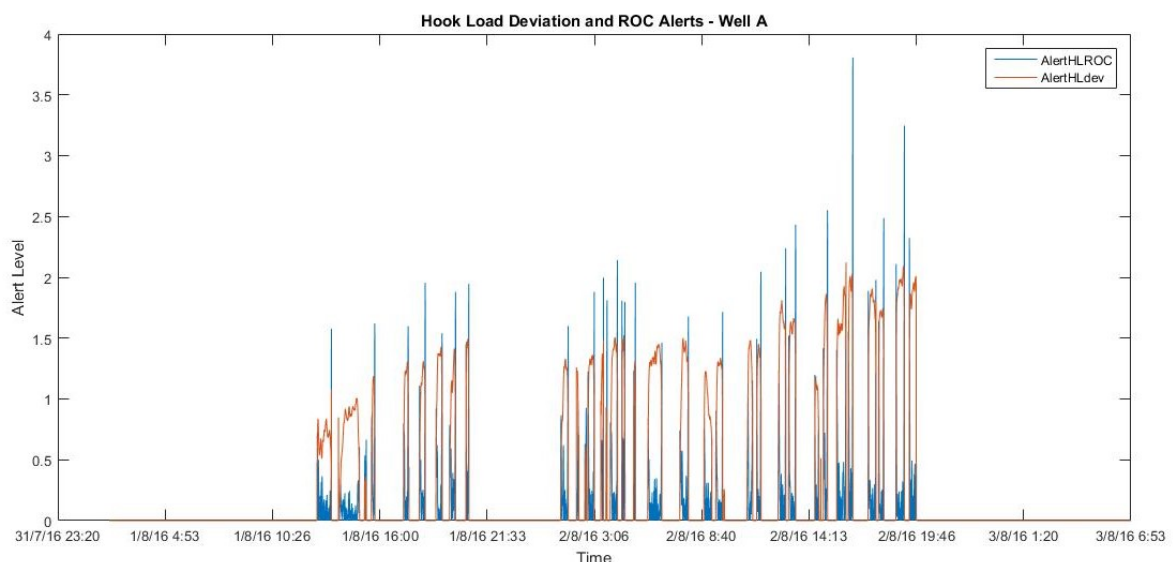The hook load alerts are presented in the following plot.

Figure 17 Hook Load Deviation and ROC Alerts - Well A

The SPP alert shows that only ROC alerts would be of relevance. It is presented in the plot below.
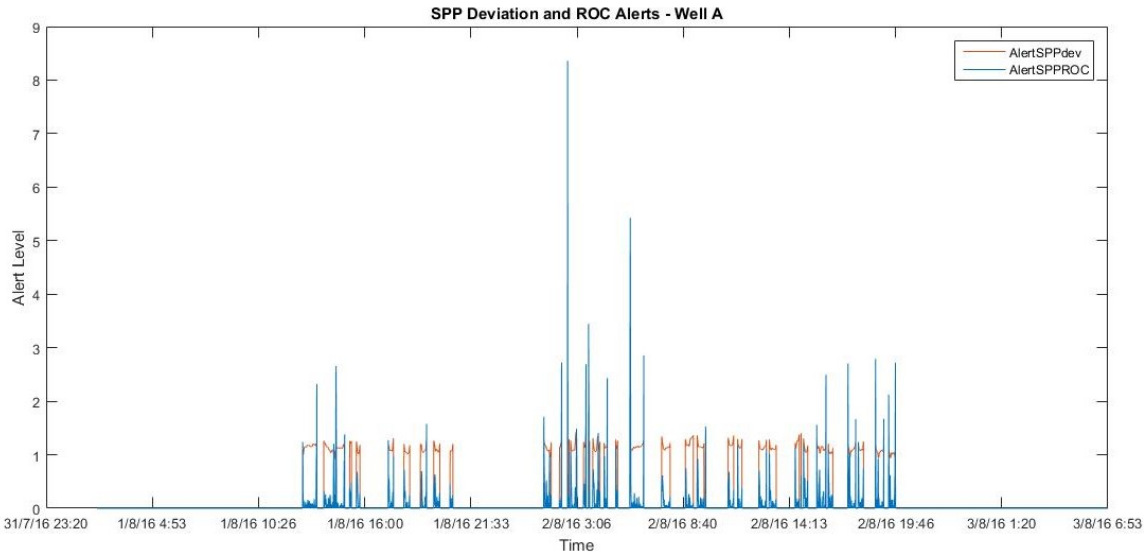

Figure 18 SPP Deviation and ROC Alerts - Well A

Finally, the torque alerts. Here we can notice that the hyperbolic shape of the deviation resulted only in one peak, as for the ROC it had three high alert zones which matched with the peaks in the SPP ROC alert curve.
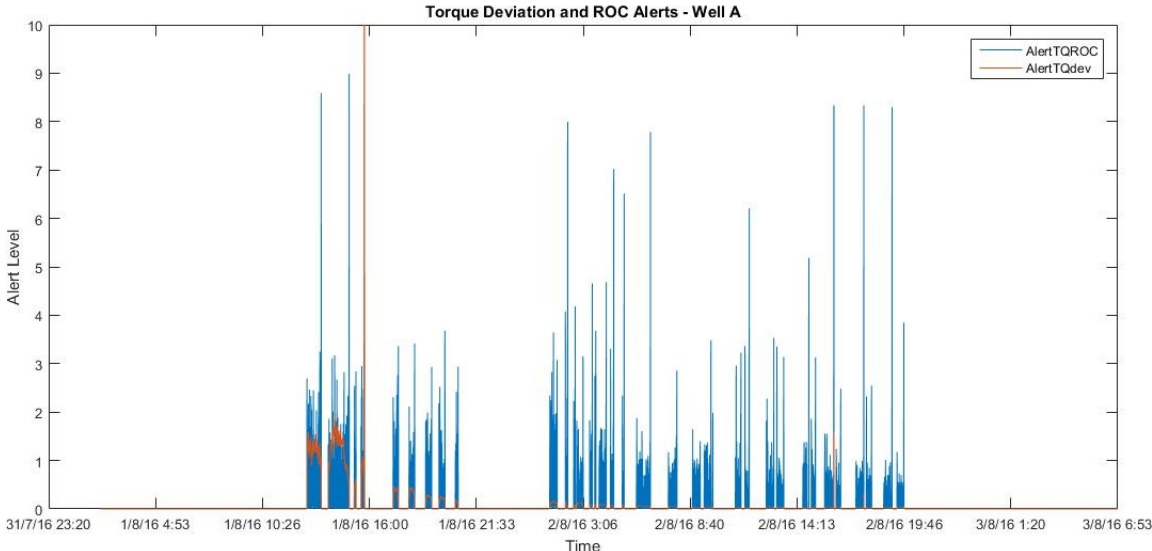

Figure 19 Torque Deviation and ROC Alerts - Well A

Now that all the alerts are available and the algorithm is tested and working so far. The final output, the risk of sticking can be calculated.

It is noted that so far the thresholds have not been defined and the values used for the sake of building the algorithm are +10% and -10%.

The pipe sticking risk look as follows in the script.

It takes as input all the alerts plus the MaxAlert, which is the sum of every maximum alert. As far, the value of each was 3. This value was presented in the paper (Kent Salmine et al. , SPE 178888-Ms) studied in the literature revue and seemed to be efficient.

Below, there is the script of calculating the final risk.

PipeStickingRisk=Risk(MaxAlert,AlertHLdev,AlertSPPdev,AlertHLROC,AlertSPPROC,AlertTQdev,AlertTQROC);

Below, the risk function is defined. It first limits the alert values to the maximum level and that is 3.

Then, the sum of the alerts is divided by the maximum alert MaxAlert of the value 18.

```
function [Risk7 ] = Risk (MaxA,a,b,c,d,e,f)
l=length(a);
for k=1:l
    if a(k)>=3
        a(k)=3;
    end
end
for j=1:l
    if b(j)>=3
        b(j)=3;
    end
end
for s=1:l
    if c(s)>=3
        c(s)=3;
    end
end
for o=1:l
    if d(o)>=3
        d(o)=3;
    end
end
for k=1:l
    if e(k)>=3
        e(k)=3;
    end
end
for k=1:l
    if f(k)>=3
        f(k)=3;
    end
end
Risk7=100*(a+b+c+d+e+f)/MaxA;
end
```

The pipe sticking risk, when plotted, results in the following plot. At this point, it is confirmed that the algorithm works and the functions are able to provide the desired outputs.

The following curve shows two remarkable increases and the latter reaches a higher value. This suggests that the first one can be associated with the near miss case around 1/8/16 21:33 and the second one with the actual sticking incident.

For that, the first increase should not exceed 50% which is the decided threshold for whether a sticking is happening or not. The second should be higher that 50% since the sticking is confirmed.

Anyway, besides adjusting the upper limits the curve needs to be smoothed and adjusted in a way to avoid misleading peaks. This is to be achieved through adjusting the alert thresholds.
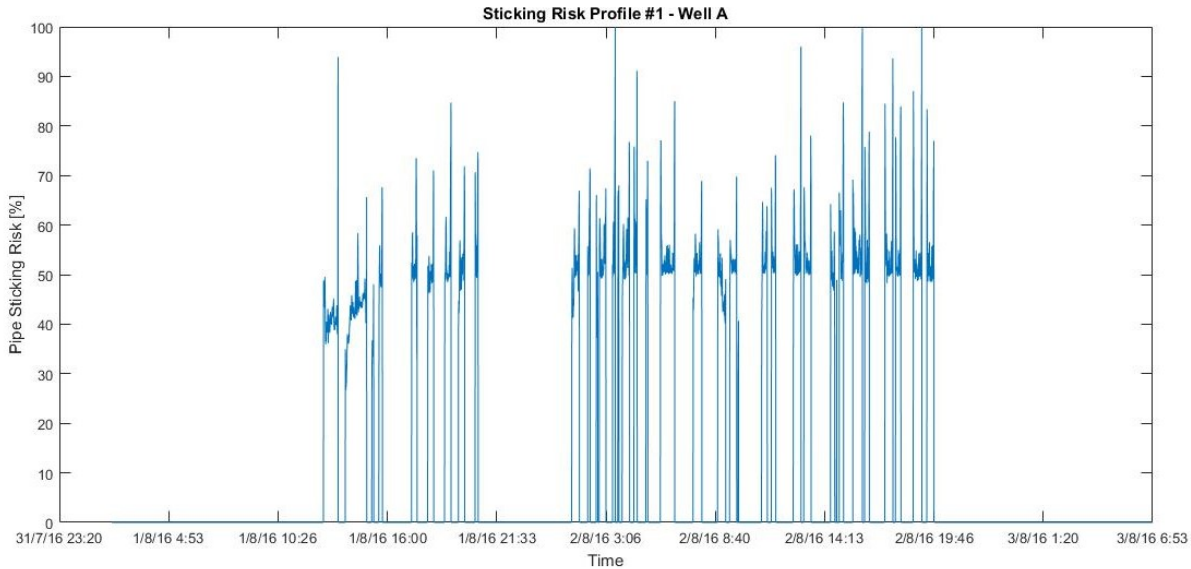

Figure 20 Sticking Risk Profile #1 - Well A

At this point, the thresholds would be changed and the effects of each change noted in order to understand and be able to choose the right ones that would provide the conditions mentioned above.

The first different values of thresholds tested are presented in the table below.

Table 4 Secong set of Thresholds - Well A

Threshold	Hook Load		SPP		Torque	
%	Dev	ROC	Dev	ROC	Dev	ROC
+	+10	+12	+10	+5	+200	+15
-	-12	-12	-12	-20	-10	-20

These values resulted in a smoother curve that is presented below.

The gradual increase in the risk is shown better but the values in all are higher and needs to be lowered. That can be achieved with higher threshold values.
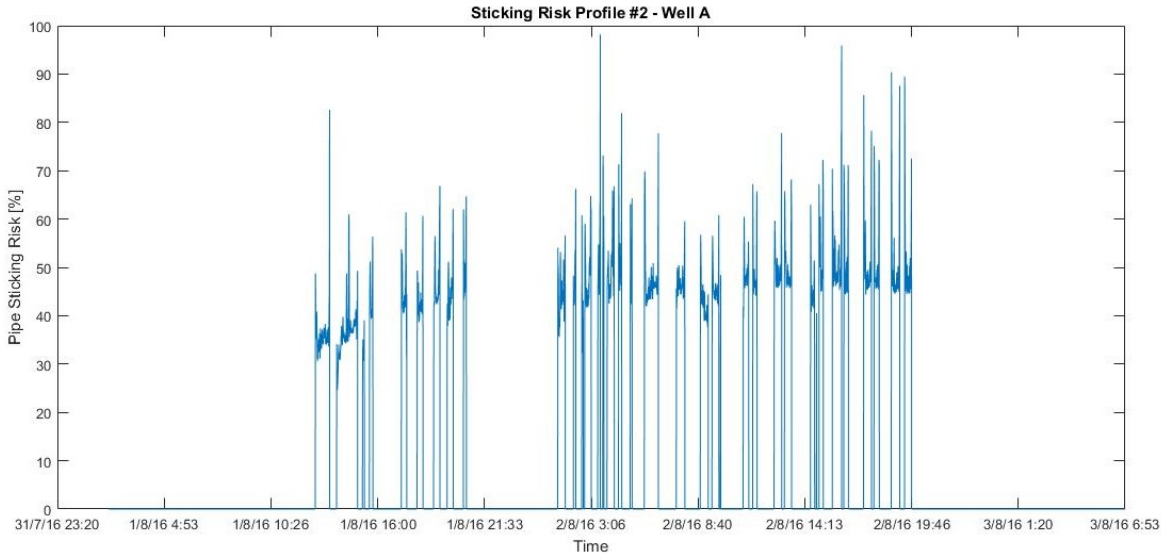

Figure 21 Sticking Risk Profile #2 - Well A

When higher values are chosen, the result is the following curve. This curve still shows the wanted increase of risk.

At this point the threshold values used created a range. In order to have the values fitting with the y-axis line of 50%, the values need to be chosen in those ranges.
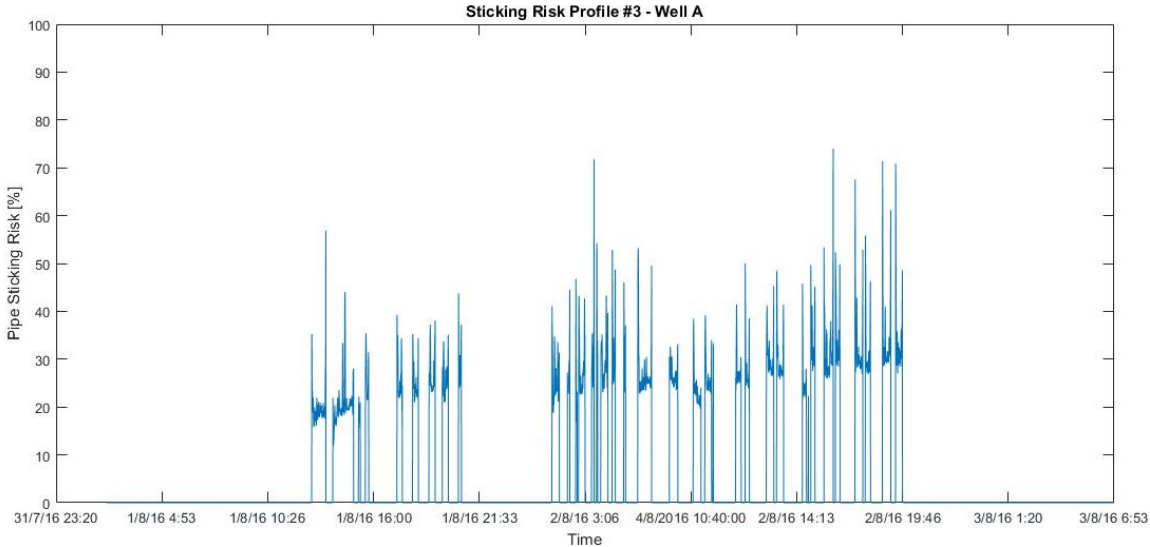

Figure 22 Sticking Risk Profile #3 - Well A

With looking back to the deviation and rate of change curves, it was noticed that within the defined ranges there are deviation values that are the minimum of most peaks. These values are covered and if they were chosen to be the thresholds only the extra deviation would be accounted for and then deviations would be accounted for more efficiently.

Those values are taken from each deviation or rate of change and are run through the algorithm.

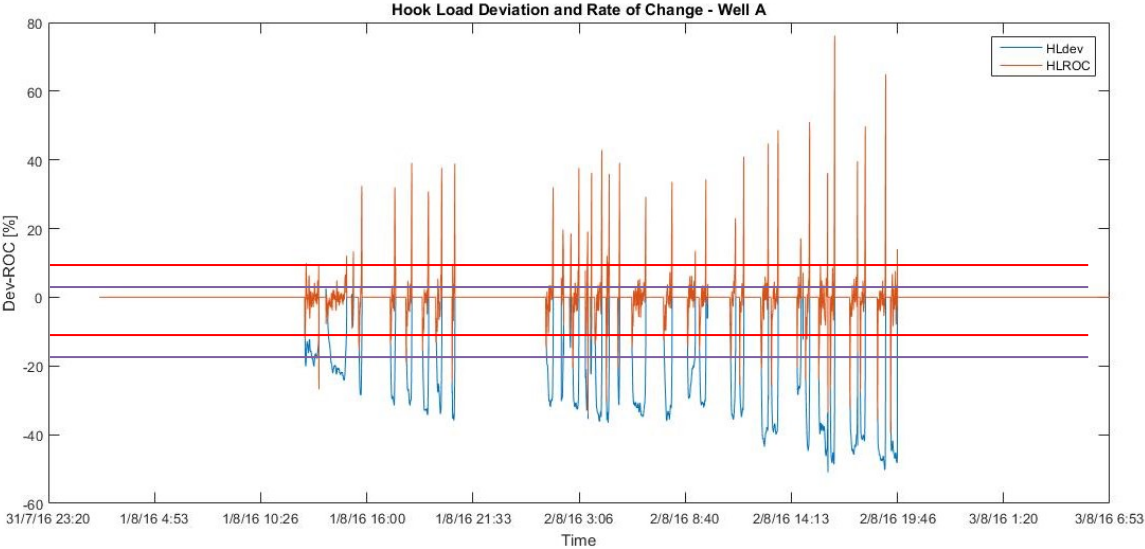Below, those threshold values are shown in the respective plots.

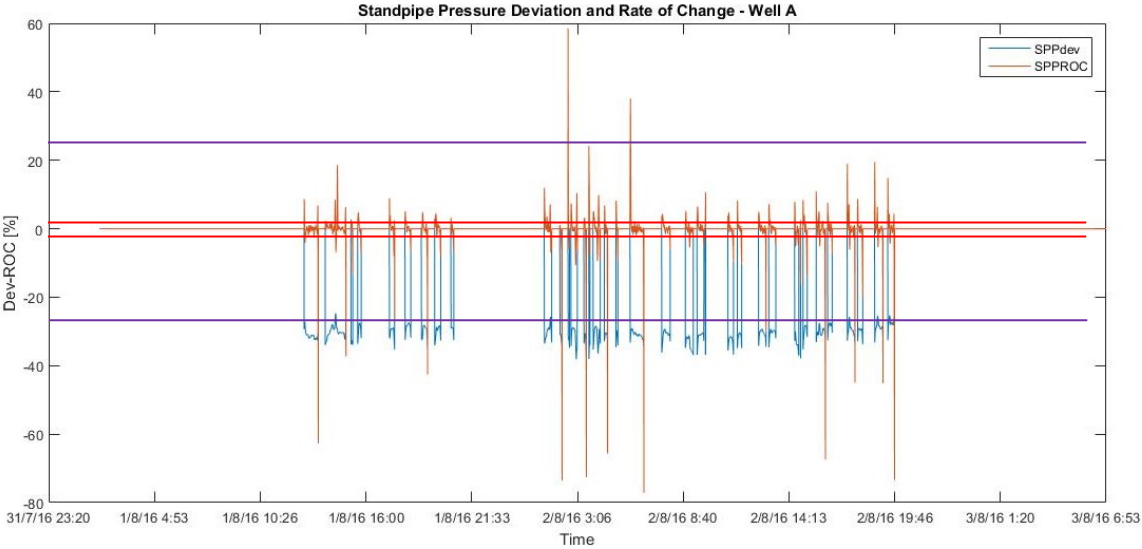
Figure 23 Hook Load Thresholds

Figure 24 SPP Thresholds

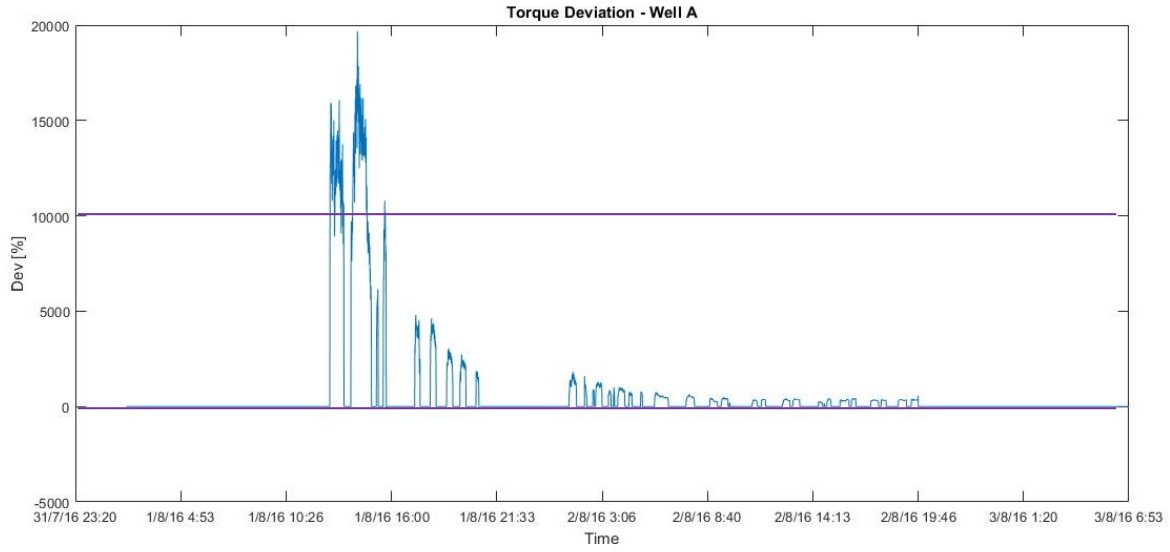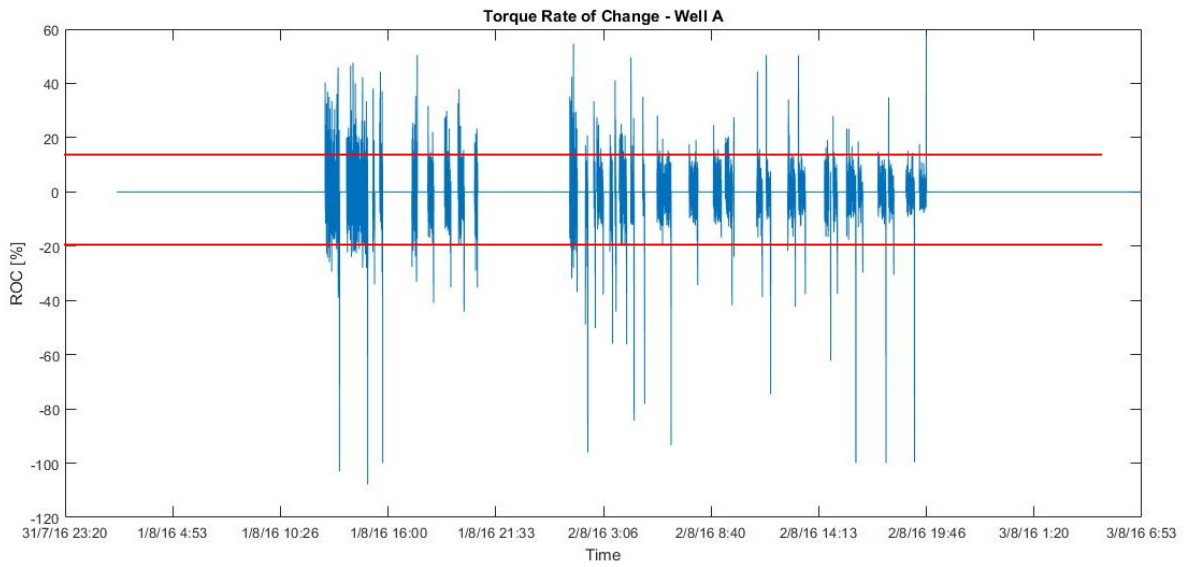**Figure 25 Torque Deviation Thresholds**

Figure 26 Torque ROC Thresholds

The new threshold values are summarized in the table below.

Table 5 Final Thresholds - Well A

Threshold	Hook Load		SPP		Torque	
%	Dev	ROC	Dev	ROC	Dev	ROC
+	+3	+8	+25	+3	+10k	+15
-	-18	-12	-27	-2	-10	-20

As those values ran through the algorithm, the sticking risk was as follows in the plot. Those values are more acceptable than any result before and it was logical to pick values where only the remarkable peaks are effective. The risk profile is accepted and the threshold choosing method is standing until being proven accurate through the next well.
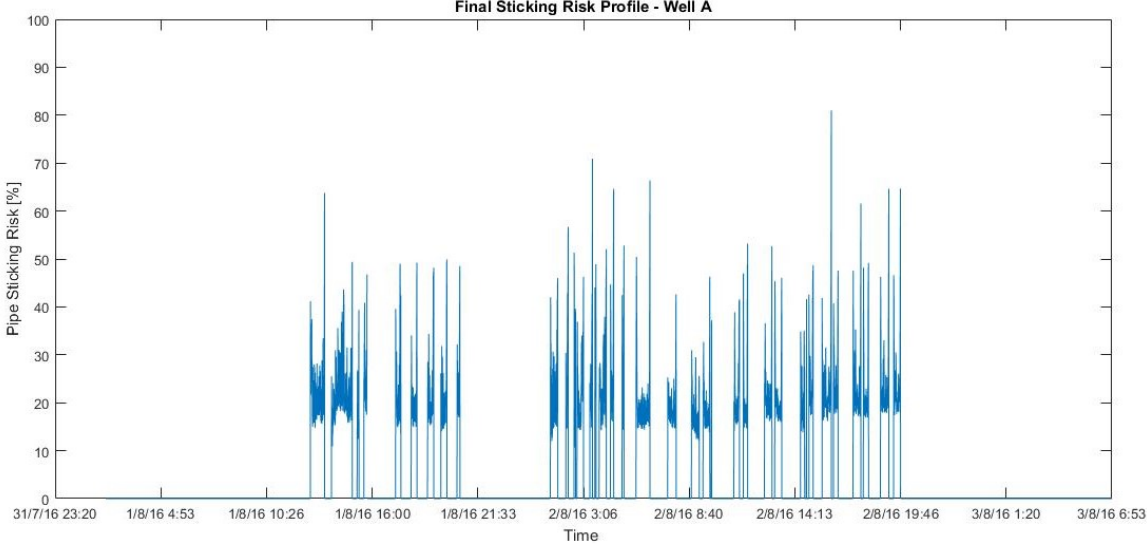

Figure 27 Final Sticking Risk Profile - Well A

The curve above shows a very early alert for the final sticking as it gives a 02:05h head-start. The value seems too good to be real especially compared to the value presented in the related studied literature. But it is explainable, since the curve was fitted to the purpose.

Well B: Sticking while POOH

The second well, well B, has an occurring of sticking while pulling out of hole. The sticking occurred after the target depth was reached.

Around 5th May 2016 17h, with a measured depth of 5201 m, the pipe was stuck at 2348 m while tripping out. The crew attempted to free the pipe through the following sequence:

- Get rotation with torque up to 55 kNm and to run in hole with jarring downward but with no go.
- Jarred downwards 10 times, applied 60 kNm torque and attempted again.
- Jarred up 5 times and pulled with 345 ton.
- Jarred 5 times down with no torque.
- Jarred up 5 times and pulled with 345 ton.
- Continued jarring up and down with torque only when jarring down.
- Performed slip and cut then drop check.
- Continued jarring up and down in sequences.
- Maintenance.
- Waited on wireline cutting equipment.
- Installed slips with 215 ton tension.
- Cutting toolstring and correlating.
- POOH to 275 m.

The process can be seen in the graph below through the bit position in time and depth.
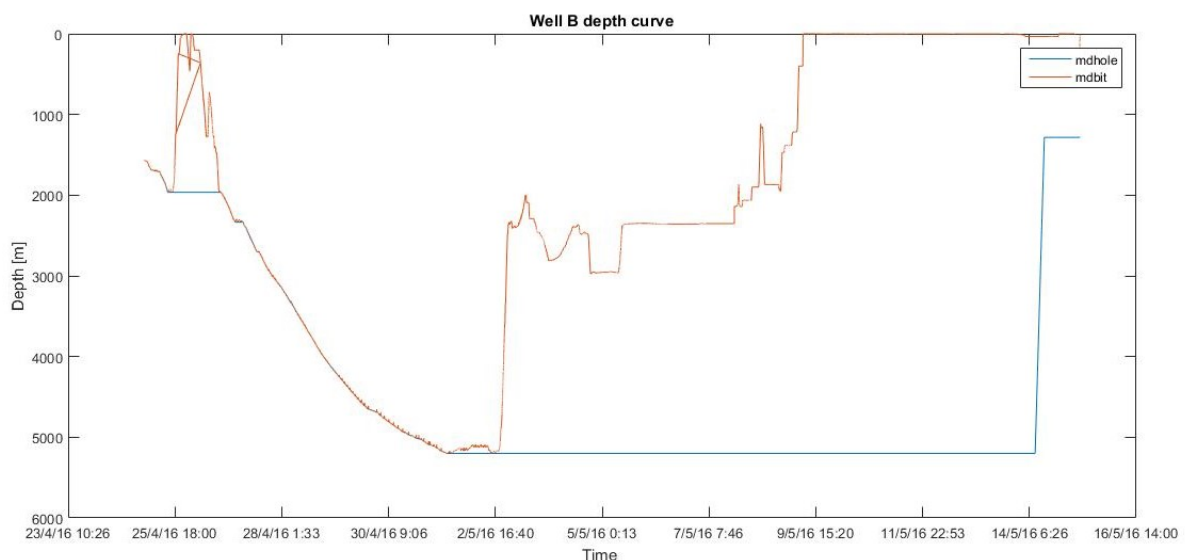

Figure 28 Well B depth curve

Similar to well A, the data for well B was plotted real-time vs. simulations and the best fitting curve was chosen to be used in the algorithm.

In the plot below, it is seen that HLUP follows the measured curve till the sticking happens and thus it was chosen.
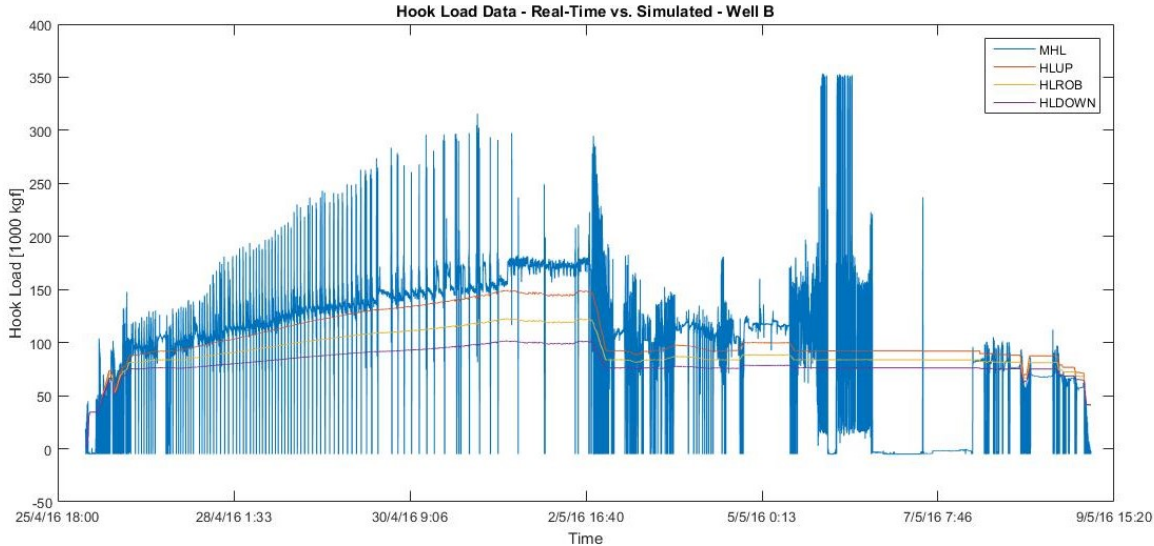

Figure 29 Hook Load Data Simulated vs R-T - Well B

The standpipe pressure is acceptable, but differs from well A where there was just a value too be added. Here, the curves cross two times where one is just before the sticking occurred. That might result in a strong indication.
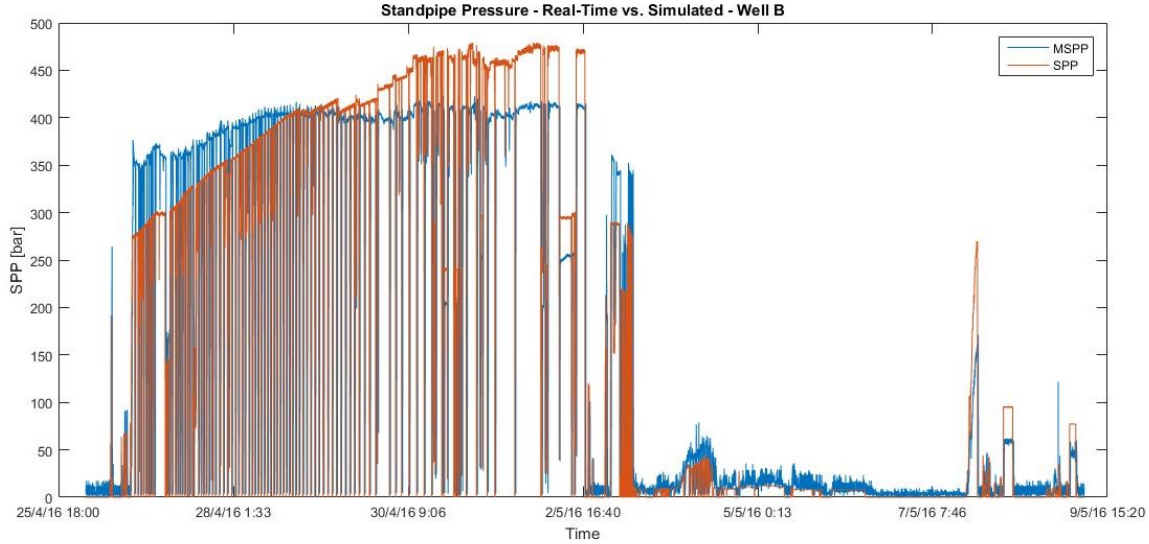

Figure 30 SPP Simulated vs R-T - Well B

The last curve of the input data below show the torque simulated curves matching the real-time curve with slight deviations before the occurring of the sticking.
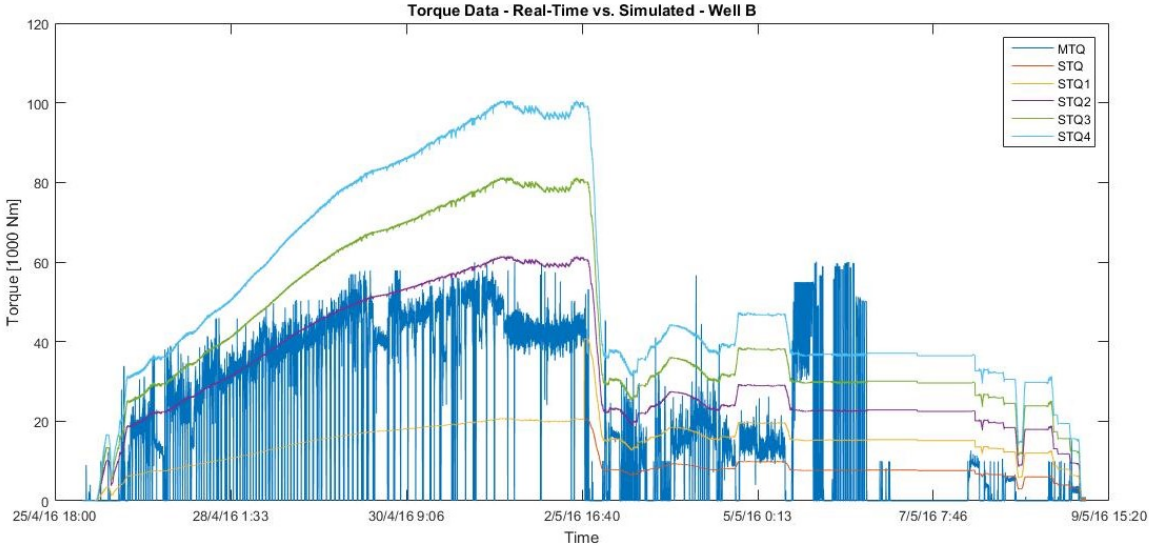
The curves so far promise good indications to before the sticking event happens. This can be proven through running it through the algorithm and picking the right thresholds.

Only few inputs are to be changed in order to adapt the old algorithm to this well. Mainly those are the type of operation in scope and the indexing of the inputs.

Once the algorithm filters out all operations other than the POOH, only small data points are left. This would make reading the curves much more challenging.

Below, the deviation curves for HL, SPP and Torque are presented.
The thresholds are going to be picked at this point in order to test and to prove working the method of choosing them that has been noticed through the first well.
In case those thresholds provide a sound alert in this well, this method is then decided to be the way to go for thresholds.
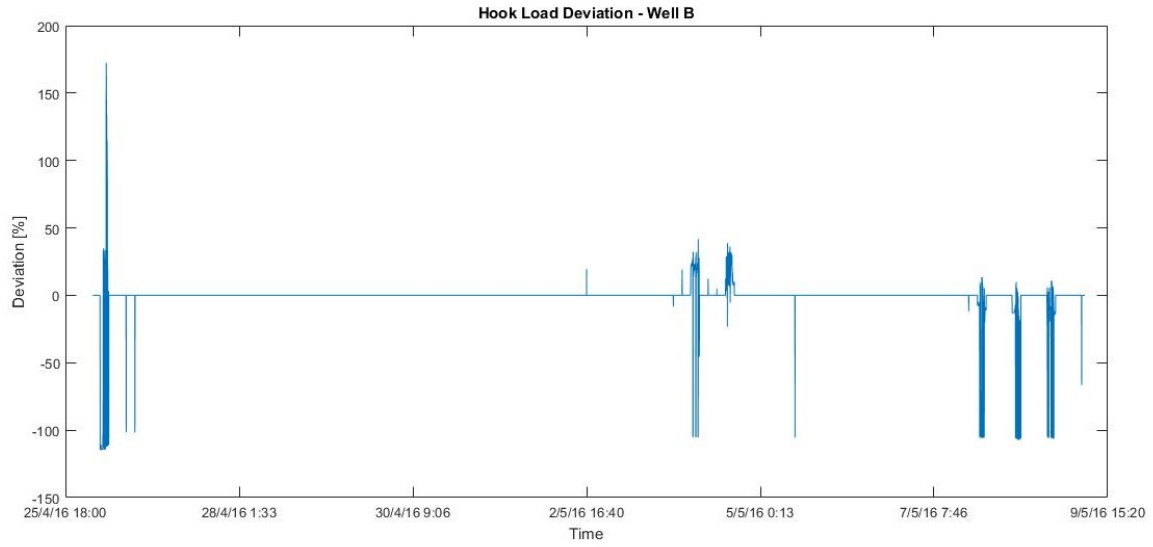
Figure 32 Hook Load Deviation - Well B
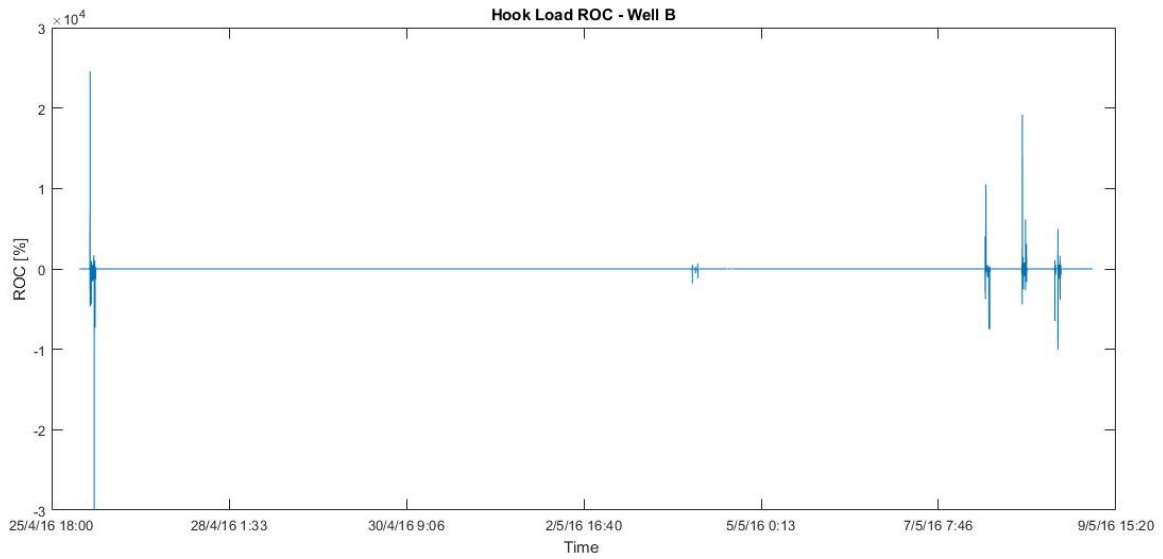
Figure 33 Hook Load ROC - Well B
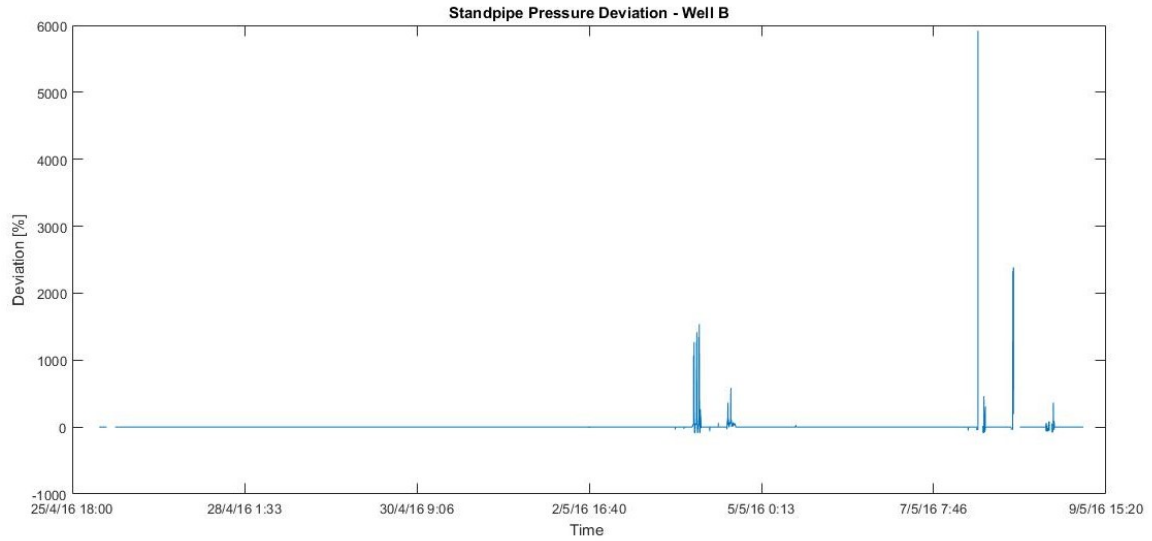
Figure 34 SPP Deviation - Well B
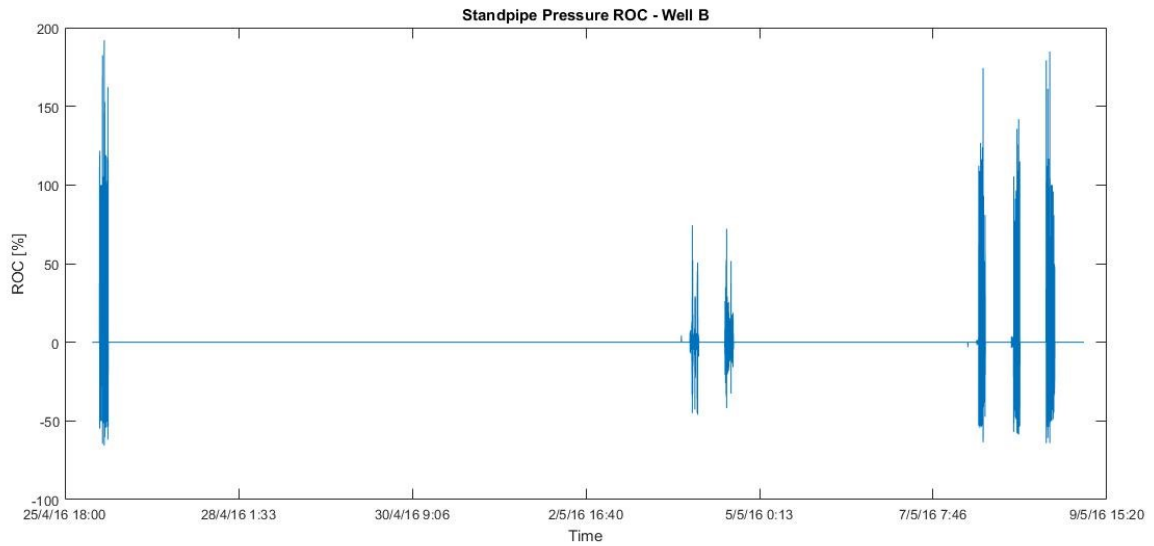
Figure 35 SPP ROC - Well B
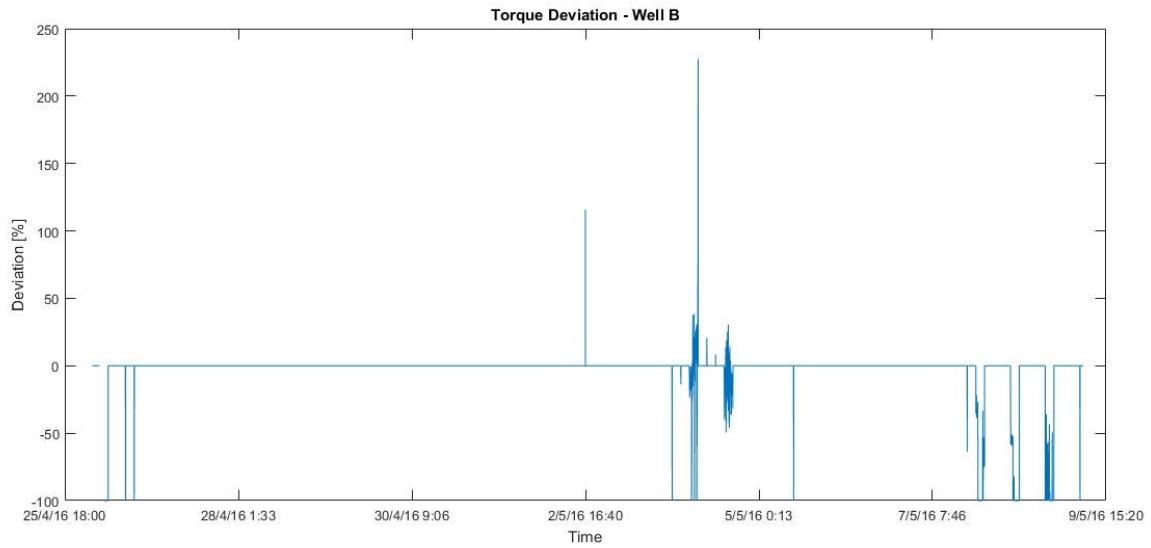
Figure 36 Torque Deviation - Well B
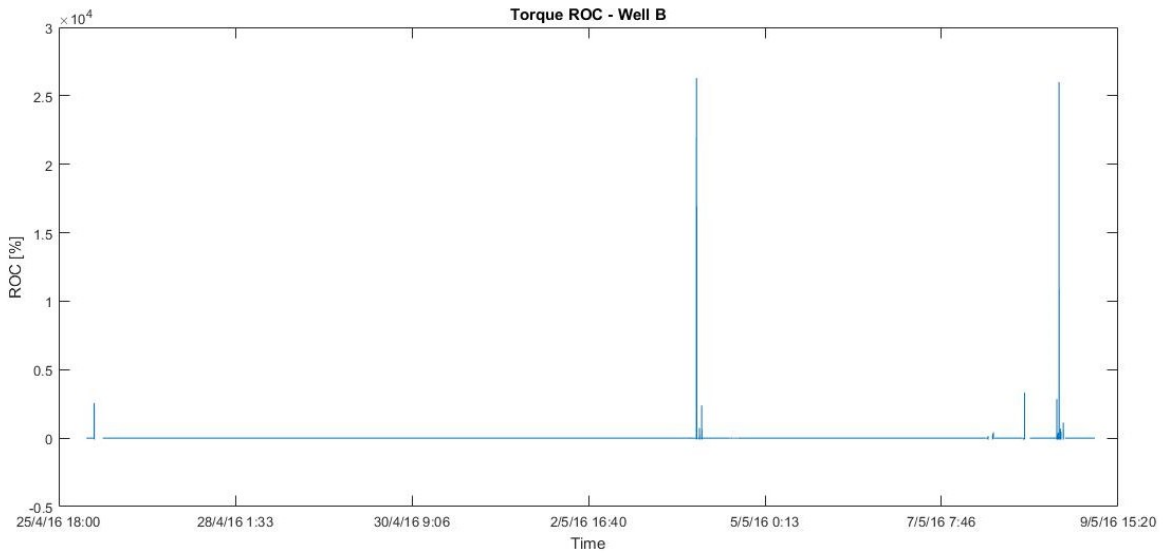
Figure 37 Torque ROC - Well B

The thresholds deducted visually are summarized in the table below.

Those thresholds are not precise but they would be enough to tell if there would be a decent alert signaling the sticking before it occurs.

Table 6 Thresholds - Well B

Threshold	Hook Load		SPP		Torque	
%	Dev	ROC	Dev	ROC	Dev	ROC
+	+10	+4000	+10	+10	+30	+1000
-	-40	-1000	-40	-10	-50	-10

After running the entire algorithm, the result is presented in the plot below.
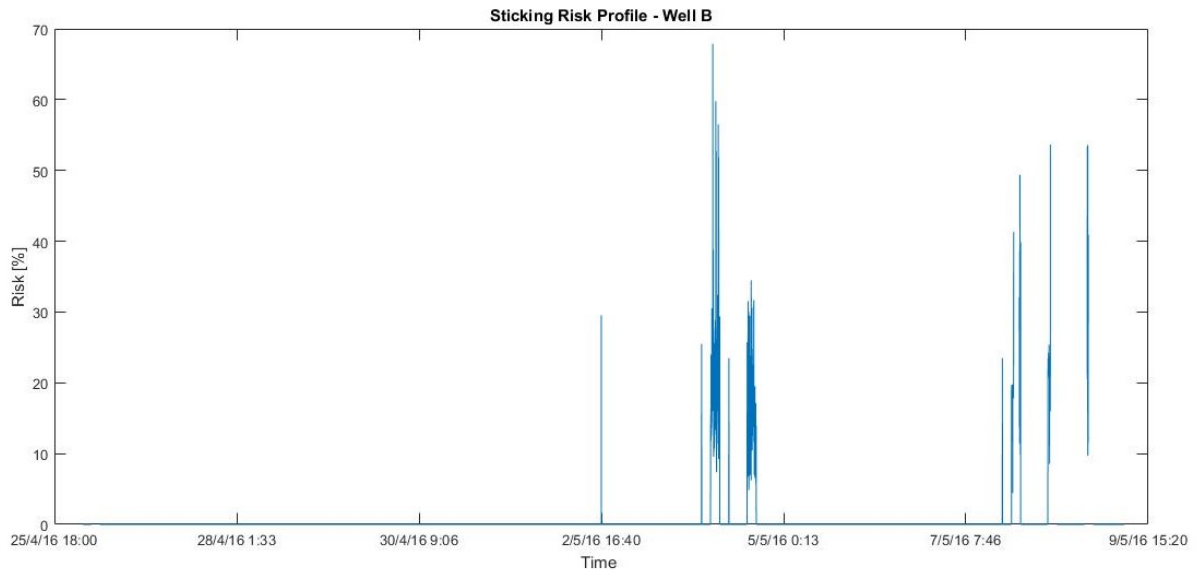
Figure 38 Sticking Risk Profile - Well B

It can be seen that there is a significant alert that precedes the sticking event with 12:30h. The thresholds chosen were efficient and this is enough to prove the logic behind choosing those thresholds adds up.

At this point, those two wells provide alerts with good head-starts. The algorithm is now going to be tested on two well, well C and Well D. The purpose of this testing is to see if the algorithm is enough to provide an alert in similar cases.
Well C has a sticking occurring while POOH while the sticking in well D occurs while drilling. In order for the goal of this thesis to be met, the thresholds are going to be kept the same and nothing would change besides the inputted data.

Well C: Testing Well (POOH)

The third well was run through the algorithm with the same parameters and thresholds as well B since the sticking is while POOH.

The output is presented in the plot below.
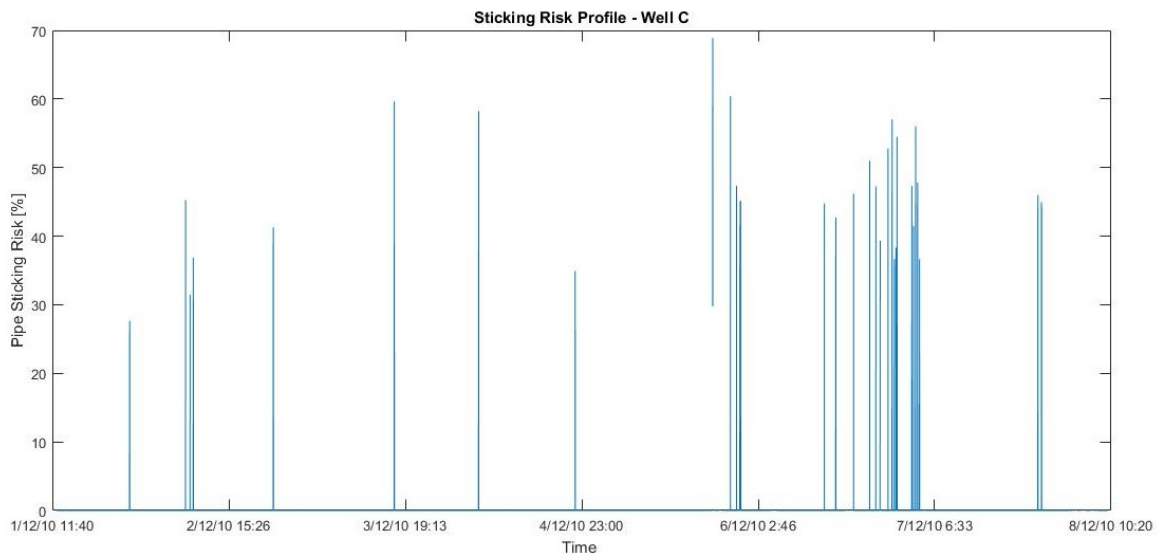
Figure 39 Sticking Risk Profile - Well C

Not all peaks exceed 50%. A first look to the plot cannot tell whether it worked or not. The events in this plot need to be checked against the actual record of event in order to determine how successful this method in predicting the sticking event.

The sticking events that have occurred in reality are summarized in the table below.

Table 7 Sticking Events Summary Well C

Event #	Time of Occurrence	Description
Event 1	Dec-2 16:00	Experienced stuck pipe when pulling string up at the depth of 1105m MD. Established circulation and rotation and were able to work string free.
Event 2	Dec-5 23:15	Torque increased and pack-off was observed. Pressure increased before pumps were shut down. 30 bars were trapped in DP after pack-off. String stuck with hole at 2497m MD. String worked free and pressure in DP dropped off.
Event 3	Dec-7 01:15	Increase in torque and pack-off at 1569m (hole MD 2497m). Shut down pumps. String stuck and a hook load of 225 ton is experienced because of rig heave. Worked string free and circulated.

Event 4	Dec-7 16:15	String got stuck while attempting POOH. Worked pipe up and down with attempts to establish circulation without success. With max overpull, string was free to rotate. While working string, torque gradually increased. Attempted jarring up and down with no success. Concluded that hole packed off above the jar. Increased torque, pipe rotation and gradually pressured up string. Observed decrease in torque and pressure with return in trip tank. Circulated and then continued POOH.

The event summerized in the table can be matched with the pipe sticking risk plot. This is displayed in the plot below.
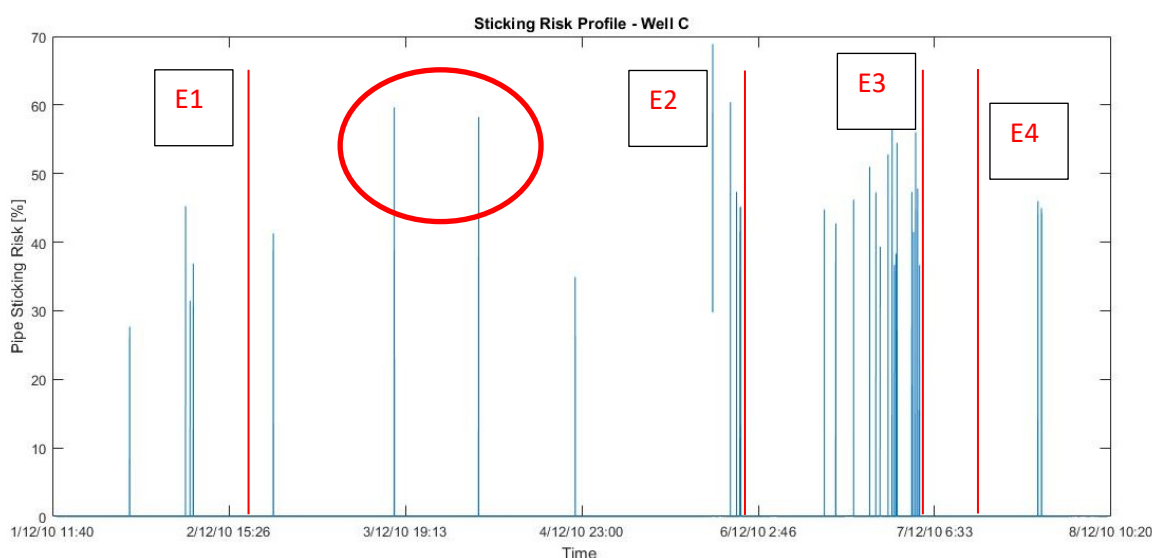
Figure 40 Sticking Risk Profile vs Actual Events - Well C

It is observed that for each sticking event there is a risk exceeding 50% except for the first event where the value was a little bit below.

The first event was less relevant compared to the next three events. The second event was signaled with a very strong risk percentage while the third and fourth had a consistently increasing strong signal. Those signals are enough to tip the crew with the sticking through the following head-starts in the table below.

Table 8 Head-starts summary - Well C

Event #	Head-start (h)
Event 1	06:56
Event 2	05:10
Event 3 & 4	07:30

Among the peaks that exceeded the 50% line, there were two single peaks. Those peaks are different from the other risk indicators, for being a single point and far from any other points.

These two points can be seen as measurement errors and can be put aside.

Well D: Second Testing Well (Drilling)

For the second testing well, well D, the sticking events occurred while drilling. The data from well D is used with the same parameters and threshold values of well A except for the Torque thresholds. Those thresholds had to be adjusted since the values in well A were based on badly-fitting simulation because of the lack in simulation inputs.

The difference is that in well A, the torque contribution to the overall sticking risk was reduced while in this well the contribution is reasonably based on the threshold choosing method.

The plot below represents the outputted plot from running well D through the same algorithm on well A. Signaled in red are the sticking events.
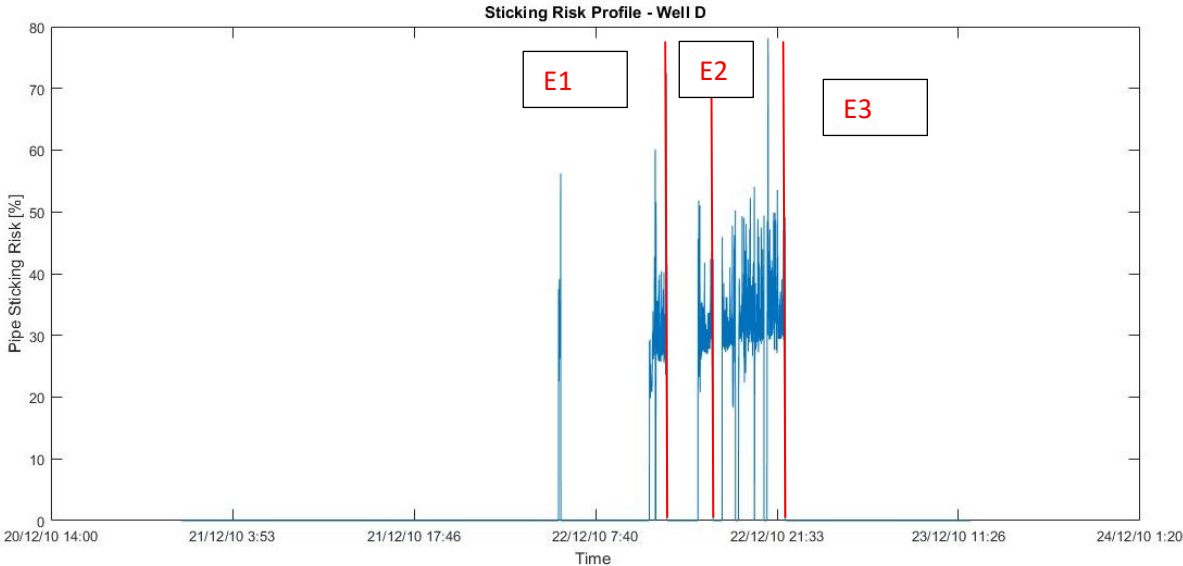
Figure 41 Sticking Risk Profile vs Actual Even - Well D

The plot above shows three sticking events. Those events show an increase similar to the ones in well A.
Those events match with the recorded history of the well. It is summarized in the table below.

Table 9 Sticking Events Summary - Well D

Event #	Time of Occurrence	Description
Event 1	Dec-22 11:29	Stuck pipe observed while pulling up for connection while drilling a 12 ¼ " hole from 2944.5 m to 2961 m MD. Attempted to rotate but without success. Jarred string several times, moving around 1m each time. Increased flow and attempted to rotate, without success. Reduced flow and jarred string free.
Event 2	Dec-22 15:25	Pipe got stuck after connection while drilling from 2961 m to 2980 m. The string came free with 36 kNm and 800 lpm.
Event 3	Dec-22 22:10	Well static after flow check for 10 mins. Observed overpull when pulling out of hole and string was stuck at MD of 3038. Established circulation in steps and pulled the pipe free.

The sticking events match with the plot perfectly. Testing this well is successful and provides the following head-starts for the events.

Table 10 Head-starts summary - Well D

Event #	Head-start
Event 1	01:15
Event 2	01:23
Event 3	03:28

Discussion

In order to reach the desired result from this thesis, the testing wells needed to provide a head-start to the right events where sticking occurred. The head-starts were noted and are actually enough for the crew to react and avoid or mitigate the sticking if this was tested in reality.

In the literature, head-starts were ranging between 48mins and few hours. So far, the values recorded are much better. This can be due to the difference in the wells nature as the wells in literature are mainly drilled in shale plays and the ones used in this thesis are North Sea offshore wells. Other possible reason is the difference in data like better quality of measurements in real-time or that the simulated data provided by ProNOVA is more accurate than the simulations used.

The results of the two testing wells are summarized in the table below.

Table 11 Testing wells Head-starts

Well C-POOH		Well D-Drilling	
Event #	Head-start (h)	Event #	Head-start
Event 1	06:56	Event 1	01:15
Event 2	05:10	Event 2	01:23
Event 3 & 4	07:30	Event 3	03:28

It was noticed while creating the algorithm through wells A and B that well B had a much higher head-start given; 12:30h compared to 02:05h for well A. This was seen at first as single case. But now that the results of the two testing wells are compared, this seems like a pattern. This method gives much earlier alerts when the sticking is occurring while POOH.

In the process of creating the algorithm, some details were taken from the mentioned literature but the core functions and the reasoning was adapted to the type of data provided. It was very helpful to have the operations provided aside for each well. Such information would allow better use of the real-time data.

An important issue was the finding of thresholds. Literature only described the role these thresholds and what they might look like to have a feeling for them. But there were no indication on how to get them.

The method developed in this thesis was logical since knowing the needed outcome would allow fixing a range for the threshold and the smaller range gave out the values much easier. Those values did work greatly and count as successful thresholds but they are taken graphically and lack accuracy.

Improving them is believed to improve the head-starts for the while-drilling sticking events. There might not be a significant difference after all once both scenarios are optimized.

In the sticking risk plots of the two wells, there have been single peaks that exceeded the 50% value. Those peaks are single points and were neglected in the process. But this raises the issue of whether using a window to average the data points before using was enough to surpass the bad measurement points.

The result of this method is very data quality dependent and this sheds more light on the importance of obtaining good data in the industry and the issues of data management in the future of drilling.

Conclusions

This thesis has proven it possible to predict impending pipe sticking in the main two drilling operations that sticking occurs through. The objective was to create an algorithm that takes as input the real-time data and a simulated data and used them to give an alert prior to any sticking event regardless to the reason or type of sticking.
At this end, the objective has been reached successfully.

This result depended on many factors such as the quality of the measured data and the accuracy of the simulated streams in matching the measured ones. This issue is wider in the oil and gas industry as there is accumulation of great amounts of data while there is less interest in interpreting the data and making more value of it that just stored bits.

This used approach is considered simple and straight forward. There is definitely more that can be withdrawn from the data to put the industry ahead of classical problems such as pipe sticking.

The calculated deviation and rate of change can be used as primary information and there is a huge potential of what can be deducted and used as indicators. Also, there is potential to use more trend analysis and experiment with data channels to reach more advanced and useful results such as differentiating between types of sticking.

In short, there is great potential for next steps in this study but the road is long to go until the full use of the real-time data is achieved and the knowledge is passed from human experts to machine as KPIs.

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Appendices

Hook Load Data - Well C

Standpipe Pressure Data - Well C

Standpipe Pressure Deviation and ROC - Well C

Torque Data - Well C

Torque Deviation - Well C

Torque ROC - Well C

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Hook Load Deviation and ROC - Well C