University of Stavanger

FACULTY OF SCIENCE AND TECHNOLOGY

MASTER'S THESIS

Study programme/specialisation: MSc. Petroleum Technology / Drilling and Well Engineering	Spring/ Autumn semester, 20...... Open / Confidential
Author: Felix James Cardano Pacis	
Programme coordinator: Øystein Arild Supervisor(s): UiS – Prof. Kjell Kåre Fjelde; UiS – Prof. Mesfin Belayneh Agonafir; Exebenus – Dr. Dalila Gomes; Exebenus – Dr. Tim Robinson	
Title of master's thesis: An End-To-End Machine Learning Project for Detection of Stuck Pipe Symptoms During Tripping Operations	
Credits: 30	
Keywords: Hook Load Signatures Machine Learning Data Analysis Stuck Pipe Recurrent Neural Network	Number of pages: 90 + supplemental material/other: 28 Stavanger, 30th June 2021

Abstract

Non-productive time due to stuck pipe costs the Oil and Gas industry substantial losses amounting to $250 million annually [1]. Thus, it is imperative for companies to invest in tools that can aid in prevention. This study integrates different concepts and methodologies from Petroleum Engineering, Data Analysis, and Machine Learning (ML). It aims to identify and extract hook load signatures before a stuck pipe event that can be used to train an ML model. The lack of transparent and consistent frameworks in many published papers using the same approach proved to be a problem. Hence, it is also our aim to present all the algorithms used.

In a Machine Learning project, data preparation accounts for about 80% of the work [2, 3]. For this reason, the author developed two web-based applications for cleaning and exploring raw drilling data. These provided time savings given the time constraints of this project.

Once the data was prepared, maximum and local minimum hook loads were extracted for tripping out and tripping in operations, respectively. During the study, a new concept for extracting the local minimum hook load was developed. It was able to identify the trend deviation as early as 4 hours and 30 minutes before the reported stuck pipe. Furthermore, all the extracted maximum and local minimum hook loads distinguished trend deviation between normal and deteriorating downhole conditions. This was not possible when basing solely on the real-time hook load.

Moreover, a long short term-memory network was trained using 50% of the extracted hook load signatures. This model was designed to predict and identify hook load trends during tripping operations. Then using the remaining data, the model was evaluated. Results showed that the model predicted hook loads with a mean absolute error of <3% from the average expected value. The model also resembled trends with a delay of utmost 20 minutes or six stands, particularly during the deteriorating conditions. Despite the model failing to forecast, it detected a deteriorating condition three hours before the stuck pipe incident. These results were heavily dependent on the amount and quality of data. Out of seven wells provided, only three were functional, having at least 0.2 Hz of measurement.

Further studies involving gathering more high quality drilling data and retraining the model are recommended to be able to create a model capable of forecasting the trend deviations earlier than the currently developed model.

Acknowledgements

I want to express my sincerest gratitude to the following people and entities who made this study possible:

To my internal supervisors Professor Kjell Kåre Fjelde and Professor Mesfin Belayneh Agonafir, for entrusting this project to me and their all-out support throughout the whole study. Their expertise in the field and their patience, encouragement, and enthusiastic guidance are much appreciated. Their guidance helped me a lot with the research and writing of this thesis.

To Exebenus especially Dalila Gomes and Tim Robinson, for providing real-time drilling data and sharing their expertise in Machine Learning. This has given me invaluable insights.

To the University of Stavanger for aiding me with knowledge and essential skills.

To Norway for providing international students free access to higher education.

To my family and friends who are always there pushing me and believing in everything I do.

Thank you all so much!

For knowledge and progress!

List of Abbreviations

ANN	Artificial Neural Network
BHA	Bottom Hole Assembly
CSV	Comma-Separated Value
ECD	Equivalent Circulating Density
HKLA-M	Hook load
LWD	Logging While Drilling
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MWD	Measuring While Drilling
NN	Neural Network
RNN	Recurrent Neural Network
ROP	Rate of Penetration
RPM	Revolutions per minute
SPP	Standpipe Pressure

Table of Contents

List of Figures

List of Tables

List of Listings

1 Introduction

1.1. Background, Motivation, and Challenge

A stuck pipe event can be described as an inability to rotate the string from the surface or an inability to reciprocate the string by way of the hoist without being damaged. Some physical reasons for a stuck pipe can be due to the accumulation of cuttings downhole, excessive friction between the borehole wall and the string due to well geometry, and differential sticking due to thick mud cake or by overbalanced drilling. Stuck pipe incidents are one of the major causes of non-productive time (NPT) while drilling, which leads to substantial economic losses. These losses can be attributed with (i) the time to dislodge the pipe until normal operation is possible, (ii) to 'fishing' operation if the non-stuck part of the pipe is to be retrieved, (iii) to the cost of the irretrievable equipment, (iv) or a combination of these. Stuck pipe can be responsible for about 25% of the total NPT [4] that cost companies more than $250 million a year [1].

As well trajectories today have become more complex and challenging due to the need to reach new targets, longer depths, and departures, it is imperative for companies to invest in tools that can assist in preventing stuck pipe [5]. Conventional preventive approaches include flagging trend deviations between physics-based hook load values with real-time measurements. These existing software tools may predict the upcoming stuck pipe event; however, they are based largely on human interpretation and are unreliable [6, 7]. A small number of drilling parameters may not be recognized as an upcoming stuck pipe because the changes are too small, or the changes can be attributable to another event not related to stuck pipe [8]. Moreover, traditional approaches in modeling require iterative tuning for optimal target results. These models fail to perform optimally for lacking the capability of handling missing data and taking noise into consideration [9].

More recently, there has been a focus on advancing computer-based methods for preventing stuck pipes. Technological advancements in computing technology allowed the generation of large volumes of data known as Big Data; however, their true value has not been sufficiently tapped. These advancements accelerated statistical and ML models in the Oil and Gas (O&G) industry [9, 10]. ML involves training the models based on historical drilling data and applying the trained model to similar situations [11]. To turn collected raw data sets into useful information, data mining approaches integrate visualization, statistics, and database systems with ML techniques [9, 12]. Data mining can be descriptive mining to uncover the current trend patterns and correlation in the data or predictive mining to predict future variables based on the existing data [9, 13].

The literature review by Noshi et al.[9], revealed that there are a lot of published papers using ML for stuck pipe prevention. Different ML models have been built with varying degrees of success, type of model, and number and type of parameters used. Evidently, there is a lack of consistent principle, workflows, and methods that explicitly applies to the use of ML in preventing stuck pipe. Furthermore, a lack of transparency on the data further complicates the evaluation and reproduction of these publications.

The motivation of this study is to generate a data-driven model for hook load prediction. This model should distinguish the hook load trend between normal and deteriorating downhole conditions.

1.2. Objectives and Scope

The present study focuses on identifying and extracting hook load signatures before a stuck pipe event that can be used for training a Machine Learning model. This study also aims to serve as a stepping stone to further advance the application of ML in the O&G industry, particularly in preventing stuck pipe incident. To accomplish the above stated, the following objectives are proposed:

- Understand the activities involved, and the relationship among available drilling parameters during the drilling phase of a well.
- Efficiently gather, clean, and prepare the data for analysis and modeling.
- Identify the type of operation and stuck point from the drilling data
- Extract hook load signatures before a stuck pipe incident
- Implement a ML algorithm that accurately predicts the hook load value and correct trend
- Present the complete human-readable algorithm

1.3. Methodology

The core of this study is coding and for such purpose Jupyter Notebook [14] will be used. A web-based application enables the user to combine software code, the output, and explanatory text in a single document. It is user-friendly and handles Python [15] - which is our choice of programming language; all thanks to its simplicity and readable syntax - 69% of ML engineers prefer Python [15], making it the most used language for ML [16]. Several packages were installed to set the programming environment. This list is found in Appendix A.

In building data-driven models, an essential prerequisite is access to an appropriate and sufficient amount of data. For this study, Exebenus will provide raw drilling data from wells with stuck pipe incidents. After collecting the data, it will be pre-processed to identify and remove anomalous values. After cleaning the data, it will be explored to determine the type of operation and the stuck point. Afterward, the local minimum and maximum hook load will be extracted for tripping in and tripping out operations, respectively. These extracted hook loads will be used for training and evaluating the model. This whole process is discussed in detail in Chapter 3.

The final part of this study consist of evaluating the extracted hook load signatures and the model performance. Evaluation will be based on the residuals and the trend. The complete information about this is found in Chapter 6.

All codes implemented in this project are found in Appendix B to F.

2 Review of Related Literature

2.1. Drilling Rig System

Drilling operation is conducted to connect the surface with the reservoir, which may contain water, oil, or natural gas. Figure 2-1 shows a typical land rotary drilling system, composed of rotary, circulation, hoisting, power supply, and pipe handling system. The following section briefly describes the function of each main system:

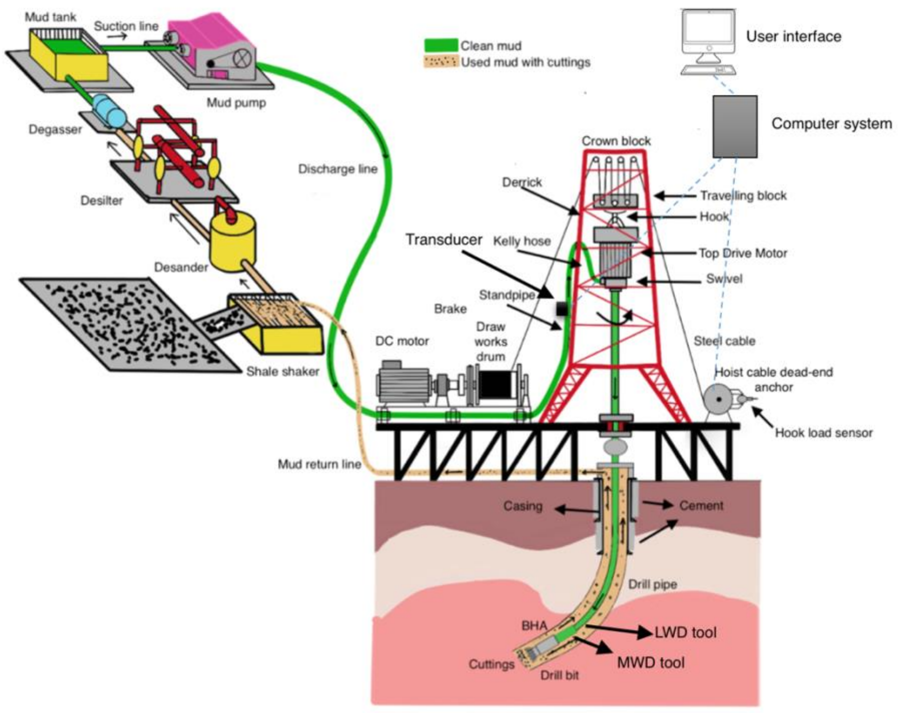


Figure 2-1. Schematic diagram of a land drilling rig.

2.1.1. Hoisting System

The hoisting system of a drilling rig is responsible for raising, lowering and suspending the drill string, and lifting casing and tubing for installation into the well during operations. The hoisting system consists of three major components [17]:

i. Derrick

This is a long steel tower used in the drilling rig to provide structural support for the hoist system. It must be capable of supporting the entire load on the system. The derrick is rated based on its ability to carry the compressive load and its height. The height of the derrick determines the number of pipes that can be inserted or removed from the hole at once. The higher the derrick, the longer the section of pipe that can be handled, the more efficient the operation would be.

ii. Block and Tackle System

The block and tackle links the drawworks and the loads that will be lowered into or raised out of the hole. This consists of the travelling block, crown block, and drilling line. The crown block is stationary, while the travelling block can move up and down. Block and tackle system provides a mechanical advantage that helps in handling large loads efficiently. The mechanical advantage, MA_{bt}, of a block and tackle is the load supported by the traveling block, F_{tb}, divided by the load imposed on the drawworks which is the tension in the fast line, F_{fl} [18]:

$$MA_{bt} = \frac{F_{bt}}{F_{fl}} \tag{1}$$

The ideal mechanical advantage in the block and tackle can be determined from a force analysis of the traveling block. Assuming a friction-less system, using Figure 2-2 , the tension in the drilling line is constant throughout. Thus, a force balance in the vertical direction yields,

$$N_{tb}F_{fl} = F_{bt}, \tag{2}$$

Where N_{tb} is the number of lines strung in the travelling block.

By inserting equation 1 to 2:

$$MA_{bt} = \frac{\frac{F_{bt}}{N_{tb}}}{F_{bt}} = N_{tb} \tag{3}$$

Where the mechanical advantage of the block-and-tackle system, MA_{bt}, is equal to the number of lines strung between the crown block and traveling block. This means that the greater number of lines and pulleys provide higher lifting power [17, 19].

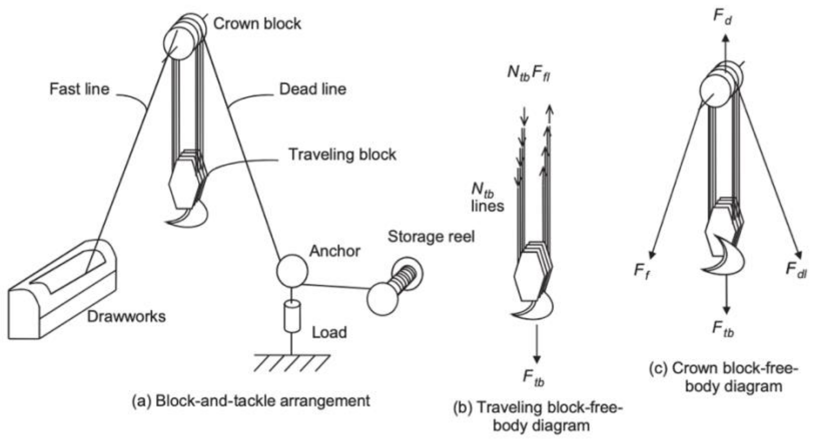


Figure 2-2. Schematic of drawworks and block and tackle [20]

iii. Drawworks

Drawworks are the main operating component of the hoisting system. It is a winch that reels the drilling line in or out causing the traveling block to move up or down. Drawworks consist of brakes, mechanical and electromagnetic, used to control the weight-on-bit (WOB) during drilling. WOB and revolutions per minute (RPM) are the two most important parameters to optimize penetration rate. This will be discussed further in the following chapters.

2.1.2. Rotating System

The rotating system consists of equipment responsible for rotating the bit and drillstring. There are two drive systems used on a rotary drilling rig: the kelly system and top-drive system. For a kelly system (Figure 2-3), a rotary table provides rotation. The upper end of the drill pipe is screwed onto the saver sub. The saver sub is used to protect and minimize wear and tear on the threads at the bottom of the Kelly. The Kelly is about 40 ft in length with a square or hexagonal shape, and it is hollow throughout to transport the drilling mud. A master bushing serves as a rotary motion transmission from a rotary table to a Kelly. A rotary table rotates a Kelly bushing and it simultaneously rotates a Kelly and transmits rotary motion and torque to the drill string and drill bit. Kelly system is used in old-styled rigs due to its limited capability to drill with only one single drill pipe during connection.

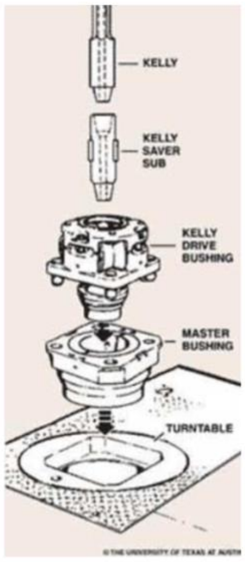


Figure 2-3. Parts of a Kelly system [21]

In a top-drive system (TDS) (Figure 2-4), the drillstring is rotated with a top-drive motor suspended in the derrick or mast of the rig. A top drive comprises one or more electric or hydraulic motors connected by a quill into the drill string. TD motor is suspended from a hook below the traveling block, enabling the motor to move up and down the derrick. The primary advantage of TDS is its capability to make a connection with a joint stand (3 drill pipes), and it lessens the manual labor involved in drilling, as well as many associated risks.

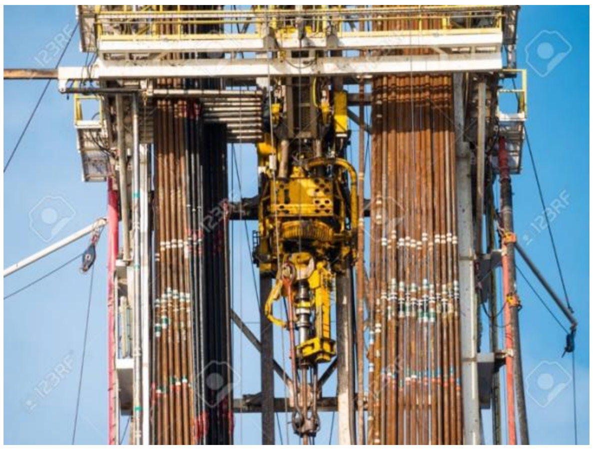


Figure 2-4. Top-drive motor in the middle and pipe stands as seen on the sides [22]

2.1.3. Circulating and Drilling Fluid System

Rig's circulating system provides the hydraulic power to enable the complete circulation of the drilling fluid in the whole system. The proper circulation system in a rig is vital to ensure a trouble-free operation. Figure 2-5 shows the end-to-end process wherein the green pipes represent clean and unused mud, while the peach-colored means used mud with contaminants such as drilled cuttings taken from the bottom of the well. The main components of the circulation system are mud pumps, mud pits, mud mixing equipment, flowlines, nozzle, and contaminant removal equipment (e.g., shale shaker, desander, desilter, and degasser) [23]. The main functions of the circulation system are to:

- Carry the drilled cuttings to avoid accumulating downhole
- Provide hydraulic pressure during overbalanced drilling to prevent flow of formation fluids into the surface
- Cool and lubricate bit to extend bit life
- Coat the open hole with mudcake to prevent loss circulation

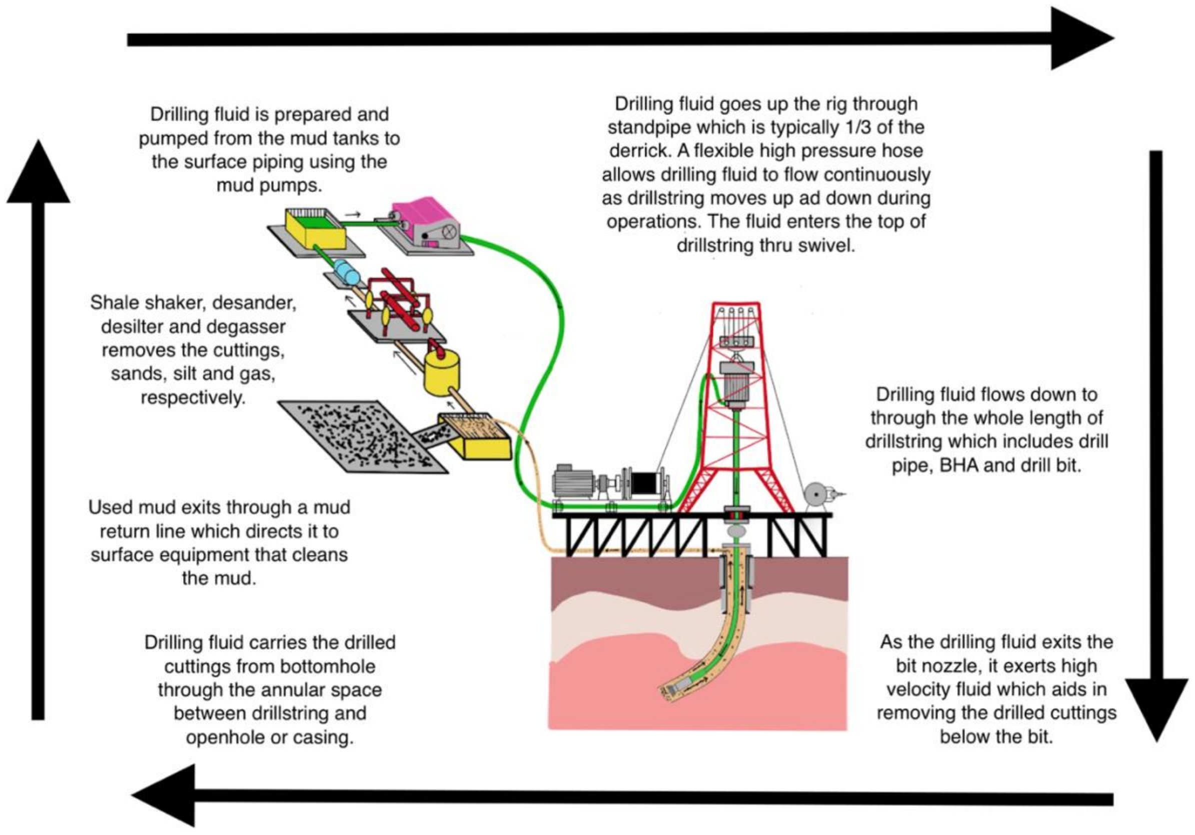

Drilling fluid is prepared and pumped from the mud tanks to the surface piping using the mud pumps.
Drilling fluid goes up the rig through standpipe which is typically 1/3 of the derrick. A flexible high pressure hose allows drilling fluid to flow continuously as drillstring moves up ad down during operations. The fluid enters the top of drillstring thru swivel.
Shale shaker, desander, desilter and degasser removes the cuttings, sands, silt and gas, respectively.
Drilling fluid flows down to through the whole length of drillstring which includes drill pipe, BHA and drill bit.
Used mud exits through a mud return line which directs it to surface equipment that cleans the mud.
Drilling fluid carries the drilled cuttings from bottomhole through the annular space between drillstring and openhole or casing.
As the drilling fluid exits the bit nozzle, it exerts high velocity fluid which aids in removing the drilled cuttings below the bit.

Figure 2-5. Land Rig Circulation System

2.1.4. Well Control System

Due to the explosive nature of oil and gas and the high pressure encountered during well drilling, it is imperative to equip rigs with a safety system. The well control system is tasked to prevent the uncontrolled release of high-pressure fluids from the formation into the surface. Blowout preventer (BOP) usually operated remotely via hydraulic actuators, is the primary equipment in this system. BOPs consist of several large valves that are stacked on top of each other. They are placed on top of a well that seals the well when activated. From Figure 2-6, an annular preventer is used to seal flow through the annular space between the drill string or casing and the annular preventer. Below annular preventer is the various type of ram preventers which has its own unique task. Blind rams are not capable of cutting the drill pipe. Hence, they are used to close the wellbore when there is no drilling string in the wellbore. Unlike blind rams, shear rams isolate both the pipe and the annular space by shearing off the pipe when closed. On the other hand, pipe rams (not seen in the figure) isolate the annular space by closing around the pipe when closed to prevent flow.

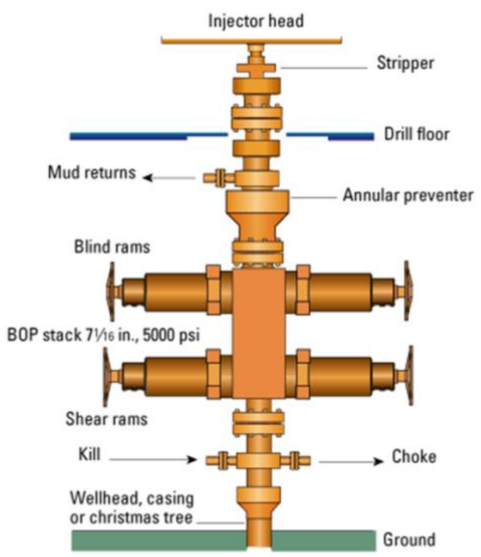


Figure 2-6. Schematic diagram of Blowout Preventer (BOP) [24]

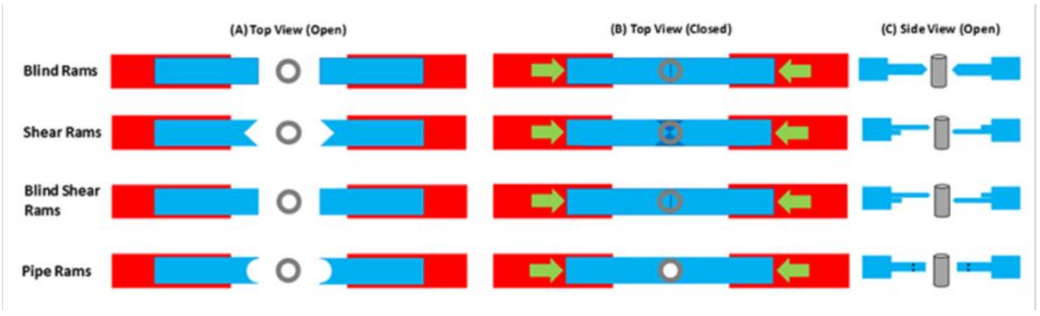


Figure 2-7.Schematic of Various Ram-Type Preventers [24]

2.1.5. Pipe Handling System

In the past, drill pipes are prepared and moved around the rig by manual pipe handling. To increase the speed of operation and have a safer workplace, rig operators look for automating pipe handling. A full range of high-performance pipe handling systems is available for onshore and offshore applications. From NORSOK D-001 [25], automated pipe handling systems include:

- vertical pipe handling systems
- horizontal pipe handling system
- horizontal to vertical pipe handling system

Figure 2-8 displays an automated racking board pipe handling system mounted on a rig that mechanizes the process of lifting and moving stands of drill pipe and collars from the well center to the racking board. This is a part of The Iron Derrickman® Pipe Handling System designed to provide hands-free tripping of drill pipe and drill collars to maximize safety and efficiency.

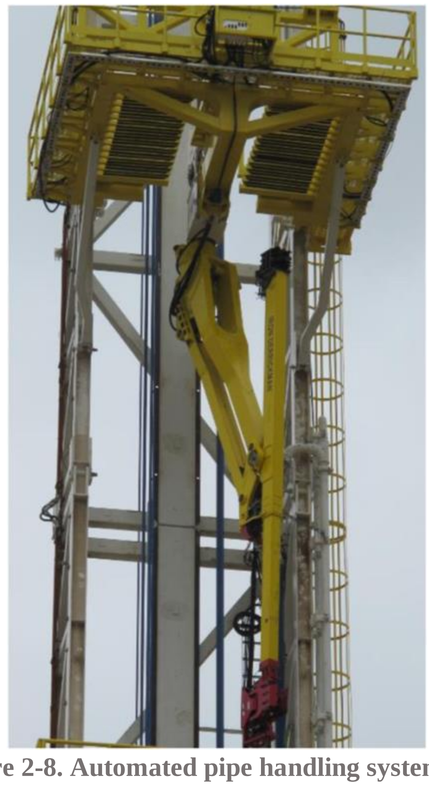


Figure 2-8. Automated pipe handling system [26]

2.2. Drilling Parameters

Still referring to Figure 2-1, throughout the drilling process, real-time measurements are recorded. The BHA may comprise of logging-while-drilling and measurement-while-drilling (MWD) tools. LWD tools measure in situ formation properties (e.g., porosity, natural gamma radiation, permeability), and MWD tools measure properties associated with drilling efficiency and well geometry (e.g., inclination, azimuth) [27]. The measurement results can be transmitted to the surface through mud pulse telemetry, wired drilled pipe, electromagnetic telemetry or recorded in memory and downloaded when the tools reach the surface. These pressure pulses are converted into electrical signals by transducers. The electrical signals are then coupled into a computer system, where they will be decoded into a computer-readable file. The computer system may also be coupled into the various surface equipment. To not complicate the drawing, dashed lines represent communicative couplings. Surface-based parameters may be measured directly or indirectly such as hook load, RPM of the drill string, surface torque applied to the drillstring, the pressure of the pumped drilling fluid, and SPP for the drilling fluid. Computer systems may also receive data from the drilling crew through a user interface (e.g., drill pipe diameter, drill pipe thickness, drilling fluid parameters, and drill bit type). All the measured and collected parameters may be stored in at least one database. Other systems may forward the data into another computer system, such as computer systems from service companies' home offices [8]. Table 1 shows the drilling parameters that are always present from Exebenus data; thereafter, the description and the theories associated with each parameter are presented.

Table 1. Drilling Parameters

Drilling Parameters	Unit
Rate of Penetration (ROP)	m/hr, ft/hr
Stand Pipe Pressure	Psi, kPa
Rotary Speed	Rotations per minute (RPM)
Torque	kN-m
Hook load	Klbm, lbm
Flowrate in and out	gal/min
ECD	
Mud weight	kg/m3, ppg
Block Position	ft

2.2.1. Torque and Drag

Torque is defined as the force multiplied by an arm that causes an object to rotate. To drill holes, torque is applied to overcome the rotational friction between the drillstring, including the bit and the borehole wall.

Drag is the friction force, which is the product of the contact force of the drilling string on the wellbore and the coefficient of friction. The effective tension on the drill string is due to the static weight of the drill string and the drag forces. This additional load is added to the static weight when pulling out of the hole and deducted from the static weight when running into the hole. Similarly, due to friction, there is a difference between the torque applied at the rig floor and the torque available at the bit. Thus, torque and drag are often associated with each other.

Drag and Torque Along Straight Sections

Figure 2-9 shows the free body diagram of mass-friction in the inclined well geometry. Applying equilibrium condition, Aadnøy [28] derived the force at the top of the string along straight sections:

$$F_2 = F_1 + w\Delta s(cos \propto \pm \mu sin \propto) \quad (4)$$

Where,

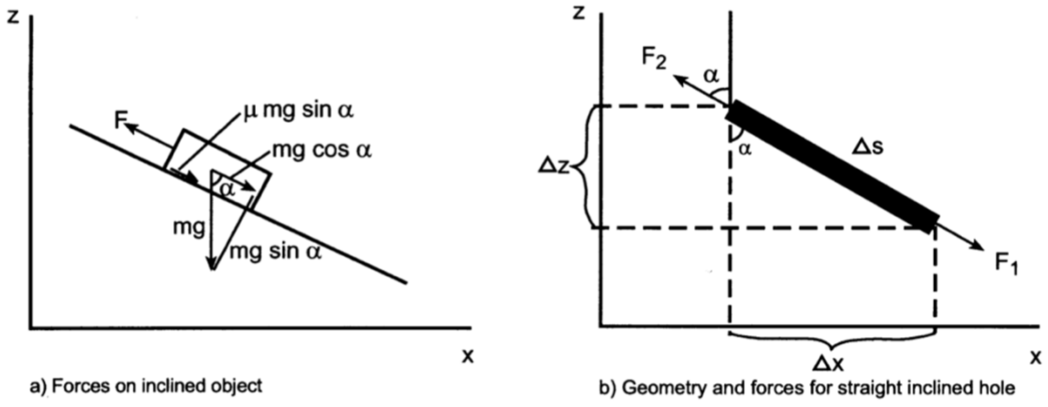
α : well inclination

F_1: force at the bottom

F_2 : force at the top

$w\Delta s\ cos\alpha$: static force (or self-weight)

$\pm w\Delta s\mu\ sin\alpha$: the drag force, $(+)$ for pulling the pipe, and (-) when lowering the pipe



a) Forces on inclined object
F
μ mg sin α
mg cos α
α
mg
mg sin α
z
x
b) Geometry and forces for straight inclined hole
F2
α
Δz
α
Δs
F1
Δx
z
x

Figure 2-9. Forces and geometry in straight hole sections [29]

The same principle applies to rotating friction, the torque. The applied torque is equal to the normal moment (wΔsr) multiplied with the friction factor μ. The torque becomes:

$$T_2 = T_1 + \mu w \Delta s r \sin \propto \tag{5}$$

Since the drill string is submerged in mud, the buoyance correction factor is considered. Hence, the buoyed unit mass of pipe:

$$W = \beta w_{drill\ pipe} \tag{6}$$

Where,

$$\beta = 1 - \frac{\rho_{mud}}{\rho_{pipe}} \tag{7}$$

Equation 7 is valid only for cases of equal fluid densities on both sides of the drill pipe.

Drag and Torque for designer well geometry

For designer wells with varying inclination and azimuth, up to this date, the Johancsik et al.[30] model is still regarded as one of the most precise ones [31]. This model is used for computing the normal force per unit length for any curved well geometry. The solution discretizes the drill string into segments. From Figure 2-10, the normal force per length of each segment can be calculated using equation (8):

$$N_i = \sqrt{\left(\beta W_i \sin\left(\frac{\theta_{i+1} + \theta_i}{2}\right) + F_i \left(\frac{\theta_{i+1} - \theta_i}{s_{i+1} - s_i}\right)\right)^2 + \left(F_i \sin\left(\frac{\theta_{i+1} + \theta_i}{2}\right)\left(\frac{\alpha_{i+1} - \alpha_i}{s_{i+1} - s_i}\right)\right)^2} \qquad (8)$$

Where,

θ : inclination

α : Azimuth

W_i : Weight per unit length

β : Buoyance factor

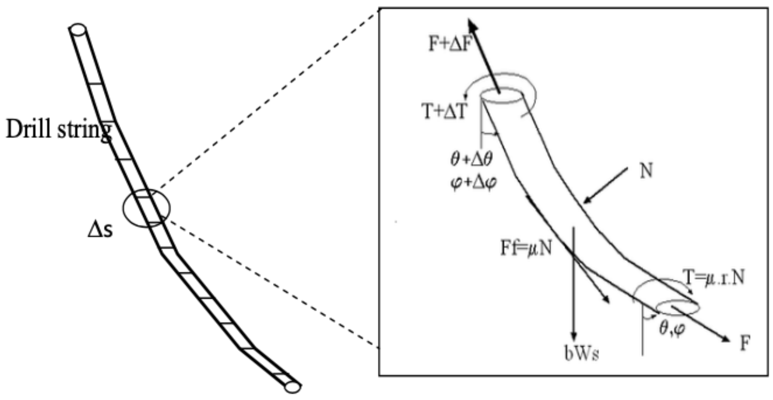


Figure 2-10. Segmented drill string and loads [32]

Although the computation is more complex for designer wells, the same concept applies to drag – it acts opposite the motion. Thus, the frictional force due to drag is added to the static weight when pulling out of the hole and deducted from the static weight when running into the hole.

2.2.2. Hook load

The general definition of hook load is the summation of the vertical force pulling down the hook attached to the bottom of the travelling block. However, in the industry, there is inconsistency as to how it is measured. This force may include the drillstring weight, ancillary equipment, the top drive unit, and hydraulic and mechanical frictional forces [33, 34]. These differences result from different ways of measuring hook load based on where the sensors are located. For example, the sensors can be placed at the deadline anchor or a load cell at the hanging point of the top drive. The hook load measurement will then include the weight of the top drive and drilling line friction effects. Furthermore, it is also possible to directly measure the string weight at the top of the drill string using an instrumented Internal Blow-out Preventer [35].

For simplicity, according to Aadnøy [28], the static hook load, regardless of wellbore orientation, is equal to the buoyed pipe weight multiplied by the projected vertical height of the well. During dynamic conditions wherein the string moves inside the well, the additional forces due to drag must be accounted for. Drag is added to the static weight when tripping out of the hole since forces from the weight of the drill string and friction are in the same direction. Drag is deducted from the static weight for tripping in since friction is opposite the direction of drillstring weight. For this case, the formula for hook load based on coulomb mass-friction can be written as:

$$Hook\ load = \ W\Delta s(cos \propto \ \pm \mu sin \propto) - WOB \qquad (9)$$

Where,

(+) means tripping out and (−) means tripping in of the drill string.

W : buoyed weight

$\Delta s(cos \propto)$: projected height

$WOB:$ non-zero weight on bit during drilling mode, and zero for tripping operations

$\Delta s\ \mu sin \propto$: drag force

Generally, three main factors cause a reduction in hook load:

i. Buoyancy effect

During drilling, the drillstring is immersed in drilling fluid inside the well. Due to the up-thrust forces, the hook load will be reduced. Also, since rocks have a higher density than mud, cuttings in suspension will increase the effective density of the annular mud. The added density reduces the specific string weight and thereby also the total reference string weight.

ii. Bit on bottom

A reduction in hook load could be observed when the bit touches the hole's bottom as some of the load is transferred into the formation.

iii. Contact friction

Particularly in-high angle wells, hook load is reduced as the drillstring makes contact on one side of the borehole. This is similar to pack-off and differential sticking, where the accumulation of cuttings tries to hold some of the drillstring weight.

Hook load is an important drilling parameter that helps the driller estimate and control the weight on bit to maximize drilling efficiency. It also provides a vital information about the downhole conditions. For example, abnormal hook load may indicate poor hole cleaning or excessive tortuosity [33].

2.2.3. Standpipe Pressure

Standpipe pressure (SPP) is the summation of pressure loss within the whole circulation system that arises due to fluid friction. During drilling, clean mud is pumped from mud tanks to the surface piping (standpipe, rotary hose, swivel, kelly) to the drillstring (drill pipe, drill collar, drill bit) the annulus between the drillstring and the open hole or the casing. Circulating mud has initial energy represented by the mud pump discharge pressure. Figure 2-5 illustrates the hydraulic system on a land drilling rig. When returning mud pressure in the pit is zero, this implies that the energy is totally lost in the system; thus, the discharge pressure represents the total pressure loss in the system in this case. These pressure losses can be divided into four areas shown in Figure 2-11: in the surface equipment, in the drillstring, across the bit, in the annulus between the wellbore or casing and the drill string.

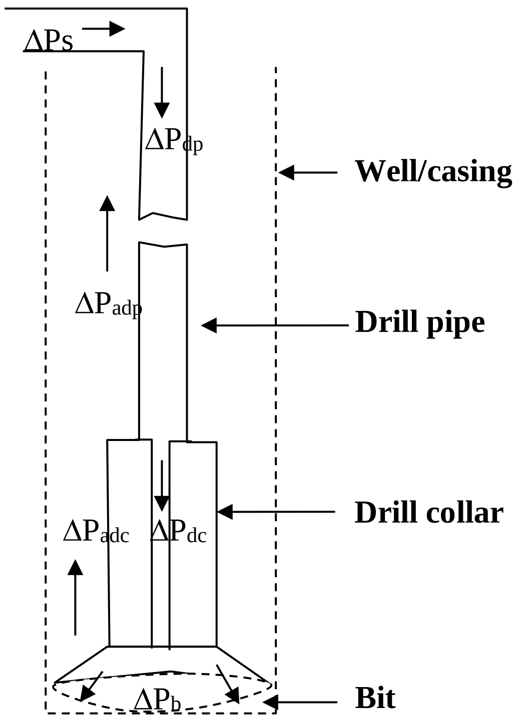


Figure 2-11. Pressure losses in drilling system

SPP can be expressed as [28]:

$$P_p = \Delta P_{fs} + \Delta P_{fdp} + \Delta P_{fdc} + \Delta P_b + \Delta P_{fadc} + \Delta P_{fadp} \tag{10}$$

Where,

ΔP_{fs}= Pressure loss in surface flow lines.

ΔP_{fdp} = pressure losses in the drill pipe.

ΔP_{fdc} = Pressure losses in the drill collar.

ΔP_{b} = Pressure losses in the nozzles of the drill bit.

ΔP_{fadc}= Pressure losses in the annular spacing between the well and the drill collar.

ΔP_{fadp} = Pressure losses in the annular spacing between the wellbore and the drill pipe.

Pressure drop equations depend on the following:

- Flow regime: laminar or turbulent
- Rheology of the circulating fluid
- The pipe and hole geometry

In general, SPP increases with drilling depth, an increase in viscosity, mud weight and flowrate, and smaller annulus. SPP helps select the right size of bit nozzle, proper mud pump liner, and optimum flowrate to achieve adequate hole cleaning and cuttings transport. Real-time monitoring of SPP is of prime importance as it aids in identifying potential downhole problems. For example, washed out pipe or bit nozzle, broken drillstring, lost circulation could cause too low SPP. On the other hand, a high SPP could indicate plugged drill bit or increased mud density or viscosity [36].

2.2.4. Rate of Penetration

This is the rate at which the bit crushes and moves through the formation. High ROP produces a greater amount of cuttings; thus, mud rheology must be properly designed to avoid cutting accumulation. ROP is measured in feet per hour or meters per hour. During tripping operations, the penetration rate has a value of 0 or -999 that indicates no new drilled rock. This is confirmed as well by a constant measured depth in the drilling data.

2.2.5. Rotary Speed

The rate at which the drill string rotation is measured in revolutions per minute (rpm). During drilling operations, it is not always possible to rotate the drillstring. For instance, drilling a deviated hole using a mud motor, slide drilling is performed wherein only the bit rotates. During tripping operations, it depends on the driller's preference to rotate the string.

2.2.6. Mud weight

Mud density expressed in lbm/gal or kg/m^3. Mud weight controls the wellbore hydrostatic pressure, thus preventing the influx of fluid during overbalanced operation. Too high mud weight could cause formation fracture and lead to losses. Mud weight can be altered by the addition of additives such as barite which increases the density. The presence of cuttings in suspension in the drilling fluid also increases mud weight. Two mud weights can be measured, mud going inside the well and the returning mud out of the well.

2.2.7. Equivalent Circulating Density

During static conditions, the pressure in the well is only provided by the mud weight. However, during dynamic drilling, the circulation of fluids creates opposing frictional forces which change the effective pressure exerted against the formation. This additional force must be taken into account; thus, ECD is used rather than mud weight when measuring the bottom hole pressure. ECD is the effective density exerted by the drilling fluid that considers the pressure drop in the annulus above the point being considered. The ECD is calculated as [37]:

$$ECD(ppg) = MW(ppg) + \frac{\Delta P_{annulus}(psi)}{0.052 \cdot TVD\ (ft)} \tag{11}$$

Where,

$\Delta P_{annulus}$: pressure drop in the annulus

MW : static mud weight and

TVD : true vertical depth to the point of interest

2.2.8. Flow rate

This is the volume of mud being pumped in or going out of the system. Ideally, equal flowrate in and out indicates a good well condition. This means that no losses of mud to the formation or no addition due to an influx of formation fluids. During tripping in operations, flowrate is attributed to filling in the pipe with mud. For tripping out, this is attributed to the pumping of mud inside the well to accommodate the volume previously occupied by the unscrewed joint. In any operation, the well must always be filled with mud enough to control the influx of formation fluids.

2.2.9. Block Position

This is the height of the travelling block that ranges up to 90ft. When paired with hook load, block position serves as a guide in determining the current activity in the rig. This will be elaborated under Section 2.3.

2.3. Tripping Operations

Tripping operation is the act of moving the string in (tripping in) or out of the well (tripping out). Bit are off the bottom during this operation such that the WOB and ROP are zero. Tripping in is performed while drilling to extend the drillstring and reach the oil or gas reserve. Similarly, running and setting in the casing are considered tripping in, except that the casing has a larger diameter and heavier than the drill pipes. Conversely, when a bit replacement is necessary, a survey needs to occur, or a downhole tool failure is experienced, the complete drillstring must be tripped out and then back in. In this context, tripping out operations involves activities in which the string moves toward the surface (e.g., back reaming, where you maintain or enlarge the diameter of the hole by rotating the bit while tripping out). Similarly, tripping in operation involves activities in which the string moves towards the bottom of the well (e.g., running in liner or casing).

Figure 2-12 shows a rig floor where the rig crew operates and performs drilling operations. During tripping in operation, the slip holds the joint inside the well while the workers are busy preparing the next stand. Using the elevator and drill pipe connector, the drilling crew screws the new stand with the current joint being held by the slip. After screwing, the driller (not seen on the figure) raises the top drive to remove the slip, and then the joint is lowered inside the hole and set back in slips again.

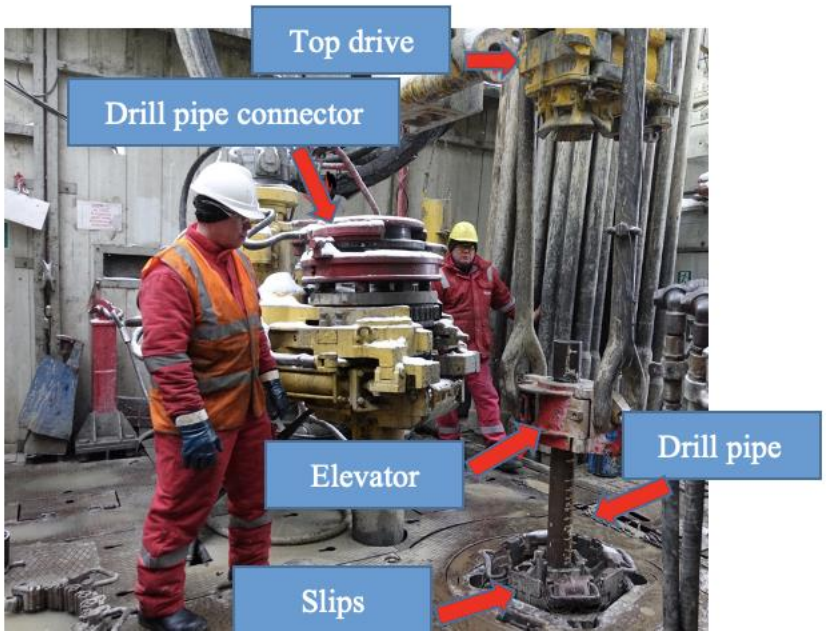


Figure 2-12. Rig floor [38]

Figure 2-13 shows the interaction of block position and hook load during tripping in operation of one stand. While the slip is in place holding the joint, this is reflected as a zero hook load and a flat block position. When the slips are removed, the block position reflects it as a slight increase before running in, while the hook load records its maximum measurement for that window since all the weight is now transferred to the topdrive. As soon as the joints are tripped in, the hook load measurement starts to decrease as it stabilizes until the slips are placed back again for the next stand. Generally, the hook load is expected to increase as more joints are added.

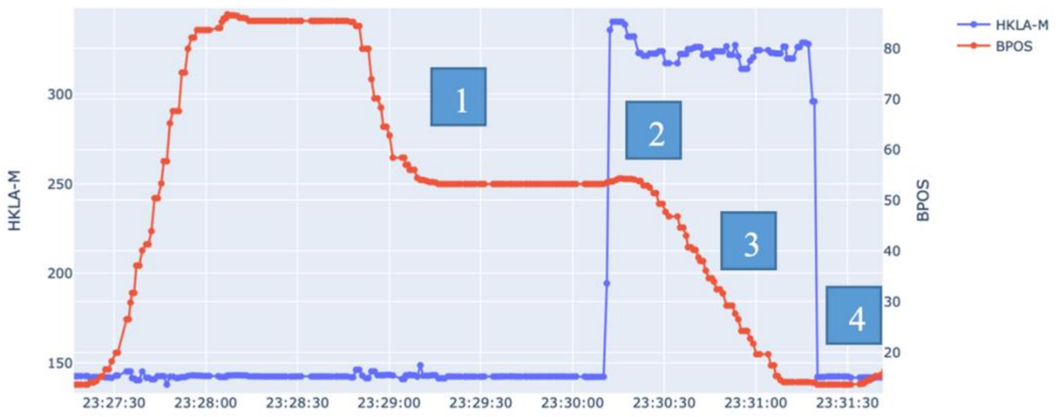


Figure 2-13. Snapshot of tripping in single stand. 1: Slip is in place during connection. 2: Drill string is connected to the hook and raised a bit to remove slip. 3: Drillstring is tripped inside the well. 4: Slip is in place for new connection.

Figure 2-14 shows the drilling parameters during tripping in operation. The plotted parameters DMEA, DBTM, HKLA-M, TQA, RPMA, ROPA, and WOBA-M, correspond to measured depth, bit depth, hook load, torque, rotation per minute, rate of penetration, and weight on bit, respectively. In this case, the HKLA-M and DBTM increase. The ROPA, TQA, WOBA-M, and RPMA are all zero. The DMEA is constant, indicating that no new drilled hole. Incorporating these parameters confirms that tripping in operation is taking place where the pipe is not rotated.

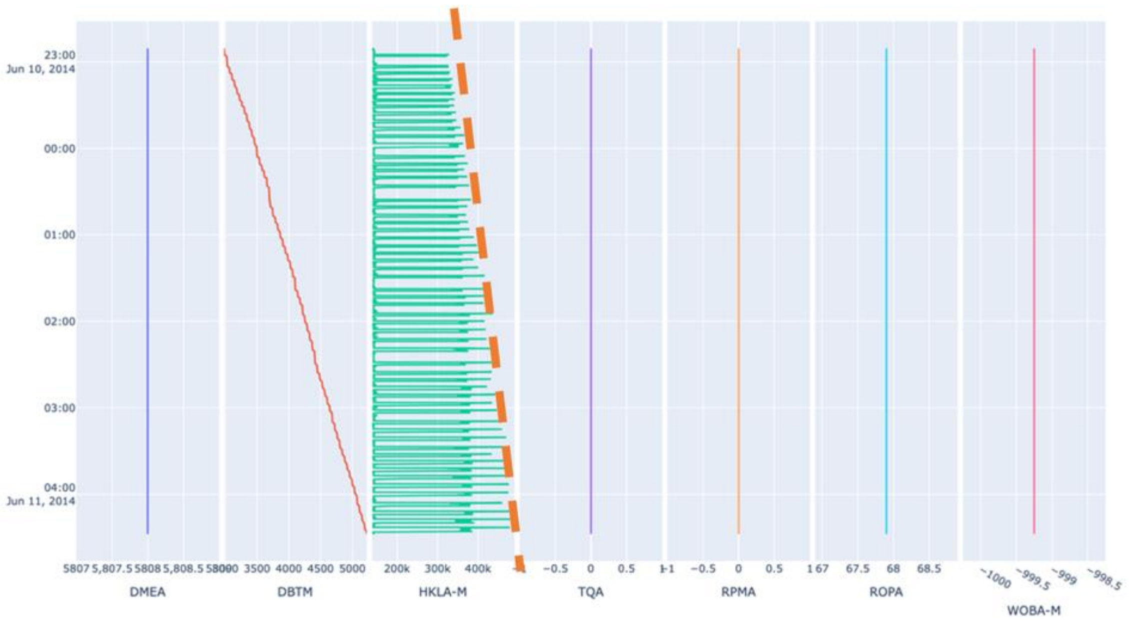


Figure 2-14. Drilling parameters during tripping in operation (running in casing).

During tripping out, the step-by-step process is similar to tripping in operation except that the stand is unscrewed while the slip holds the remaining joint. The interaction between the block position and hook load displays differences as well. For example, using Figure 2-15, during tripping out operation, after removing the slips, the block position continues to move upward. In addition, the hook load is expected to decrease as more joints are unscrewed.

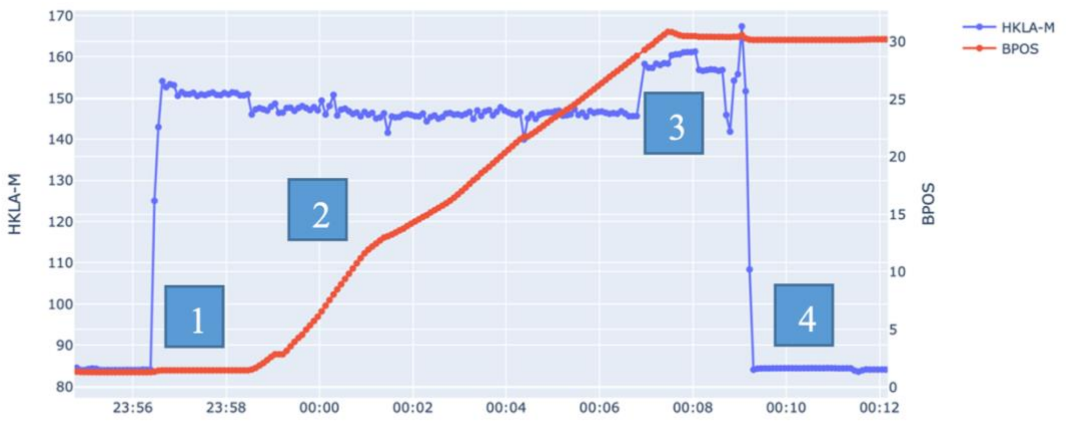


Figure 2-15. Snapshot of tripping out single stand. 1:slip is on while disconnecting a stand. 2: Drill string is raised to remove the slip, and trip out of the well. 3: A stand is out of the well. 4: slip is put back before disconnecting the stand.

Figure 2-16 shows the drilling parameters during a tripping out operation. The plotted parameters DMEA, DBTM, HKLA-M, BPOS, TQA, RPMA, and ROPA, correspond to measured depth, bit depth, hook load, block position, torque, rotation per minute, and rate of penetration, respectively. In this case, the HKLA-M and DBTM are decreasing. The zero ROPA and constant DMEA indicate no new drilled hole. This means that the operation is tripping out. Although, when checking the TQA and RPMA, it has measured values. Incorporating these parameters confirms that back reaming operation is taking place.

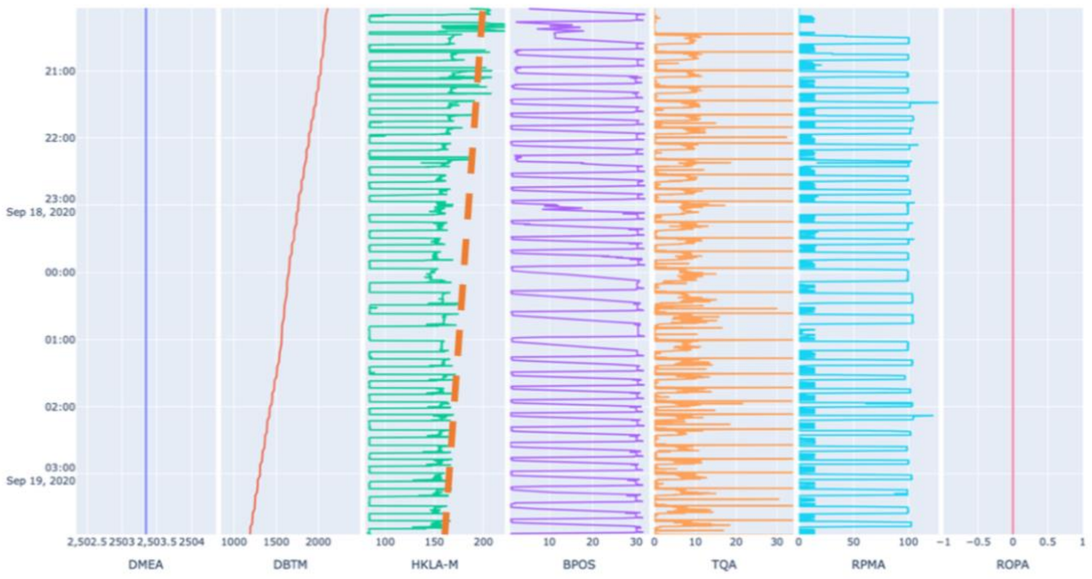


Figure 2-16. Drilling parameters during tripping out operation (back reaming).

The behavior of the hook load during these tripping operations is the focus of this study. This will be further discussed in the following chapters.

2.4. Stuck Pipe

A pipe is considered stuck or frozen in drilling if it cannot be freed and pulled out of the hole without damaging the pipe and without exceeding the drilling rig's maximum allowed hook load [39]. Generally, stuck pipe problems can be categorized based on their cause, either because of differential pressure issues, inadequate hole cleaning, or mechanical blocking [40].

2.4.1. Differential-Pressure Pipe Sticking

Differential-pressure sticking, often called differential sticking, is very prevalent in the drilling industry[18]. Differential sticking happens when the drillstring is embedded into the filter cake against the borehole wall by the pressure difference between formation and wellbore (Figure 2-17). This typically happens in depleted zones or permeable zone characterized by a high loss of circulation [41, 42]. When the drilling fluid losses to the formation, it leaves behind the solid phase. These remaining solids settle onto the side of the borehole wall. This nearly impermeable filter cake can become very thick and sticky. Meanwhile, if the hydrostatic pressure of the mud is much higher than the formation pressure, it sticks the drill string into the filter cake. Since filter cake has a high friction coefficient, the force required to move the drill string increases and sometimes above its strength capacity thereby, differential sticking occurs.

The differential pressure can be expressed as Eq.12:

$$\Delta\rho = \rho_m - \rho_{ff} \tag{12}$$

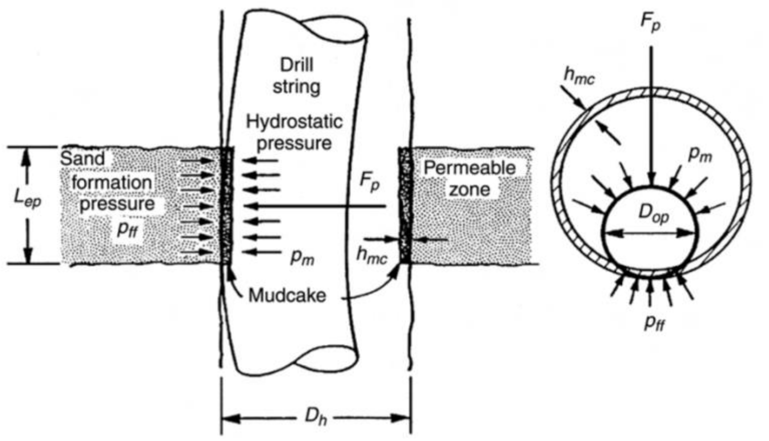


Figure 2-17. Differential pressure sticking [39]

Whereas the force required, F_p, to free the stuck pipe:

$$F_P = f\Delta p A_c \tag{13}$$

From Bourgoyne A. [43], A_c can be expressed as:

$$A_c = 2L_{ep}\left(\left(\frac{D_h}{2-h_{mc}}\right)^2 - \left[\frac{D_h}{2-\frac{h_{mc}(D_h-h_{mc})}{D_h-D_{op}}}\right]^2\right)^{0.5} \tag{14}$$

Where,

$$D_{op} \leq (D_h - h_{mc}) \tag{15}$$

In these equations:

Δp : differential pressure

f : coefficient of friction, 0.04 – 0.35 for oil or water based muds with no added lubricant

L_{ep} : length of the permeable zone

D_{op} : outside diameter of the pipe

D_h : diameter of the hole

h_{mc} :mudcake thickness

A_c : area of contact between the pipe and mudcake surfaces

From equations 13 and 14, the factors that cause differential-pressure pipe sticking are high differential pressure, thick mudcake due to high fluid loss to the formation, low-lubricity mud cake, and the length of pipe embedded in the mudcake. When differential sticking occurs, rig site indications can be full unrestricted circulation, mud losses, increase in torque and drag, an inability to reciprocate the drillstring and in some cases, to rotate it [39, 44].

2.4.2. Inadequate Hole Cleaning

Drilled cuttings must be taken out of the wellbore to avoid cuttings bed inside the hole. Failure to remove the cuttings can lead to packing off of the drillstring – another type of stuck pipe. Accumulation starts when the circulating drilling fluid is not viscous enough or fast enough that the gravity forces exceed the drag forces on the solids. This means that instead of up and out of the hole, the solids flow down the hole. When this accumulation is not mitigated, the hole is filled up with solids that build up around the string, eventually sticking the string (Figure 2-18). According to Mitchell et al. [18], the circulating flow rate slows down when pumps are not running fast enough or due to hole enlargement, e.g. washed-out formation.

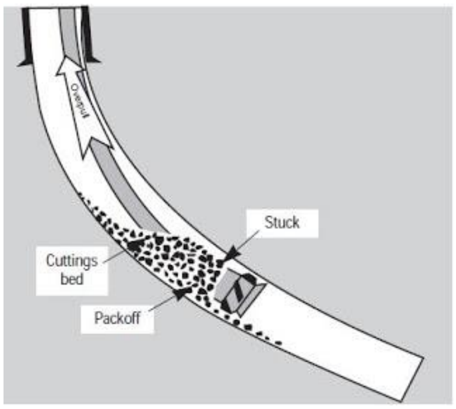


Figure 2-18. Pack-off due to cuttings accumulation

An example of how drilling parameters correlate during inadequate hole cleaning-induced stuck pipe is discussed in Section 2.5.

2.4.3. Mechanical Stuck pipe

Mechanical sticking occurs for several reasons: key seating, under-gauge hole, and severe doglegs; borehole instabilities such as mobile and fracture formations can get the pipe stuck.

Key Seating

During drilling, the upper part of the drill string is in tension while the lower part is in compression. Necessarily between these two, there exists a neutral point where tension nor compression exists. In drilling the deviated part of a well, this portion of the hole is opposite the drill pipe in tension. During this time, the drill pipe exerts a pulling force that with the aid of continuous mud circulation, broaching action of tool joints, and drill pipe rotation, could result in the drill pipe drilling itself into the wall, which is called key seating [45].

Sudden overpull as BHA reaches a dogleg path and cyclic overpull at tool joint intervals on trips could be early indicators. Minimizing dog-leg severity and performing reaming or wiper trips prevent key seating [44].

Under gauge hole

Any hole that is considered smaller than expected is deemed to be an under-gauged hole. Swelling formations may decrease the diameter of the hole. Using higher mud weight will balance the rock stresses and can keep the borehole in-gauge. Another reason for under gauge hole is bit wear as a result of drilling hard abrasive rocks. When a new in-gauge bit is run without reaming and wiper trip, there is a potential for jam and leading to pipe stuck. A thick filter cake and fill packing around the bottom hole assembly could cause a reduced diameter [28, 44].

Pulled bit or stabilizers are under gauge, sudden set down weight, and circulation may be slightly restricted could be early indicators. Using gauged bit, stabilizers, BHA, roller reamers, and higher mud weight could keep the hole in-gauged [44].

Junk

Any object that has fallen unintentionally into the wellbore can jam the drill string. This is a result of poor housekeeping or failure of downhole equipment. Sudden erratic torque, metal shavings at the shaker, missing tools, and inability to make holes are the rig indicators of junk in [44].

Collapsed casing or tubing

This happens when either the casing or tubing collapse rating is reduced due to wear, corrosion, or excessive formation pressure exceeding the collapse pressure rating. Typically, this is discovered when BHA is run into the hole and jams. Proper cement practices, avoiding casing wear, and usage of corrosion inhibitors could prevent this problem [44].

Cement Sticking

Cement has two ways to cause stuck pipes. One is unstable cement blocks falling around and accumulating at the bottomhole. Cement fragments, erratic torque with unrestricted circulation are the rig indicators. Two is when the drill string is run before the cement curing time, and the sudden surge in pressure results in cement to flash set. A sudden increase in torque, loss of string weight, increase in pump pressure leading to restricted circulation and cement in mud returns are the indicators of this pipe sticking problem. Knowing the right top of cement and the cement setting time could prevent [44].

Borehole Instability

Borehole instability is the undesirable condition of an openhole that does not keep its gauge size and structural integrity. Mechanical failure caused by in-situ stresses, erosion, and chemical interaction between the mud and formation are the leading causes of borehole instability. Furthermore, borehole instabilities have types: hole closure or reduced diameter, washouts, fracturing, and collapse [39].

Reduced diameter

The reduced diameter of the openhole could be caused by drilling reactive formations such as water-sensitive shale and reactive clays. The shale absorbs the water from the circulating mud and swells into the wellbore. Shakers screens blind off, restricted circulation, hydrated or mushy cavings, and an increase in pump pressure are the early indicators of drilling a swelling formation. Using an inhibited mud system, minimized open hole time in shale, and regular wiper trips or reaming trips could prevent this issue [39]. Some wells kept the hole stable by using sufficiently high mud weight and minimal open hole exposure time. However, some wells showed hole enlargement despite high mud weight used [28].

Hole Enlargement

Hole enlargement results from the hydraulic force from the bit nozzles that hydraulically erode the borehole away, mechanical abrasion caused by drillstring and shale sloughing. As observed in the Central North Sea, drilling at about 500m with unconsolidated formation gradually increased that drag over several meters. This happens when little or no filter cake is present or excessive jetting. An increase in pump pressure, fill in bottom, overpull on connections and shakers blinding are the indicators of drilling unconsolidated formation. Avoiding pressure surges and an adequate filter cake could help stabilize the formation [28, 39, 44].

Collapse

Borehole collapse happens when the ECD is too low compared to the hoop stress around the borehole wall. Eventually, pipe sticking and loss of well could persist. The most important remedy is to increase mud weight [28, 39].

Fractured and Faulted Formation

Fractured and faulted formations are typically found near faults. These rock fragments can fall into the wellbore and eventually, when adequate accumulation occurs can lead to jamming the drill string. Hole fill on connections, fault-damaged cavings at shakers, and instantaneous sticking can be early signs of this issue. Through RPM change and BHA configuration, minimizing drill string vibration could help prevent the rock fragments from falling [44].

2.5. Physics-Based Stuck Pipe Detection

Engineers use “roadmaps” to detect deteriorating downhole conditions. Roadmaps are made up of precalculated physics-based models and real-time measurements displayed together graphically [6]. These physical models are integrated with automatic calibration. Automatic calibration provides a reliable picture of the expected well behavior and ensures that relevant learnings are carried forward into the next time step. By analyzing the deviations between modeled and actual measured values, an estimation of the current state of the well is derived in real-time. When the current well conditions are deviating from normality, the drilling crew are warned of a deteriorating well condition or if the well conditions limit the drillability of the well [6, 46]. The difficulty in this approach is defining what "normal" is, which significantly depends on the engineer's interpretation [7].

In particular to stuck pipe detection, hook load measurement analysis identifies any decrease or increase in friction of the drillstring run inside the well. As mentioned previously, there is no straightforward in measuring the “normal” friction factor. Thus, it is much more sensible to monitor the trend of the hook load rather than one specific calculated ideal value. For this particular approach, engineers simulate different hook load values using various friction factors. Typically, the friction factor ranges from 0.1 to 0.5 for RIH and POOH plus one curve with 0 friction factor for bit rotating on the bottom [7]. In practice, while this friction factor approach may work, it is often unable to deal with complex situations where hook load does not show large variations and sometimes possess hidden trends [6].

Cayeux et al. [46] presented an early symptom detection based on real-time evaluation of the downhole condition. From Figure 2-19, during POOH a sudden increase in sliding friction after 21:00 was observed. The pick-up chart on the right-hand side shows how the hook load measurements deviate more and more above the bit depth 2800m MD. After several alarms were raised and taking no action, overpulls were experienced by the driller (Figure 2-20). It was later found out that the cause was dragging the BHA into a cuttings bed. This can be observed in Figure 2-21, the increase in torque and ECD resulting from the reduction in the annular space between the drill string and borehole wall due to the formation of cuttings bed. [33]

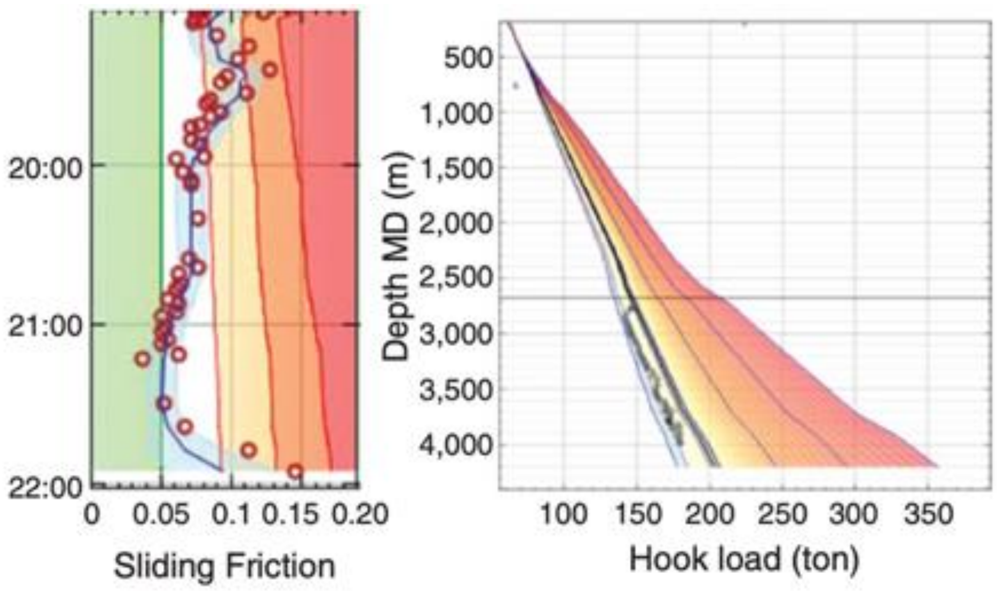


Figure 2-19. Real-time monitoring of sliding friction and hook load. [46]

In Figure 2-20, the actual measurements (blue curve) are compared with the hook load model calculations and its associated tolerances (green curve region)

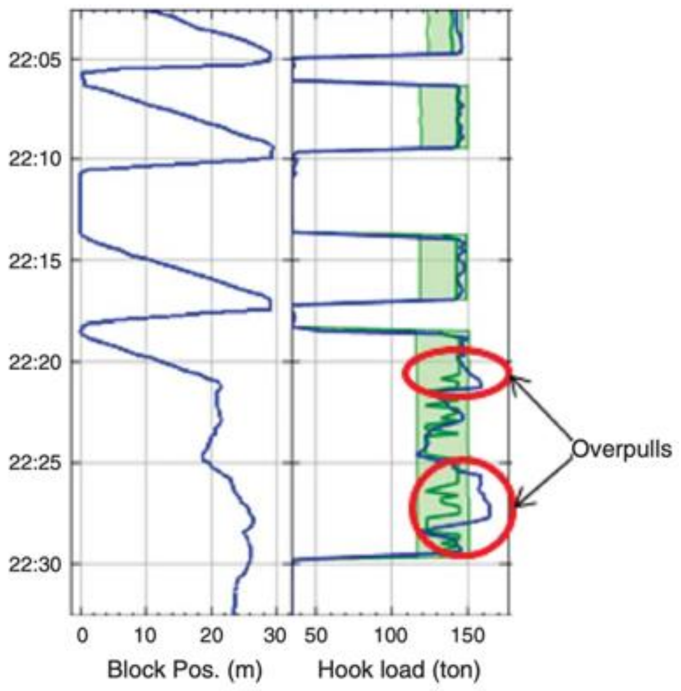


Figure 2-20.Observed overpulls during real-time monitoring. [46]

In Figure 2-21 measured values (blue curve) are plotted with model calculations and their associated tolerances (green curves). The plot on the right, calculated downhole ECD at the weakest point (brown curve) is compared with the downhole ECD measurements (blue markers).

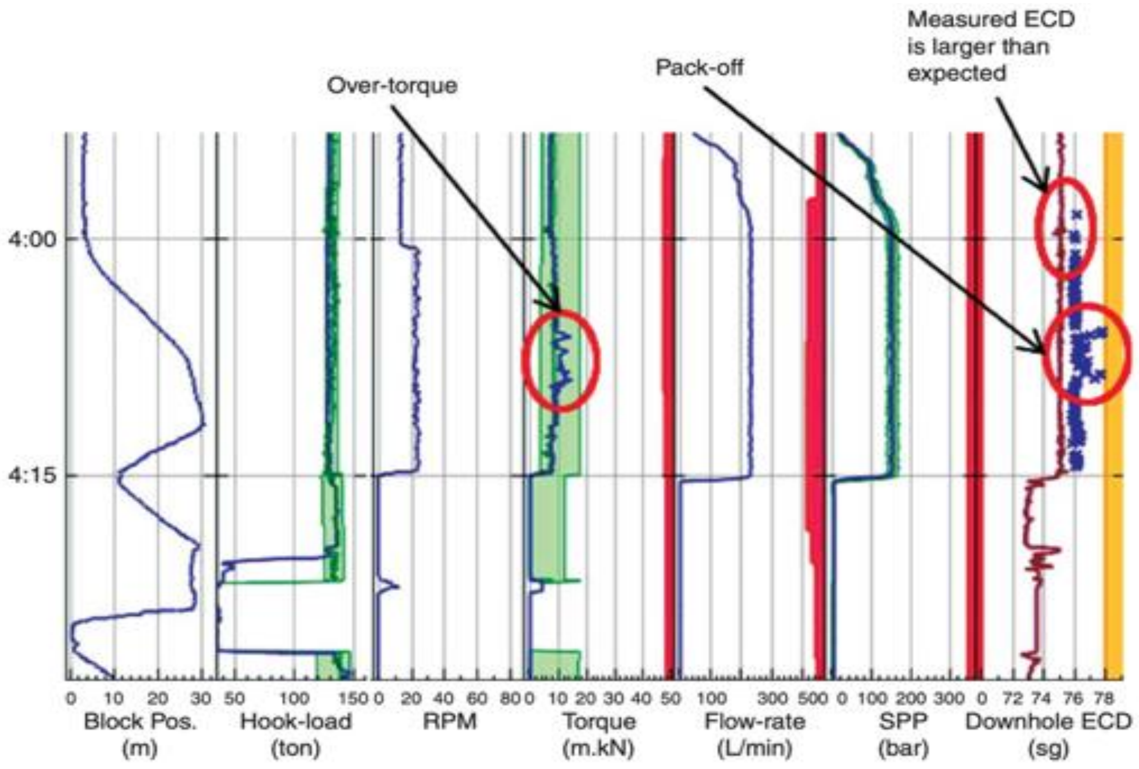


Figure 2-21. Time-based log. [46]

2.6. Machine Learning

Arthur Samuel [47] defines Machine Learning (ML) as applying artificial intelligence that equips systems with the ability to learn and improve through experience without being explicitly programmed [48]. An ML system is trained with enough examples relevant to a particular task that eventually allows the system to develop new rules for automating the task [49]. One vital feature of ML algorithms is recognizing complex patterns with reasonable predictive accuracy [50]. There are various types of ML algorithms that are available depending on:

i. Objective

Algorithms could predict a discrete class label (classification problem) or predict a continuous quantity (regression problem).

ii. Data category

From a ML perspective, data can be categorized into numerical, categorical, text, and time series. In this context, hook load measurements are a time series data since it is collected at regular intervals over time.

iii. Supervised or Unsupervised

Supervised learning algorithms learn from labeled datasets wherein the label is the target we are interested in predicting. Using these labels, the model can measure its accuracy and learn over time. On the contrary, unsupervised algorithms are designed to analyze and cluster unlabeled datasets. This is because unlabeled data does not contain targets that the model will try to predict. In this context, we used the past hook load measurements as input to predict the next hook load. This predicted hook load is the target or label. This means that a supervised algorithm is used.

Generally, the predictive model's performance depends on the database's size and the variables selected for the analysis. A robust database model yields more accurate and feasible results [51].

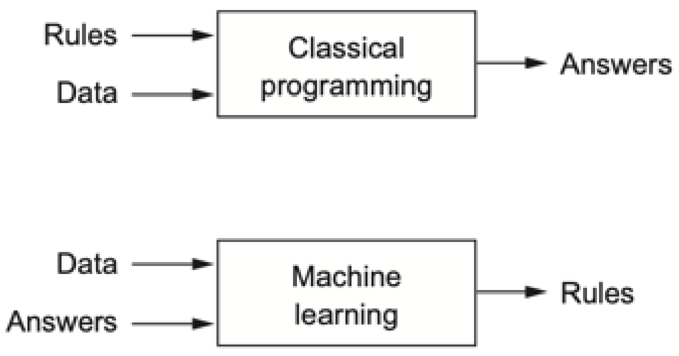


Figure 2-22. Machine learning vs. classical programming

In particular to stuck pipe prevention, there have been many models built around (Table 2). Many of which have been implemented with varying degrees of success. Evidently, there is hardly any consistent framework. For example, there is no uniform number and type of parameters and the type of models used. Furthermore, the lack of data transparency made it impossible to evaluate and follow existing works.

Table 2. Overview of randomly chosen published Machine Learning implementations.

Authors	**Type of model/s**	**Number of Parameters**	**Parameters used**
Murillo et al. **[52]**	Adaptive fuzzy logic; Artificial Neural Networks (ANN)	18 drilling and mud parameters	MD, TVD, Gel strength, mud yield point, drag, bit size, etc.
Hempkins et al. **[53]**	Discriminant analysis	20 drilling and mud parameters	MD, TVD, Gel strength, mud yield point, plastic viscosity, etc.
Siruvuri et al. **[51]**	Convolutional Neural Network	15 drilling and mud parameters	Hole depth, API fluid loss, differential pressure, etc.
Abbas et al. **[54]**	Support-vector machine, and ANN	20 drilling and mud parameters	Inclination, PV, Gel strength, MD, Azimuth
Elmousalami et al. [1]	Randomized trees	7 drilling parameters	Mud pump circulation rate, ROP, RPM, MD, etc.
Hashim et al. **[50]**	ANN	*depending on the model	Local minimum, maximum, and dynamic hook load

2.6.1. Artificial Neural Network

Artificial neural network (ANN) is a type of Machine Learning model inspired by our brains' biological neural structure. ANNs are the core of deep learning due to their versatility, power, and scalability [55]. They are capable of regression, classifying, associating, and mapping patterns among a large set of data. In the oil and gas industry, ANNs are used when traditional mathematical models fail to provide solutions to complex problems or when filling in missing data [9].

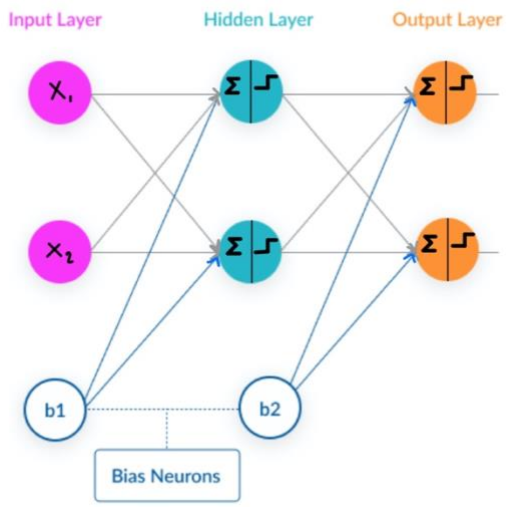


Figure 2-23. Architecture of a Multilayer perceptron with two inputs, one hidden layer with two neurons, and two output neurons.

ANN architecture comprises of an input layer, one or more hidden layers, and an output neuron layer. The inputs and outputs are numbers wherein each input connection is associated with a weight. To compute the output of Figure 2-23, equation 16 is used:

$$h_{w,b}(X) = \Phi XW + b \tag{16}$$

Where,

X : represents the matrix of input features. It has one row per instance and one column per feature. An instance is a single row of data containing one data point from every feature or sometimes called an attribute. Features are a component of observation. For example, in drilling data, the drilling parameters are the features, and one measurement of each feature at one specific time is considered one instance.

W : contains all the connection weights, excluding the bias neuron

b : contains the weight of the bias neuron

Φ **:** is called the activation function which determines the output of every neuron. The activation function takes the previous neuron's output as its input and translates it into a form that serves as an input to the next neuron. This activation function provides the ANNs the ability to solve nonlinear problems [56]. There are various activation functions in use:

i. Sigmoid function: σ(z) = 1/(1+exp(-z))

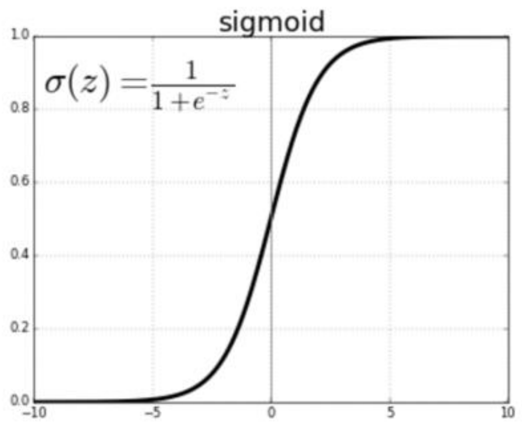


Figure 2-24.Sigmoid function curve [57]

ii. Hyperbolic tangent function: Tanh(z) = 2σ(2z)-1

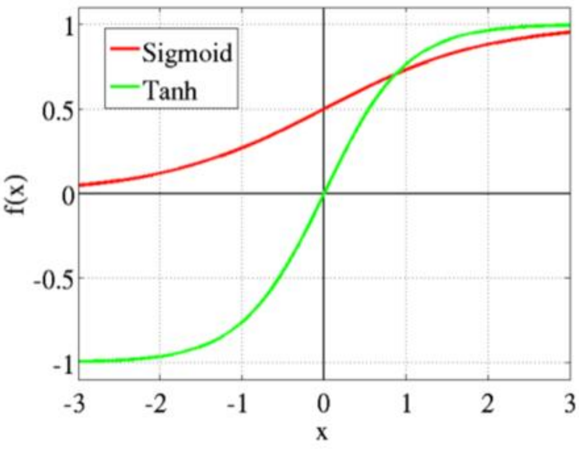


Figure 2-25. Hyperbolic and Sigmoid function curve [57]

iii. Rectified Linear Unit function: ReLU (z) = max(0,z)

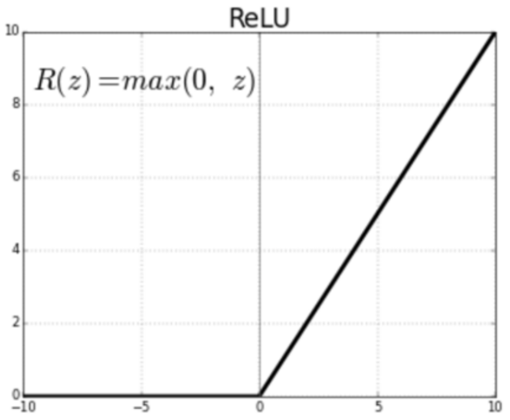


Figure 2-26.ReLU function curve [57]

Equation (16) also be presented in matrix form:

$$\begin{bmatrix} W1,1 & W2,1 & W3,1 & W4,1 & W5,1 \\ W1,2 & W2,2 & W3,2 & W4,2 & W5,2 \end{bmatrix} \times \begin{bmatrix} X1 \\ X2 \\ X3 \\ X4 \\ X5 \end{bmatrix} + \begin{bmatrix} Bias1 \\ Bias2 \end{bmatrix} = \begin{bmatrix} Z1 \\ Z2 \end{bmatrix}$$

Figure 2-27. Matrix form of ANN

Where,

$W_{a,b}$ denotes the weight in the connection between input a and neuron b

X1 denotes the first input

Z1 is processed through an activation function and could be either input to another layer or be the final output.

Since its introduction in 1986, the backpropagation algorithm has been used for training feedforward neural networks. The training process of a neural network involves defining a cost function and use gradient descent optimization to minimize it [58]. Connection weights are initialized randomly before feeding the neural network with a sufficient representative training set. The current model produces a prediction (forward pass) from the initial state. A cost function is then used to compute the error from the expected value, and then this goes back in reverse in each layer to measure the error contribution from each connection (reverse pass). Finally, a gradient descent step is used to tweak the weights to reduce error and converge with target values [55].

2.6.2. Recurrent Neural Network (RNN)

As you are reading this sentence, you are processing it word by word while keeping memories of what came before; this provides you a fluid representation of the context being conveyed by this sentence. Biological intelligence processes information incrementally while keeping an internal model of what it is processing – built from the past information and updating it constantly as new information flows in [49]. Similarly, *recurrent neural network* adopts the same principle. It processes sequential data by iterating through each sequential element and keeping a *state* that contains the relative information of what it has seen so far. In short, RNN is a type of neural network that has an internal loop (see Figure 2-28).

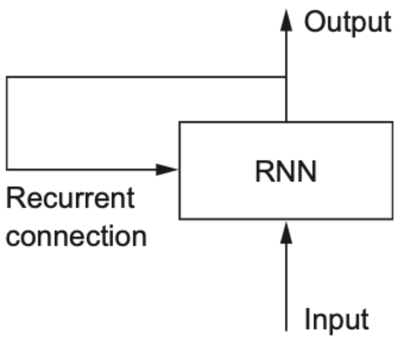


Figure 2-28.RNN: a network with a loop

An example of RNN with timesteps *t* is shown in Figure 2-29. The final output is a 2D tensor shape (timesteps, output features). Every time step in the output tensor contains information from timesteps 0 to *t* in the input sequence. Although theoretically, the RNN can retain information at time *t* about information seen many timesteps before, it also experiences a vanishing gradient similar to a non-RNN [49, 59]. In non-RNNs, as the network progresses down to each successive layer, the gradient often gets smaller and smaller, hence called vanishing gradient. As a result, this leaves the lower layer connection weights with insignificant change, and training never converges to a good solution. This is somehow similar to RNNs. It becomes impossible to learn as the duration of the dependencies to be captured increases [60]. The theoretical explanations of this effect were studied by Hochreiter, Schmidhuber, and Bengio [60].

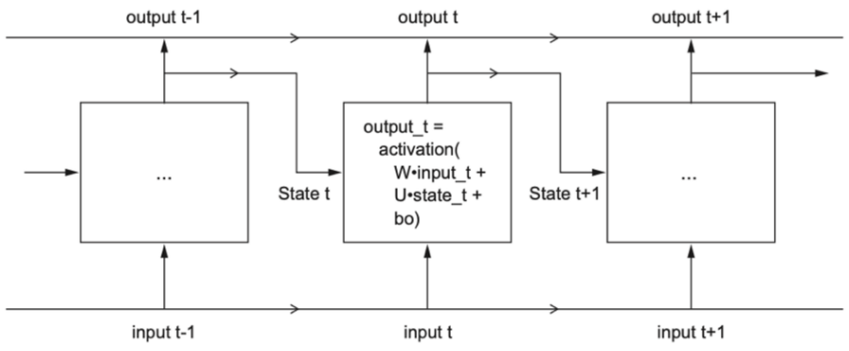


Figure 2-29. A simple RNN unrolled over time [49].

Long Short Term Memory Network (LSTM)

Hochreiter and Schmidhuber [61] developed the long short term memory network to solve the vanishing gradient problem. LSTM network is a variant of a simple RNN that adds a way to carry information across many time steps. What an LSTM essentially does is that it saves information from time *t* for later use, thus preventing the older data from vanishing during processing [49]. Figure 2-30 shows an LSTM that has a carry track carrying information *c*. Basically, when you remove the carry track, it becomes a simple RNN found in Figure 2-29.

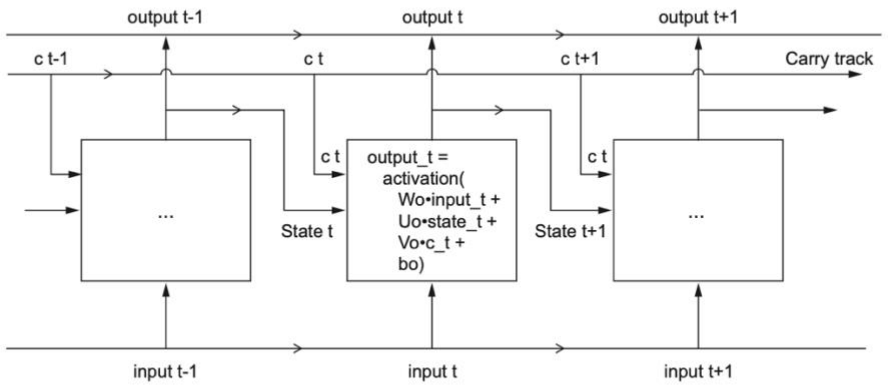


Figure 2-30. LSTM network [49]

In the O&G industry, particularly in drilling, the LSTM network has not been studied in-depth [31]. However, a couple of LSTM implementation has been on downhole data prediction by Thakur et al. [62], and Han et al. [63] worked on the ROP predictive model previously built using ANN. From their paper, the error of the model was reduced from 14% to 7% using the LSTM model [63].

2.6.3. Feature Scaling

Feature scaling is one of the vital steps needed when preparing data, as ML algorithms perform poorly when data have different scales. In the context of drilling operations, we work with different scales and units for every drilling parameter, e.g., weight on bit measurements vary from 0 to 8 Tons, and torque measurements ranging 15-25 kN-m [31]. Although we will only work with hook load measurements in this paper, there is a vast discrepancy in recorded hook load during casing operations ranging from 300 – 450 klbm with operations involving only drill pipe where hook load ranges from 140 – 300 klbm.

Min-max scaling, also known as normalization, is used when the data does not follow a Gaussian distribution, e.g., hook load measurements [64]. Values are shifted and rescaled so that they end up ranging between 0 and 1. To normalize data, the minimum value of the dataset is subtracted from every single data point and divided by the difference of maximum and minimum value (see equation 17). After normalization, the minimum value in original data becomes 0, the maximum becomes 1, and other values are between the range of 0 and 1. For this purpose, Scikit-Learn's [65] transformer MinMaxScaler was used.

$$x_{(i)norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{17}$$

2.6.4. Regression Metrics

Building an effective Machine Learning model requires evaluation metrics to see how good the model is. Different evaluation metrics are used for different kinds of problems. Similarly, evaluation metrics to be used for regression differ from those used for classification [49]. In our context, we will build a regression model that will predict the hook load value based on previous hook load measurements. Naturally, the concept of accuracy doesn't apply to regression. A common regression metric is mean absolute error (MAE) [49].

Mean Absolute Error (MAE)

The mean absolute error (MAE) of a model is the mean of the absolute values of the individual prediction errors on all instances. MAE can be calculated using equation 18 [66]:

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - X_j\right| \tag{18}$$

Where,

y_j , is the expected or true value for instance *j*

X_j , is the predicted value for instance *j*

n is the number of instances.

Residual Distribution

Residuals are obtained by finding the deviation between the model output with the true value the model is trying to predict. Examining residuals is a key part of all statistical modeling. An ideal distribution should be normal - centered on zero and narrow as possible [50]. Residual distribution is plotted where x-axis represents the residuals, and y-axis represents the density distribution.

3 Experimental Design

3.1. Methodology

This chapter presents the experimental design to realize the research objectives. Figure 3-1 outlines the experimental approach implemented in this thesis work. The experiment part will be conducted in four phases: data preparation, feature engineering, modelling, and model evaluation. The first two phases will be carried out using Python [15] and Pandas [67] for data manipulation. For the LSTM model, Keras library [68], a deep learning application programming interface (API) written in Python [15], that runs on top of TensorFlow [69] will be used.

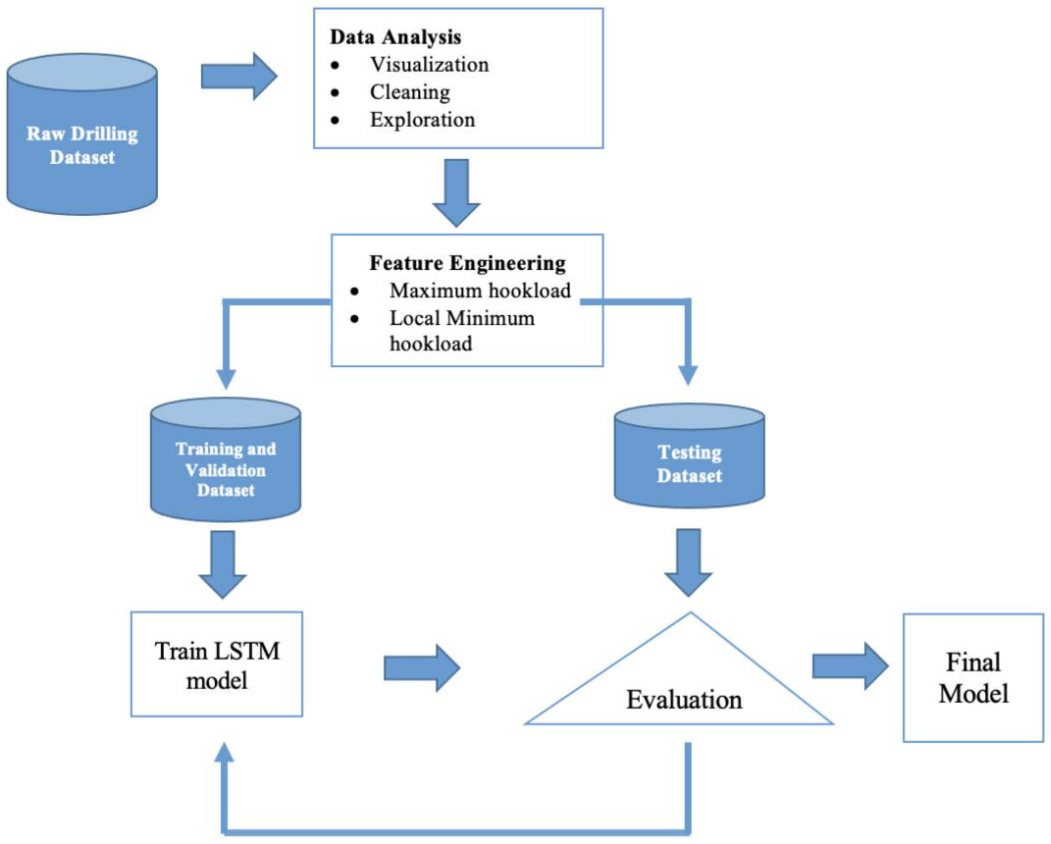


Figure 3-1. Workflow of the experimental work

3.2. Hook Load Signatures

There have been many variations in using real-time hook load measurement to prevent stuck pipe event. As opposed to Cayeux et al. [46], Mason et al. [6] identified and utilized distinct points from the hook load from each stand, instead of the whole hook load measurement. There are distinct points within the hook load data, if correctly interpreted, that can provide a much better picture of the downhole condition. Figure 3-2 illustrates a snapshot of a single joint of casing run in hole that shows the interaction between block movement and hook load. During tripping in operation, the driller slightly raises the string in order to remove the slips before being lowered into the hole (○). A peak hook load (●) is observed due to the slips removal. After the peak, a sudden drop is observed (●) which is often associated with the static friction - when part of the string load is held by the formation. Then, the average dynamic hook load is represented by the green circular symbol. Similar to roadmaps, these extracted points can also be plotted against the simulated hook load values [7]. For this approach, it is of prime importance to have a high sampling frequency to ensure that the distinct points in the hook load are properly defined. Lack of data resolution could lead to inaccurate trend lines thereby subject for misinterpretation [6, 50].

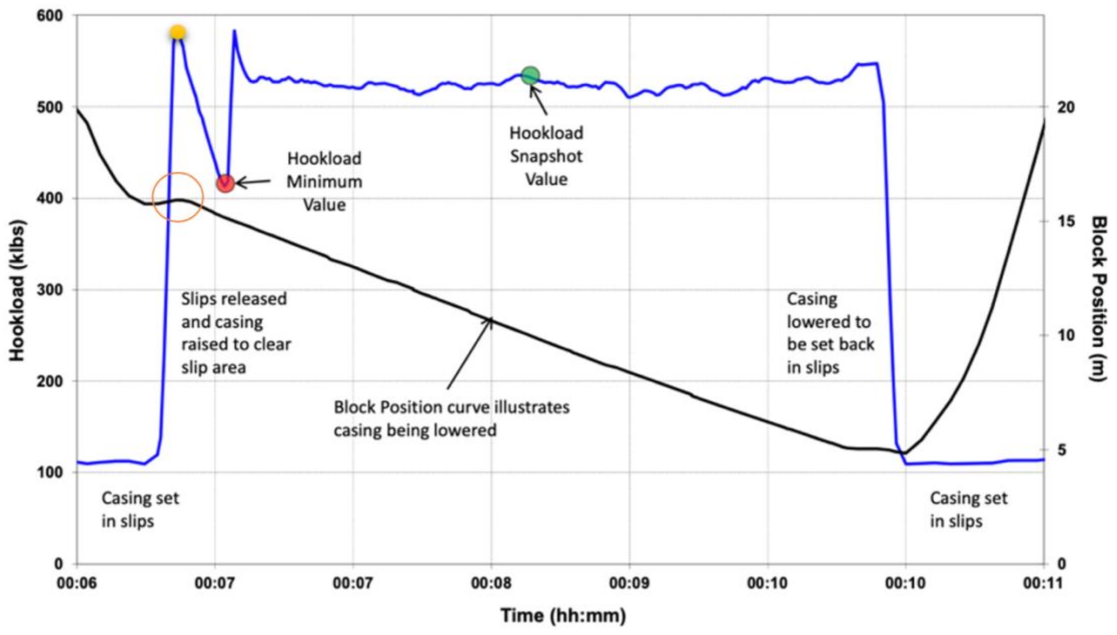


Figure 3-2. Hook load signature and block position during running in of one stand [6].

Figure 3-3 to Figure 3-5 show hook load and block position measurements with varying frequencies. Based on these figures, when the frequency of measurements is reduced, the points of interest may be missed. This increases the uncertainty on the data quality, which is paramount when building data-driven models. Hence, datasets with a frequency less than 0.2 were discarded.

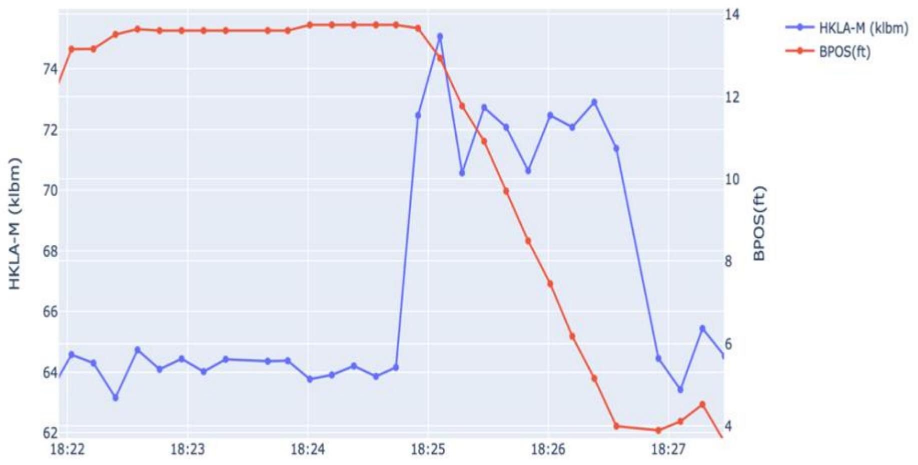


Figure 3-3. Well E: 0.1 Hz measurement

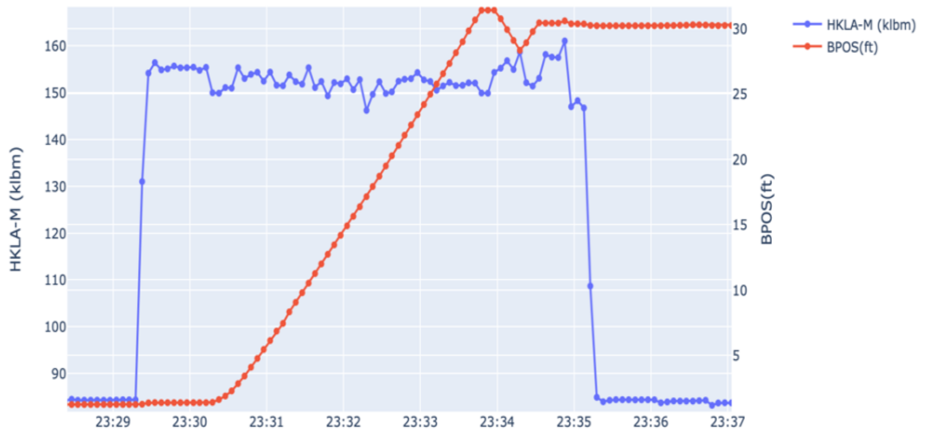


Figure 3-4. Well D: 0.2 Hz measurement

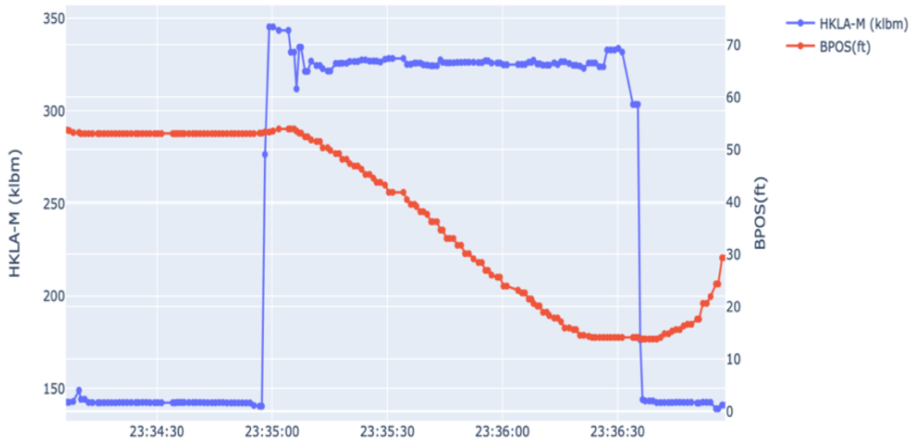


Figure 3-5. Well A: 1 Hz measurement

3.3. Data Preparation

Data preparation involves a series of processes to gather, transform, and organize raw drilling data into a format that is compatible with software the user aims to use. It is often a lengthy process and requires a domain knowledge on the data. Data preparation starts from collecting data from internal and external sources, transforming data into a compatible format, visualization, cleaning, filtering, imputing, validating, and storing for future use (FIGURE 3-6).There are no simple universal methods and tools for preparing data. Generally, data preparation involves iteration and it is not a one direction process.

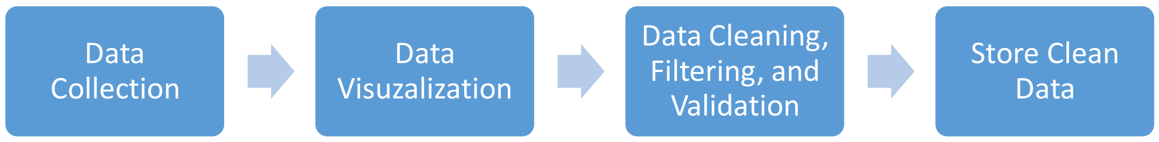


Figure 3-6.Data Preparation Sample Pipeline

According to Tunkiel et al.[70] several problems persists when working with raw real-time drilling data.

i. Outliers, and Sentinel Values

Not all values in a the dataset can be considered valid. There are a number of reasons for erroneous values. These can be caused by flaws in measurement or recording techniques. Sentinel values are typically written to show a lack of value or no measurement done for that particular variable. When data are plotted, it is easy to observe these values. These may appear as -999 in the data.

ii. Multi-Operations Lagged

In some datasets, there are more than one operation recorded (e.g. drilling, tripping, and reaming). To identify these different operations, it is best to plot the different parameters as a function of time and apply engineering knowledge.

iii. Huge number of Data

Some dataset may contain days of drilling operation up to months which is huge when considering the sampling rate. This may reach of more than a million timestamps multiplied by the number of parameters that ranges from ten up to two hundred. Although not all data is necessary, it is highly recommended to automate searching for relevant features from the available data. For example to determine the type of operation, only five parameters is useful, namely, measured depth, bit depth, hook load, rotation per minute, and torque (see Figure 2-16). Capacity of computer should also be considered when working with this amount of data.

These problems are presented and addressed in 3.3.2.

3.3.1. Data Collection

To build a data-driven model, a collection of dataset has to be available. In this project, Exebenus provided raw real-time drilling data from 7 wells in comma-separated values (CSV) and Microsoft excel format. Table 3 shows the information provided by Exebenus for each well. There were no drilling report and annotations attached. All the well data were unnamed due to data privacy and bounded by non-disclosure agreement.

Table 3. Data provided by Exebenus

Well ID	Issue reported as
Well A	Diff sticking
Well B	Diff sticking
Well C	Unknown
Well D	Pack-off
Well E	Hole Cleaning
Well F	No Data
Well G	No Data

3.3.2. Data Analysis

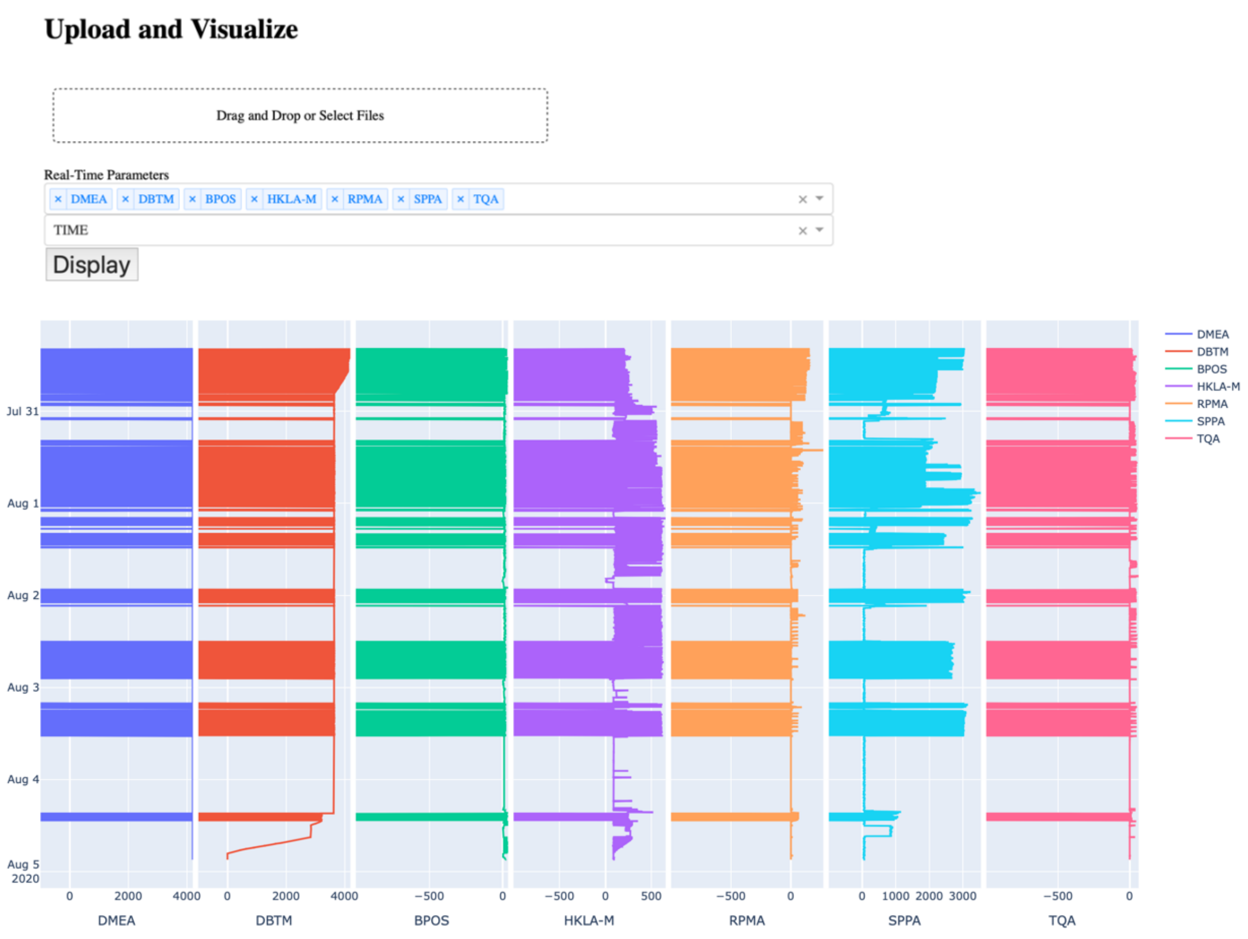
Our goal is to determine the type of operation, identify the stuck point, and prepare the data for the next step which is feature engineering. This can be done by correlating the available drilling measurements. However, data analysis is no straightforward. The raw dataset carries issues as mentioned by Tunkiel et al.[70] that needs to be addressed before we can fulfill our main tasks. In this thesis, two web-based applications were developed to enable efficient data analysis given the time constraint of the project and the amount of data to analyze.

Visualizing data

Data visualization is the initial step in data analysis in which data analysts use visualization tools in order to better understand the nature of the data. The purpose of this process is to help create a clearer view of important trends and points to study in greater detail. When working with drilling data, data visualization allows the analyst to see the available parameters, quality and characteristics of data, and the type of operation. As discussed by Tunkiel et al. [70], dataset may contain more than a million timestamps due to the sampling rate causing problems for software such as Excel. One cannot simply browse through the data due to its quantity. To address this problem, the author built a fit for purpose web-based application for data visualization. The application is written in Python [15] and Dash [71] - a framework for building web visual and analytical applications with customizable user interfaces in pure Python [15]. This application allows the user to upload files in CSV and Excel format, and plot up to 7 drilling parameters simultaneously without typing a single code. It is also possible to zoom in details particularly when the dataset is too large to fit on the screen. Anomalous values and data trends can be quickly observed. This application eliminated the arduous process of manual methods of typing algorithms to visualize the data. Appendix B.1. shows the code of the application.

Figure 3-7 shows the user interface of the visualization tool where Well B raw data was uploaded. Seven parameters were plotted namely, DMEA, DBTM, BPOS, HKLA-M, RPMA, SPPA, and TQA, respectively. In Figure 3-8, other available parameters are plotted, WOBA-M, ROPA, MFIA, MDIA, and ECD_ARC_RT, respectively. See Table 4 for the full form of these abbreviations.

Well B dataset is from July 30, 2020 to August 5, 2020. Evidently, the dataset contains sentinel values. All the parameters have values of -999 which is an indication of no measurement or error in sensor [70]. To better understand the data, it must be filtered first from these values.



Upload and Visualize

Drag and Drop or Select Files

Real-Time Parameters

× DMEA × DBTM × BPOS × HKLA-M × RPMA × SPPA × TQA

TIME

Display

Figure 3-7. Well B raw data: DMEA, DBTM, BPOS, HKLA-M, RPMA, SPPA, and TQA visualization

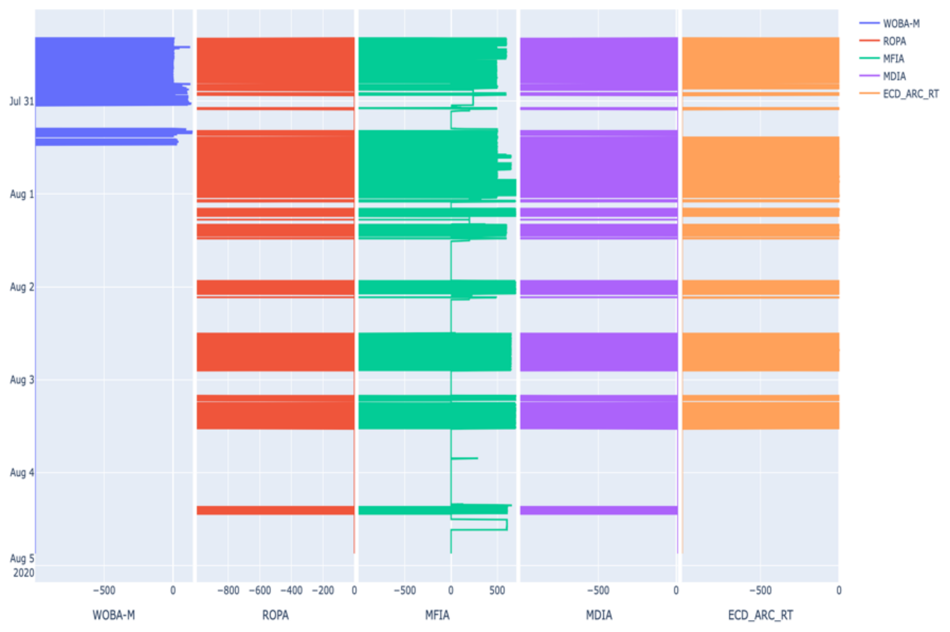


Figure 3-8. Well B raw data: WOB-M, ROPA, MFIA, MDIA and ECD_ARC_RT visualization

Table 4. Drilling Parameters

Drilling Parameter	Well Data Column Name	Unit
Measured depth	DMEA	ft
Bit depth	DBTM	ft
Block position	BPOS	ft
Hook load	HKLA-M	klbm
Rotation per minute	RPMA	rpm
Standpipe pressure	SPPA	Kpa
Torque	TQA	kft.lbf
Weight on bit	WOBA-M	klbm
Rate of Penetration	ROPA	m/h
Mud flow rate in	MFIA	galUS/min
Mud weight in	MDIA	galUS/min
Equivalent Circulating Density	ECD_ARC_RT	

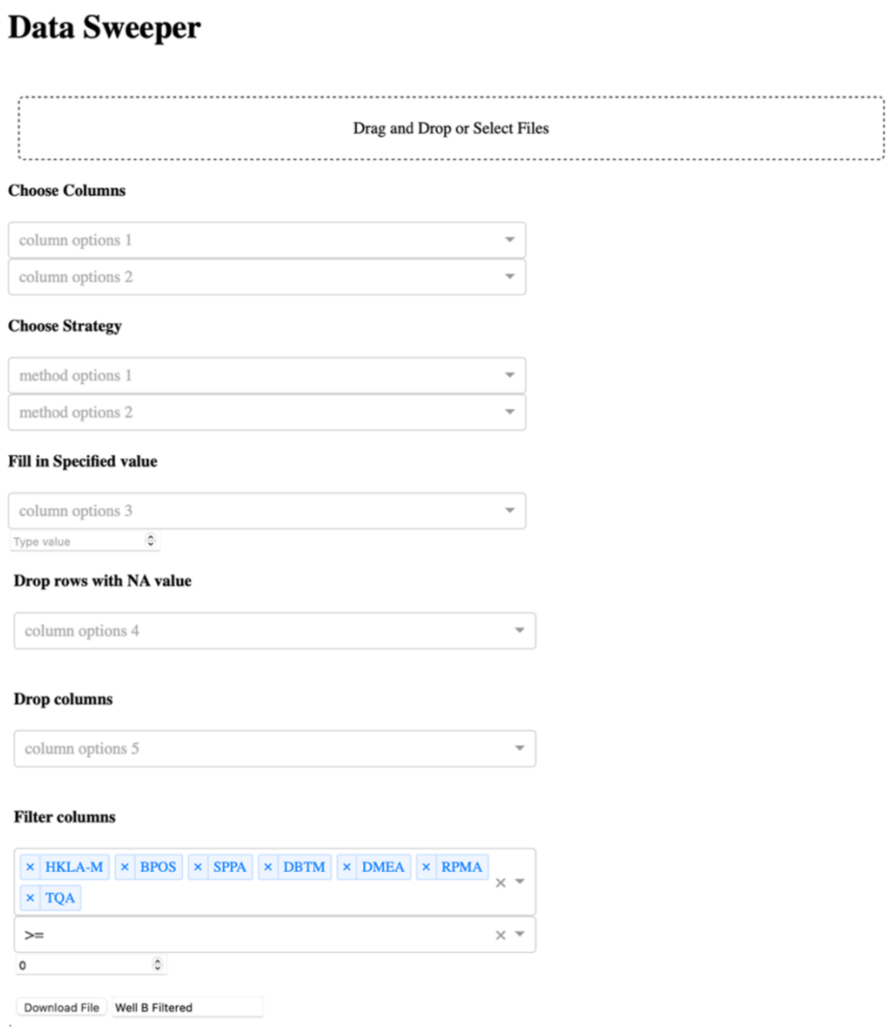
Data Cleaning

The quality of the data directly affects the ability of the model to perform its tasks [72]. Thus, data cleaning is a necessary step in building Machine Learning projects. After the initial visualization, it was evident that the data contains anomalous values and needs cleaning. Therefore, another web-based application was built to clean the data. Similar to the data visualization application, it is written in Python [15] and using Dash [71] to provide a point-&-click interface. The user can upload files in CSV and Excel format where each column contains the drilling parameters and each row is one timestep measurement of each parameter. This data cleaning application allows the user to filter data with specific values, drop unnecessary columns, fill or drop rows with missing values, and download the processed file instantly without typing a single code. This processed file is then used for further data exploration. See Appendix B.2. for the complete code of the application.

Figure 3-9 shows the user interface of the data cleaning application where Well B is uploaded. The filter option works by choosing the columns of interest and checking their values using the comparison operator selected against a specific value. When a particular value of a column does not pass the filter, the row containing that value is deleted. There are cases wherein one row may have more than one sentinel value, thereby filtering one column results in filtering multiple columns at once. Some columns may contain only sentinel values that, when filtered, will cause deletion of all the rows, and nothing will be left from the dataset. Thus, it is crucial to only consider relevant parameters according to predefined objectives. There is no fixed configuration on which and how many parameters are considered relevant. Most of the time, iteration and domain knowledge of the data and task at hand is needed.

In this paper, it is our primary objective to extract signature points from hook load before stuck pipe incident. But before we proceed, it is necessary to determine the type of operation, identify the stuck point, and prepare the data for the next step which is feature engineering.

Figure 3-9 shows Well B's HKLA-M, BPOS, SPPA, DBTM, DMEA, RPMA, and TQA are all filtered to have values equal or greater than zero. It is based on engineering knowledge that these values cannot have negative values.



Data Sweeper

Drag and Drop or Select Files

Choose Columns

column options 1

column options 2

Choose Strategy

method options 1

method options 2

Fill in Specified value

column options 3

Type value

Drop rows with NA value

column options 4

Drop columns

column options 5

Filter columns

× HKLA-M × BPOS × SPPA × DBTM × DMEA × RPMA × TQA

>=

0

Download File Well B Filtered

Figure 3-9. Cleaning Well B data

Data Exploration

After cleaning the dataset, it is now subject to exploration to get an in-depth description. This step is similar to the previous data visualization, only that the data is free from sentinel values. By plotting several parameters simultaneously, it is easier to get an understanding of the data trends. Figure 3-10 visualizes the filtered Well B data.

DBTM, DMEA, TQA, and RPMA are parameters used for determining the type of operation. Decreasing DBTM and constant DMEA means pulling out of hole operation. But by looking at TQA and RPMA, Well B is a reaming operation since it has values. Reaming is performed to enlarge an existing hole or maintain the hole in gauge.

DBTM, DMEA, BPOS, and HKLD are parameters used for determining the stuck point. It can be observed that the DMEA is constant which implies that there is no new drilled depth. From the 30th of July at 14:00, DBTM decreased until 19:00 the same day and became constant after that. This indicates a stuck incident or a stop in operation. By checking the HKLA-M and BPOS, starting from the time DBTM becomes constant, these values have gone erratic, indicating that the driller is trying to free the string by reciprocation. This cross-checking confirms that it was a stuck incident during reaming operation.

After determining the stuck point and type of operation, our next objective is to extract hook load signatures prior to this stuck incident.

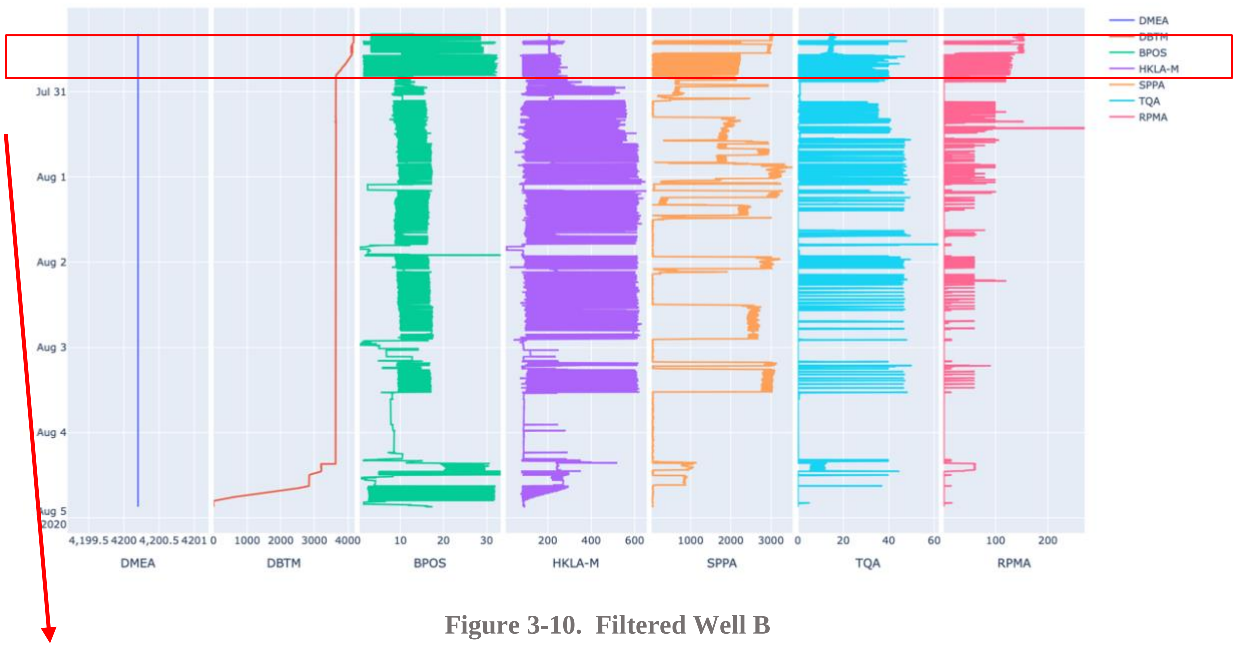
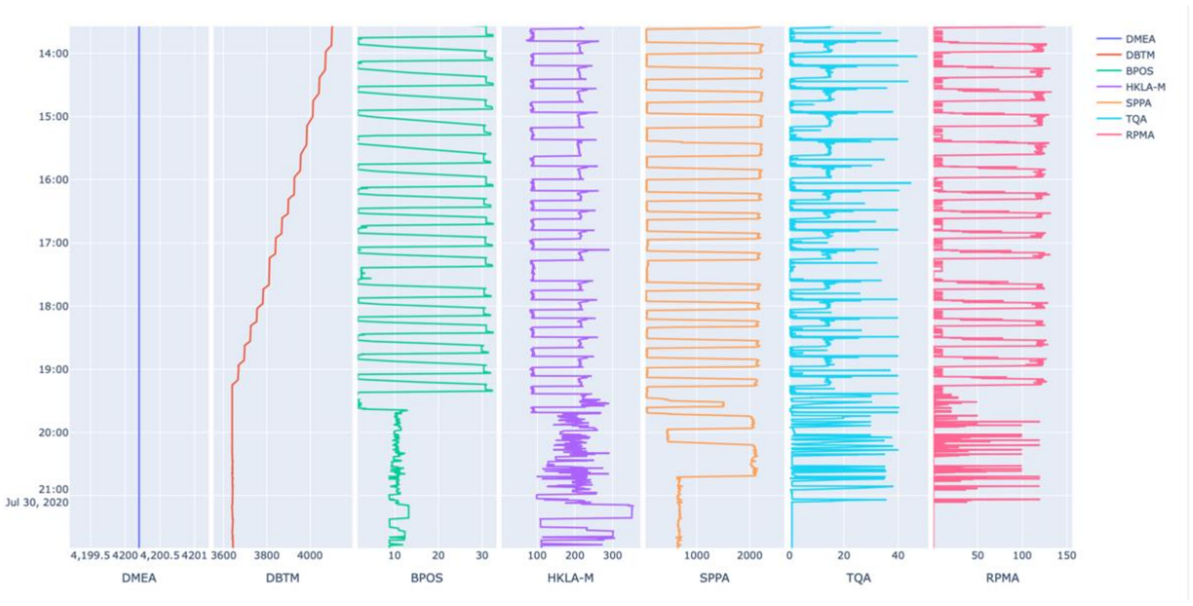


Figure 3-10. Filtered Well B



The process demonstrated in Section 3.3.2 was applied to all the given wells by Exebenus. Each well was uploaded, visualized, and evaluated on the type of operations.

Table 5 shows the summary of each well. Data analysis of wells A and D can be found in Appendix D.1 and D.2. Due to data quality issues on the frequency of measurements, the author only used Wells A, B, and D for ML implementation. These wells have at least 0.2 Hz of measurement which means drilling data is recorded every 5 seconds. This will be further discussed under extracting features in Chapter 4 Feature Engineering.

Table 5. Well data Information summary

Well Name	**Type of Operation**	**Operation before the stuck pipe**	**Measurements Frequency (Hz)**
Well A	Running in Casing	Running In Casing	1
Well B	Tripping Out	Tripping Out	0.2
Well C	Mixed Operations	Tripping Out	0.1
Well D	Tripping Out	Tripping Out	0.2
Well E	Mixed Operations	Tripping Out	0.1
Well F	Mixed Operation	Tripping In	0.1
Well G	Mixed Operation	Tripping In	0.1

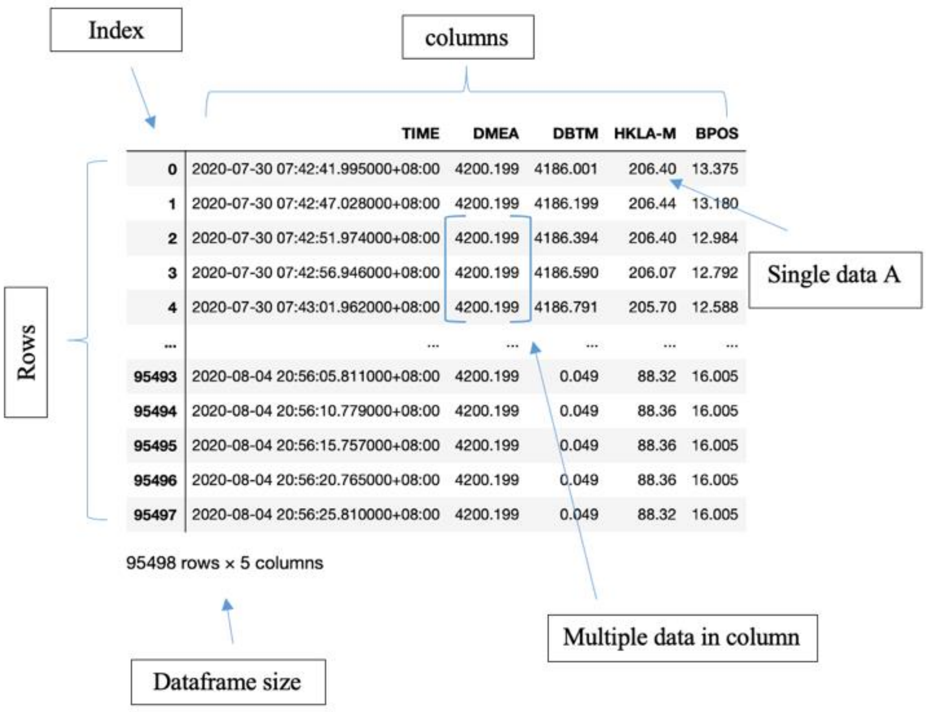
4 Feature Engineering

The success of a Machine Learning project relies heavily on coming up with a good set of features to train on [66]. No algorithm alone can supplement the information gain given by using correct features [73]. In ML, feature engineering is the process of using your knowledge about the data to make the algorithm work better by extracting specific features. The essence of feature engineering is expressing the problem more straightforwardly [49].

As mentioned in Section 3.2. , hook load signatures exist before stuck pipe events. During tripping out operations, after removing the slip to continue moving the pipe out of the well, a force is needed to initiate movement. This required force is the hook load during the static condition and the static friction. Because frictional forces always oppose the direction of motion, it is added when tripping out. This hook load is referred to as the maximum hook load. The same concept applies during tripping in operations only that static friction is deducted, and this is referred to as the local minimum hook load. This is called local minimum because, after this point, any further reduction in hookload is attributed to the dynamic movement of the string. In normal operation, static friction should not vary much when monitoring consecutive stands. This trend of frictional forces is an excellent indicator of the downhole condition as it reflects additional forces to initiate movement [6].

It is our prime objective in feature engineering to extract these hook load signatures for each dataset. Maximum and local minimum hook loads are extracted from wells with tripping out and tripping in operations, respectively. These extracted hook load signatures will be used in building a long short term memory network ML model for hook load prediction.

The processed and explored file from Section 3.3.2 is now imported to Python [15] as a DataFrame using Pandas. Similar to CSV files, DataFrame has a tabular data structure with labeled rows and columns. Figure 4-1 shows the elements of a DataFrame. Columns are the drilling parameters, and each row represents measurements at each time interval. Rows are numbered using the index, which is the default in Python [15]. Similar to rows, columns also have indexes (not seen) where “TIME” is the 0th column, “DMEA” is the 1st column, and so on. Individual data can be accessed through its row and column index. In Python, this is implemented using DataFrame variable name in Python followed by a parenthesis containing the indexes. For instance, singe data A has a row index of 0 and column index 3. In Python [15] this is implemented as DataFrame_name [0,4]. Another example is accessing multiple data from a single column. This can be accessed using DataFrame_name [2:5, 1]. What this does is it takes all the data starting from the 2nd row up to the 4th row under the 1st column which is DMEA. The end of the range is not included, for this case the 5th row. It is also possible to extract all column data from specific rows or vice versa. For instance, DataFrame_name [2:5,] returns all the data from each column found in rows 2,3 and 4. This is similar to when accessing a list. In Python [15], lists are used to store multiple items in a single variable (e.g. [55 ,22, 11, 44]). For this list, element 22 can be accessed by coding list_name[1]. Indexing has been the core of extracting the local minimum and maximum hookload.



	TIME	DMEA	DBTM	HKLA-M	BPOS
0	2020-07-30 07:42:41.995000+08:00	4200.199	4186.001	206.40	13.375
1	2020-07-30 07:42:47.028000+08:00	4200.199	4186.199	206.44	13.180
2	2020-07-30 07:42:51.974000+08:00	4200.199	4186.394	206.40	12.984
3	2020-07-30 07:42:56.946000+08:00	4200.199	4186.590	206.07	12.792
4	2020-07-30 07:43:01.962000+08:00	4200.199	4186.791	205.70	12.588
...	...	...	...	...	...
95493	2020-08-04 20:56:05.811000+08:00	4200.199	0.049	88.32	16.005
95494	2020-08-04 20:56:10.779000+08:00	4200.199	0.049	88.36	16.005
95495	2020-08-04 20:56:15.757000+08:00	4200.199	0.049	88.36	16.005
95496	2020-08-04 20:56:20.765000+08:00	4200.199	0.049	88.36	16.005
95497	2020-08-04 20:56:25.810000+08:00	4200.199	0.049	88.32	16.005

95498 rows × 5 columns

Figure 4-1. Pandas DataFrame anatomy

4.1. Maximum hook load

Maximum hook load is recorded after removing the slips as the weight of the string is transferred to the hook. The author built a *get_peak* function to extract the maximum hook load points from each connection. In this context, maximum hook load and peak hookload are the same.

LISTING 1. FUNCTION FOR GETTING THE PEAK

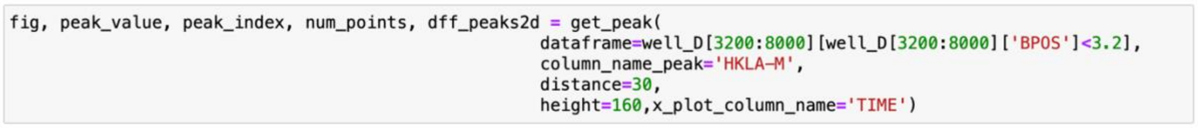
```
get_peak(dataframe,column_name_peak,distance, height,x_plot_column_name)
```

The *get_peak* function searches for the peak values of *column_name_peak* in the *dataframe* with a minimum value of *height* and at least *distance* away from each other. This function returns a figure of the peaks, a list of peak values and peak indexes, a count of peaks, and a DataFrame of data with the same index as peak values. Input values for this function are found in Table 6.

Table 6. get_peak function variables

Parameter	Python Argument	Variable type
Well dataset	dataframe	Pandas DataFrame
Column name of hook load in the DataFrame	column_name_peak	String
Minimum distance (number of data points) in samples between neighboring peaks	distance	Int
Minimum hook load value to be considered as peak	height	Int
Column name of the parameter to be plotted with hook load	x_plot_column_name	String

4.1.1. Well D Implementation



```
fig, peak_value, peak_index, num_points, dff_peaks2d = get_peak(
                                            dataframe=well_D[3200:8000][well_D[3200:8000]['BPOS']<3.2],
                                            column_name_peak='HKLA-M',
                                            distance=30,
                                            height=160,x_plot_column_name='TIME')
```

Well D is a tripping out operation that has a frequency of 0.2 Hz. For this *get_peak* implementation, it takes the Well D data with row index between 3200 and 8000 and has a block position less than 3.2ft. This index range is learned during the data analysis as this is before the stuck pipe incident occurred and has a sufficient frequency of measurements for feature extraction (frequency of measurement varies throughout the dataset). The 3.2ft is a filter. What it does is that the *dataframe* only takes the rows that have a block position less than 3.2ft. This value is based on the fact the this is a tripping out operation (block moves up), and the maximum hookload exists when the slip was first removed. By using this filter, it reduces the hook loads that will be considered thus, making the search more efficient.

The *column_name_peak* takes in ‘HKLA-M’ which is the column name of hookload in the *dataframe*. The *distance = 30* means that the maximum hookload data points must be at least 30 data points away from each other. *Height* = 160 is a threshold that says the maximum hook load must at least have a value of 160. Lastly, *x_plot_column_name* = ‘TIME’ takes the column name of time in the *dataframe* used as the x-axis data for the output plot. Table 7 shows the output variables for this implementation, and Figure 4-2 displays extracted maximum hook loads together with the block position from three consecutive stands. Figure 4-3 and Table 8 show the extracted maximum hookload for Well D. This function was applied to Well B, and results can be seen in Appendix E.2

Table 7. get_peak function output variables

Parameter	Python Argument	Variable Type
2D plot of hook load and Time	fig	Figure
List containing all the peak values	peak_value	Numpy 1D array; list
List containing all indexes of each peak	peak_index	Numpy 1D array; list
Count of peaks	num_points	Int
DataFrame containing all data with index equal to peak_index	dff_peaks	Pandas DataFrame

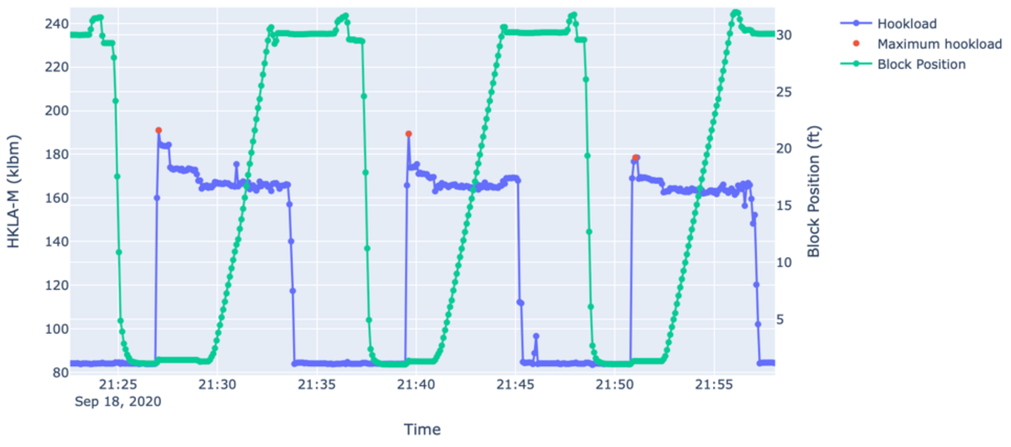


Figure 4-2. Snapshot of three consecutive stands from Well D.

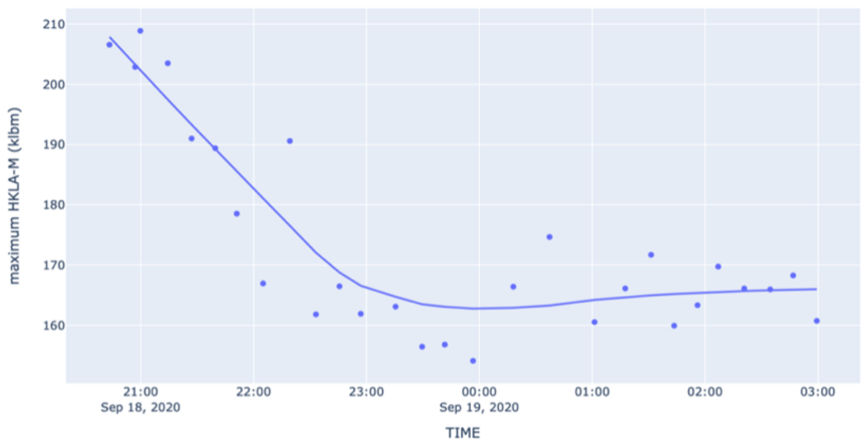


Figure 4-3. Well D maximum hook load at each stand.

Table 8. First 15 of 28 maximum hook load from Well D

	TIME	HKLA-M
3461	2020-09-18 20:43:22.060000+08:00	206.58
3625	2020-09-18 20:57:02.133000+08:00	202.88
3658	2020-09-18 20:59:47.080000+08:00	208.88
3833	2020-09-18 21:14:22.149000+08:00	203.49
3985	2020-09-18 21:27:02.255000+08:00	191.00
4136	2020-09-18 21:39:37.272000+08:00	189.38
4273	2020-09-18 21:51:02.390000+08:00	178.52
4441	2020-09-18 22:05:02.327000+08:00	166.93
4612	2020-09-18 22:19:17.310000+08:00	190.59
4778	2020-09-18 22:33:07.382000+08:00	161.79
4928	2020-09-18 22:45:37.515000+08:00	166.46
5064	2020-09-18 22:56:57.487000+08:00	161.89
5286	2020-09-18 23:15:27.596000+08:00	163.07
5455	2020-09-18 23:29:32.663000+08:00	156.42
5600	2020-09-18 23:41:37.758000+08:00	156.77

4.2. Local Minimum Hook load

Getting the local minima is tricky and requires domain knowledge. Firstly, Hashim et al. [50] and Mason et al. [6] used smoothed drilling data. It does not contain any markers showing the frequency of measurements. From Hashim et al. [50] paper, all the local minima are the first minimum after the peak (see Figure 4-4), without explicitly explaining how they picked it. This gives the notion that the local minima are always the first minimum point after the peak. However, the author argues that this is not always the case. As seen from Figure 4-5, if we choose the first local minimum (A) after the peak hook load (C), the corresponding block position (A1 = 52.4ft) is below the block position during the connection (B1 = 53.5ft). This can be interpreted that the corresponding local minimum (A) results from the downward movement (1.1ft) of the casing string, thus further reducing the hook load. This additional reduction in hook load can be attributed to added dynamic friction, which is opposite the casing weight when running in. By invoking the definition of local minimum, this hookload (A) is not attributed to the static friction. Thus, the true local minimum exists before this point. Suffice it to say that the local minimum hookload is not always the first minimum hookload after the peak (C). *Now, it asks the question: at which boundaries do the local minima exist?* As mentioned in previous Section 3.2. , local minimum hook load is the hook load that is recorded after removing the slip when some of the loads are held by the formation. However, it is hard to determine when exactly this local minimum exists when looking at Figure 4-5. There are no indications of when the formation took some of the hook's weight. The block position measurement is continuous after removing the slips – it does not stop when this formation took some of the hook load.

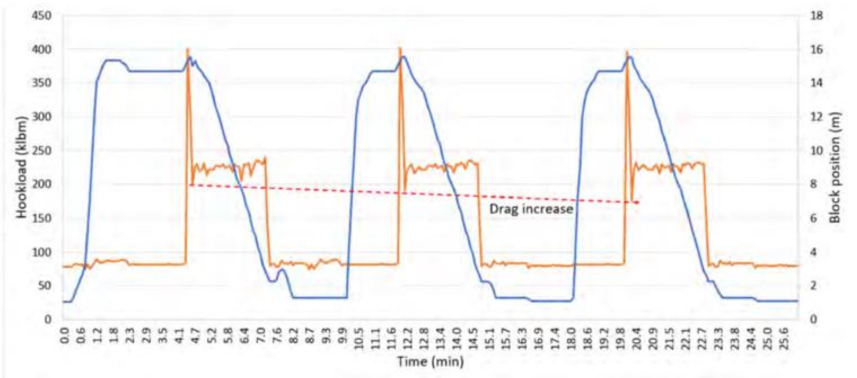


Figure 4-4. Minimum hook load for consecutive stands from Hashim et al. [50]

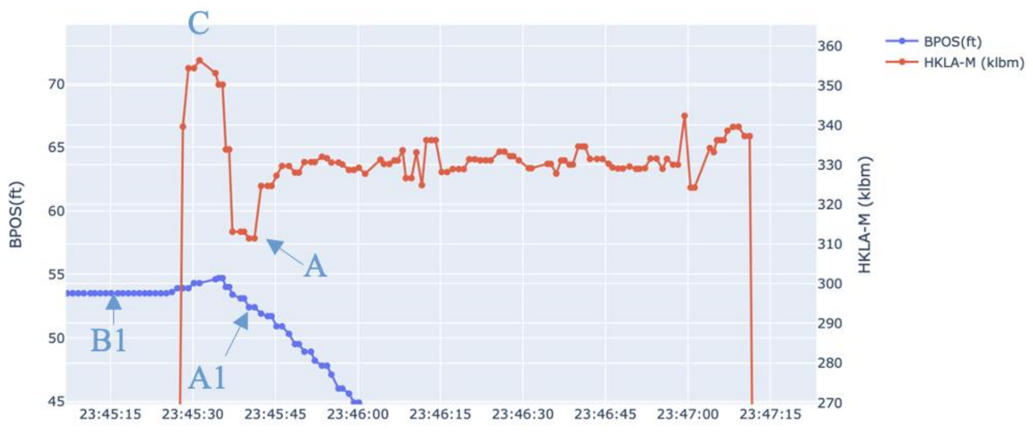


Figure 4-5. Snapshot of running in one stand

To our knowledge, there is no specific algorithm to extract local minima. Also, only Hashim et al. [50] and Mason et al. [6] papers showed their extracted local minima. Kucs et al. [7] only mentioned they used the local minima without providing explanations or figures to refer to. In this paper, the author designed algorithms to identify the local minima. Two functions are needed: one is to determine the boundaries for the local minima, and the second is to get the minimum between these boundaries.

LISTING 2. FUNCTION FOR GETTING LOCAL MINIMA BOUNDARIES
get_minima_boundaries

```
get_minima_boundaries(dataframe = well_A, peak_index, block_column, look_back)
```

get_minima_boundaries function is used for finding the local minimum boundaries. Input variables for this function are provided in Table 9. This function takes the *peak_index* from the previous *get_peak function* as input and serves as the first boundary. Then, it looks for the block position during connection from *block_column* in the *dataframe*. This is found by subtracting the *look_back* value to each peak value in the *peak_index*. Remember that the peak hook load exists after the connection time; subtracting *look_back*, we go backward. This block position during connection serves as a reference point. *get_minima_boundaries* function then searches for the second boundary by comparing the first boundary block position to all the block positions starting from the right of the block position during the peak hook load. The search for a second boundary stops when the block position is less than the reference block position which is the connection block position. The idea behind this is that the driller raises the block by around 0.5 ft. to remove the slips before running in. Using the connection block position as the reference assumes that any measured hook load with a block position lower than the connection block position is attributed to dynamic friction. Hence, it is not considered as local minima. A sample implementation on a single stand and full implementation in Well A dataset is presented for a more precise explanation of this function.

Table 9. get_minima_boundaries function variables

Parameter	Python Argument	Variable type
Well dataset	dataframe	Pandas DataFrame
List of Peak Index	peak_index	List
Block Position Column name	block_column	String
Value to locate block position during connection *case-by-case basis	look_back	Int

4.2.1. Single Stand Implementation

```
connection_BPOS_index, second_bound_index, boundaries_index = get_minima_boundaries(
                                                               dataframe = well_A,
                                                               peak_index = peak_index,
                                                               block_column = 'BPOS',
                                                               look_back = 15)
```

Example 1.1: Single stand from Well A: finding boundaries

Getting the local minimum hookload boundaries involves several steps. Take Figure 4-6 as a sample case using one stand from Well A. The first step is to use the extracted maximum hookload index as a starting point, which in this case is the (A1) and has a value of 3297. This index of the maximum hookload serves as the first boundary index. From this point, you need to find the block position during connection time. We do this by subtracting the *look_back* input value which has a value of 15. This value is subtracted from the (A1) first boundary index which results in 3282. This *look_back* value is found by manual estimation, and it is on a case-by-case basis. Using the index value of 3282, we can find the block position corresponding to that index, which in this case is (B1 = 53.5ft). This connection block position serves as the reference value. Now, what we need to find is the second boundary index. Starting from the block position corresponding to maximum hook load (A1: BPOS = 54.3ft), we compare each block position, going in the right direction, with the block position during connection (B1: BPOS=53.5ft). This search ends when the block position is less than the connection block position. For this case, it stopped when the block position is now 53.4ft. The index of this block position (C1:index=3303) is used as the second boundary.

To summarize, the first boundary is the index of maximum hook load. The second boundary is the index of the first block position, after the maximum hook load, which is lower than the connection block position. The block position during connection is only used for reference.

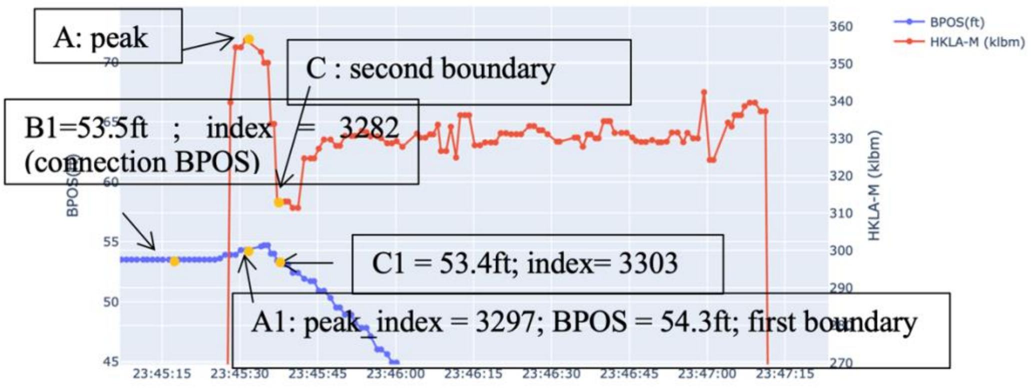


Figure 4-6. Snapshot of one stand during running in getting local minimum boundaries

Table 10 provides the output variables of the *get_minima_boundaries function. Connection_BPOS_index* contains the indexes of block position during the connection of each stand. *Second_bound_index* contains the indexes of the second boundaries. Finally, *Boundaries_index* contains a list of the first and second boundaries arranged in pairs for each stand. For example, if *peak_index* has a value of [3297, 3425], and *Second_bound_index* has a value of [3303, 3435], *Boundaries_index* will have a list equal to [3297, 3303, 3425, 3435]. In this case, each first pair is the boundaries for each stand. This *Boundaries_index* is the input in finding the local minimum hookload in the next function.

Table 10. get_minima_boundaries function output variables

Parameter	Python Argument	Variable type
Block position index during connection	Connection_BPOS_index	List
Secondary index for finding local minima. This is the index of the first block position after the peak that is lower than during connection.	Second_bound_index	List
Local minima Boundaries	Boundaries_index	List of Int

Example 1.2: Full implementation on Well A dataset: finding boundaries

This is similar to example 1.1, except that it takes the whole Well A dataset as the input. All the indexes of maximum hook load which in this case is *peak_index*, serves as the first boundary. The value of *look_back* is 15, which means 15 points are deducted from each *peak_index* to find the reference block position. Each of these reference block positions is used to find the second boundary index. Figure 4-7 and Figure 4-8 each display one stand, including the identified boundaries. It is evident from these examples that the pattern of measurements varies a lot. In Figure 4-7, there was a steep reduction of hook load after the peak, from peaking at about 343 to 340, then bottomed at around 290 klbm. While in Figure 4-8 it was gradual from 360 to 350 to 345 to 330, then it bottomed at around 310 klbm.

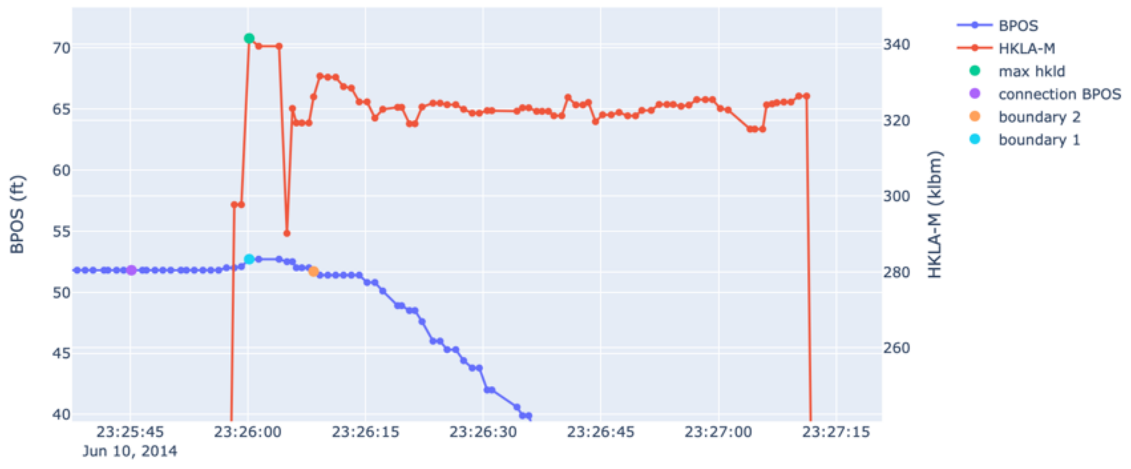


Figure 4-7. Case 1.2.1. Locating Local Minimum hook load boundaries.

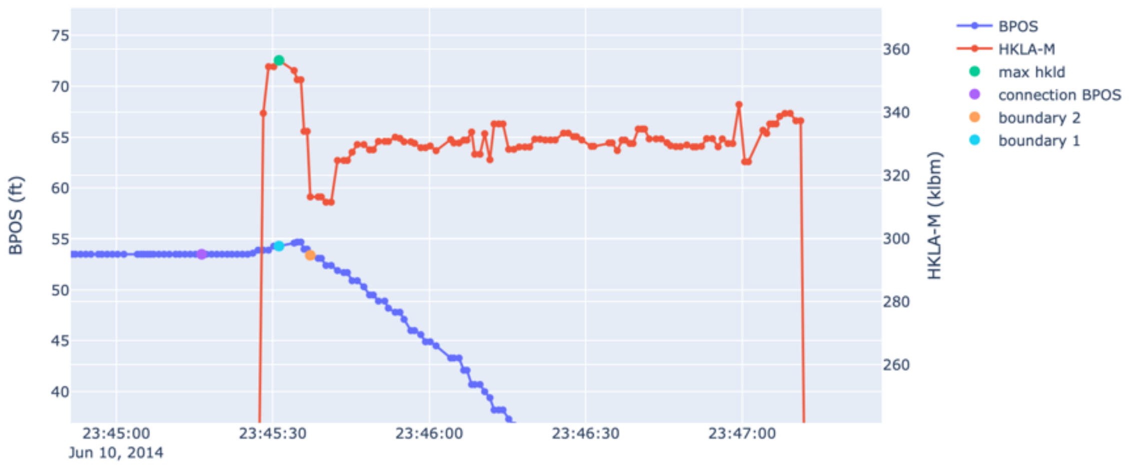


Figure 4-8. Case 1.2.2. Locating Local Minimum hook load boundaries.

LISTING 3. FUNCTION FOR GETTING MINIMA
get_minima

```
get_minima(dataframe, boundaries, column_name_peak, x_plot_column_name)
```

After identifying the local minimum hook load boundaries, it is time to extract the minimum values between these boundaries using the *get_minima* function. Table 11 contains the input variables for this function.

The *get_minima* function uses *boundaries* to get the minimum value from the *dataframe's column_name_peak*. This function takes each pair of boundaries for each stand and takes the minimum value of hook load found within that range of indexes. The *x_plot_column_name* is the column name in the dataframe that serves as the x-axis data in the output figure (Table 12). *get_minima* function is implemented on a single stand as well as full Well A dataset.

Table 11. get_minima function variables

Parameter	Python Argument	Variable type
Well dataset	dataframe	Pandas DataFrame
List of local minima boundaries	boundaries	List
Hook load Column name in DataFrame	column_name_peak	String
Column name in DataFrame for the X-axis (e.g., Time)	x_plot_column_name	String

4.2.2. Well A Implementation

```
fig,count_minima, dff  = get_minima(well_A, peak_boundaries_index,'HKLA-M', 'TIME')
```

Example 2.1: Single stand from well A: extracting local minimum hookload

Using the same case displayed in Figure 4-6 from example 1.1, the local minimum is now extracted after getting the first and second boundary indexes. From this example, the first and second boundary indexes are 3297 and 3303, respectively. The *get_minima* function takes all the hook load measurements between these indexes and identifies the minimum value, which in this case is 333.87 klbm with an index value of 3202. Observe that 3202 is in between the first and second boundary (Figure 4-9). Although, this case does not follow Hashim et al. [50] and Mason et al. [6] solution that the local minimum hook load is the first minimum hook load after the peak. This will be further discussed in example 2.2.2. using Figure 4-11.

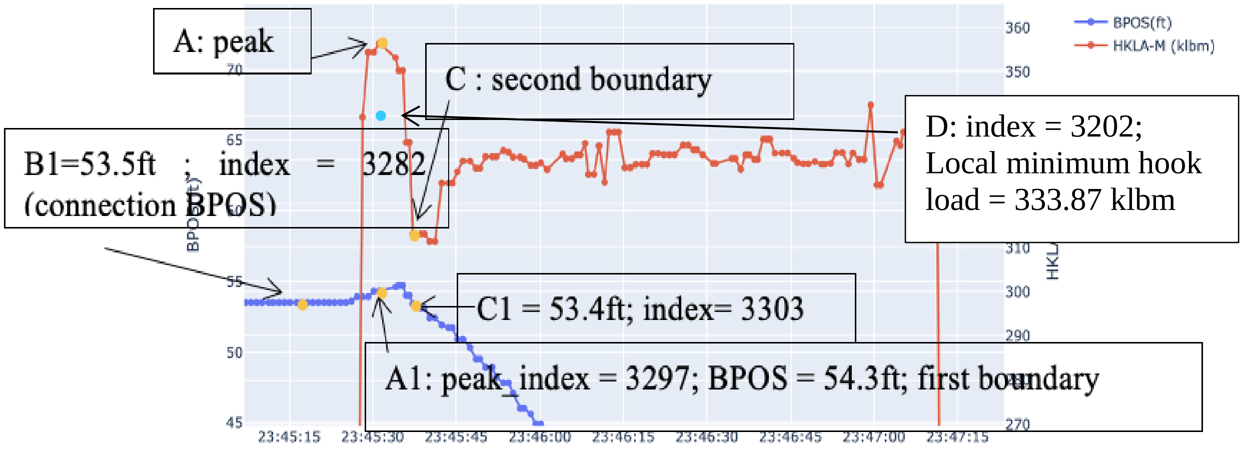


Figure 4-9. Snapshot of one stand during running in: getting local minimum hook load

Table 12. get_minima function output variables

Parameter	Python Argument	Variable type
2D Plot of local minima and Time	Fig	Figure
Number of minimum points	Count_minima	Int
DataFrame derived from well_A but only with index equal to local minimum hook load index	dff	Pandas DataFrame

Example 2.2: Full implementation in well A dataset: extracting local minimum hookload

This is similar to example 2.1, except that it takes the whole Well A dataset as the input. All the boundaries from example 1.2 are used as input boundaries. Figure 4-10 and Figure 4-11 display a snapshot of extracted local minimum hook load from a single joint from Well A.

In Figure 4-10, the local minimum hook load (●) is apparent. This example is in line with what Hashim et al. [50] and Mason et al. [6] presented in their papers that the local minimum hook load is the first lowest hook load after the maximum hook load (●).

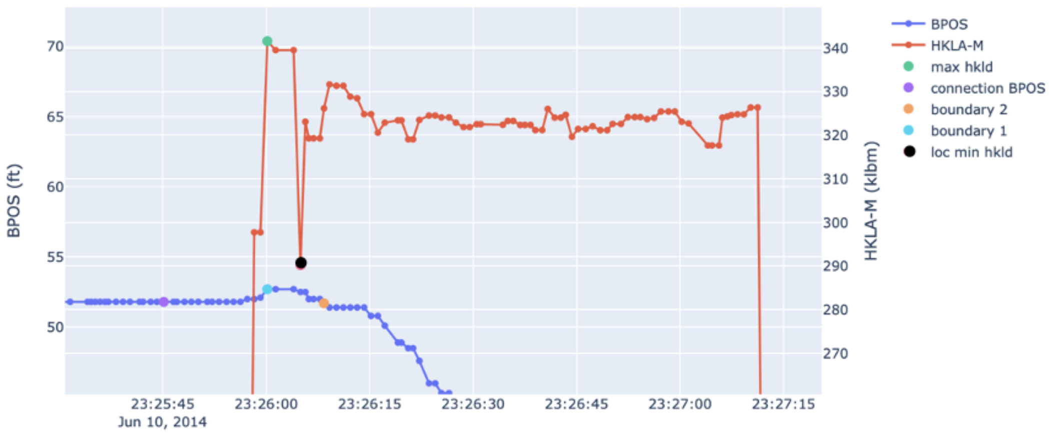


Figure 4-10. Case 2.2.1. Extracting Local Minimum hook load.

Using Figure 4-11, if we follow Hashim et al. [50] and Mason et al. [6] concept of local minimum hookload this would be (A1) which has a corresponding block position of 52.4 ft. This 52.4 ft, compared to the connection BPOS (● = 53.5 ft), is less than 1.1ft. This can be interpreted that the first minimum hook load after the peak (A1) results from the downward movement (1.1ft) of the string, thus further reducing the hook load. This additional reduction in hook load can be attributed to added friction, which is opposite the casing weight when running in, or due to additional obstacles inside the well. By the definition of local minimum hook load, this (A1) is not attributed to the static friction. Thus, the true local minimum hook load exists before this point. Suffice it to say that the local minimum hook load is not always the first minimum hookload after the peak (●).

To address this problem, the author of this paper used the connection block position as a reference point for the local minimum hook load second boundary. As a result, the local minimum hook load (●) for this case is equal to 333.87 klbm.

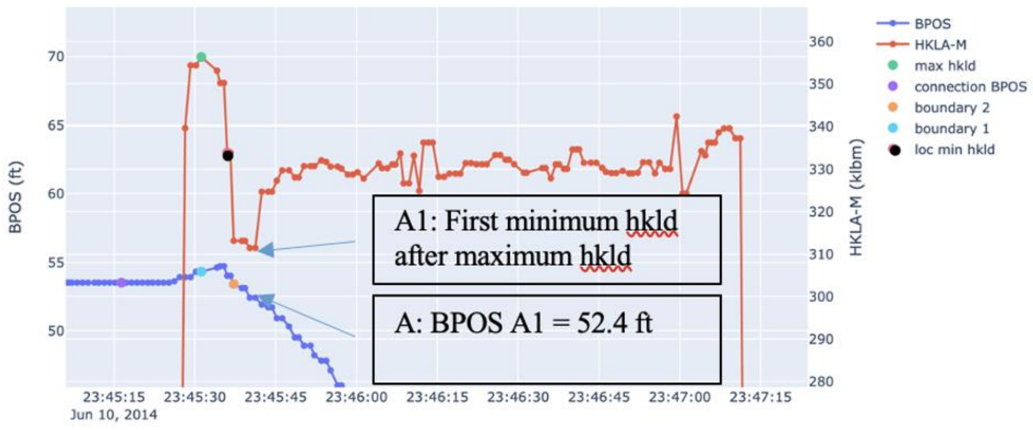


Figure 4-11. Case 2.2.2. Extracting Local Minimum hook load.

Figure 4-12 displays all the extracted minimum hook load from Well A using the author's solution. There is clear evidence of trend deviation starting at 01:30 on 11th of July, 4 hours and 30 minutes before the reported stuck pipe event. This will be further discussed in Chapter 6.

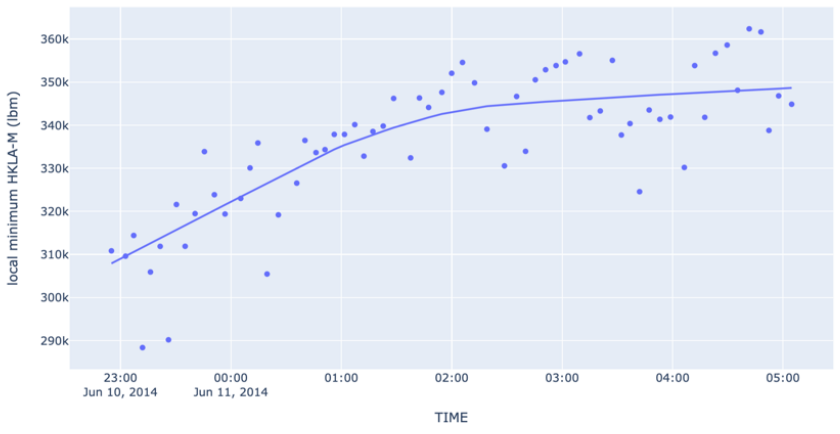


Figure 4-12. Extracted local minimum points from well A.

4.3. Summary of Extracted data

Table 13 shows the count of extracted hook load signatures. A total of 108 signature points were extracted, consisting of 43 maximum and 65 local minimum hook loads from wells with tripping out and tripping in operations, respectively. The data quality has been essential in this study as three out of the seven wells were functional. These extracted points will be used in building the ML model that will predict hook load signatures.

Table 13. Summary of extracted hook load signature points

Well Name	Type of Operation	Number of Maximum hook load	Number of Local Minimum hook load
Well A	Tripping In	Not extracted	65
Well B	Tripping Out	15	Not extracted
Well D	Tripping Out	28	Not extracted

A table of all the extracted data points from Wells A, B, and D can be found in Appendix E.2

5 Machine Learning Implementation

5.1. Splitting Data

Irrespective of the Machine Learning model to train, the dataset is divided into three parts to avoid overfitting and model bias (Figure 5-1). Overfitting persists when the ML model performs worse on new data than on their training data. Model bias is a type of error wherein certain dataset elements are not a general representation of the population, more heavily weighted or represented than others [74].

- Training Set
- Validation Set
- Testing Set

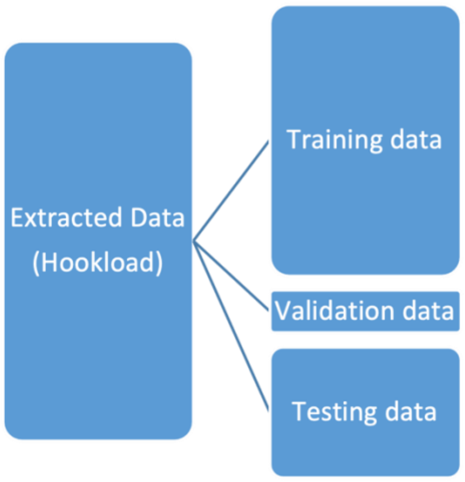


Figure 5-1. Splitting Data

The training set, as stated in its name, is used to train and fit the model. The model's parameters (e.g., weights in ANN) are tuned while observing and learning from this data. The validation set is used for unbiased model evaluation when tuning the model's hyperparameter (e.g., number of neurons in ANN). After the training, the final model is evaluated using the testing set. This testing set does not contain any data found in the former two datasets. This paves the way for an unbiased data evaluation by having unique testing data since the model has not seen and learned from this data before evaluation.

There is no specific rule as to how large the splitting should be. Generally, it depends on the amount of data available, but always the training set takes the largest share. For example, Encinas [31] had 4000 data points and applied a (60-40) ratio where 60% of the data is for training and 40% for the validation set. On the other hand, Hashim et al. [50], without mentioning the number of available data points, applied an (80-20) ratio.

When working with a time-series problem, it is crucial not to shuffle the dataset. It must maintain its chronological order after splitting. This means data is split in between defined time range – not randomly chosen individually. In this paper, we had a total of 108 data points from three wells (TABLE 13). 55 extracted hook load were used for building the model, which is split to 80% training and 20% validating data. This leaves 53 hook loads for evaluating the model. This configuration allows us to test the trained model both in normal and deteriorating downhole conditions. In Figure 5-2 and Figure 5-3, hook loads within the yellow box are used for building the model (training and validation), and those within blue are testing data for evaluating the model. Other split data can be found in Appendix E.3.

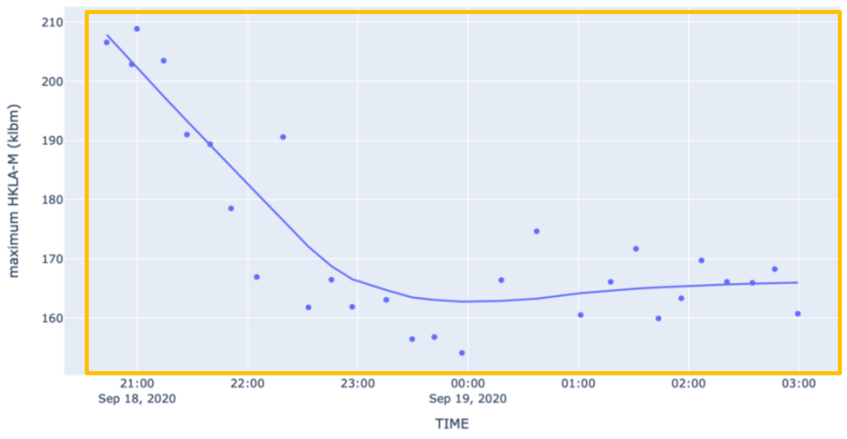


Figure 5-2. Well D maximum hook loads.

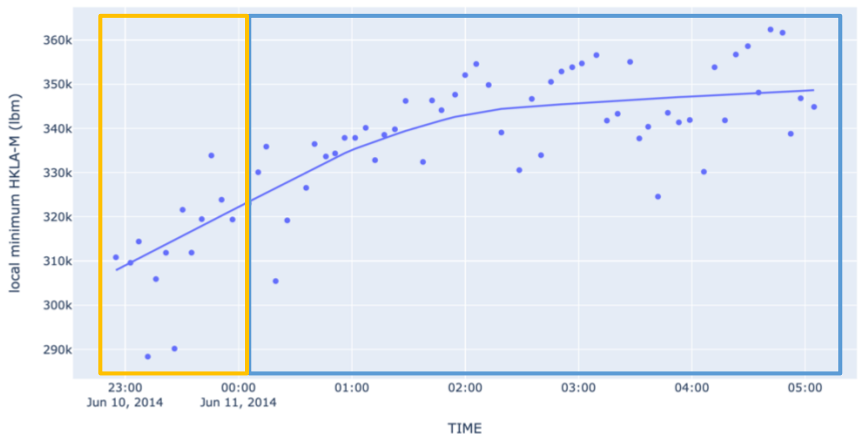


Figure 5-3. Well A local minimum hook loads.

5.2. Data Transformations

We need to transform the extracted data into a form the model expects before feeding the extracted data to train and test the LSTM model. Four data transformations are performed:

- Transform time-series data into cross-sectional data
- Transform the time series into a supervised learning problem
- Transform the observations to have a specific scale.
- Reshape from 2D array into a 3D array

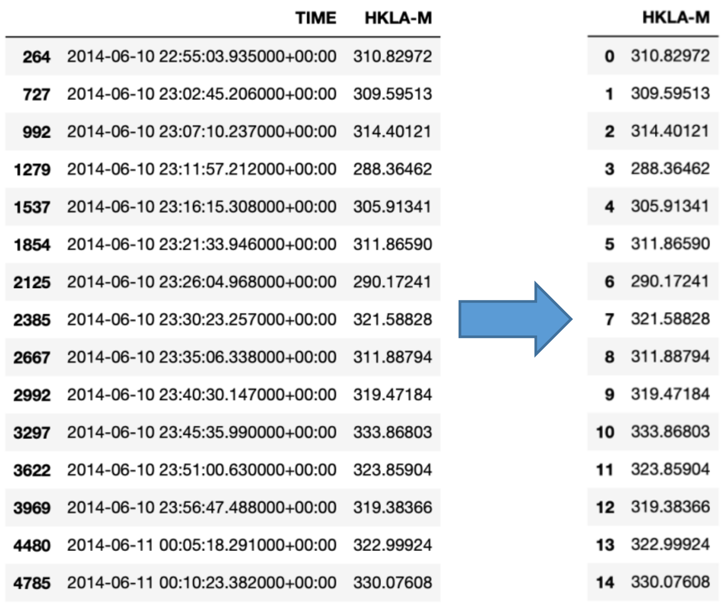
5.2.1. Well A Implementation

For illustration purposes, Figure 5-4 to Figure 5-7 shows the data transformation for 15 hook load measurements from well A. All the annotated Python code used for data transformation can be found in Appendix C.2. Listing 4.

Transform time-series data into cross-sectional data

The time-series data (left) in Figure 5-4 contains data points from multiple periods and considered as single individual data. One can observe that the hook load signatures do not have a definite time interval. A reason for this is that the driller is inconsistent with the duration of making each connection. Thus, it is not reasonable to predict when the hook load signature exists; instead, focus only on the value and trend.

To transform time-series data into cross-sectional data means transforming the data into a static one - single period, multiple individuals. This data transformation is done by removing the time dependency of the hook load. This can be done by indexing the data as the nth number of pipe stand being run. Despite removing the time dependency, it is important not to shuffle the chronological order of hook load measurements. This means that the cross-sectional data remains sequential. Notice from the two tables in Figure 5-4 that the time series data was reindexed into the nth number of the stand, but the hook load measurements still follow the same order.



	TIME	HKLA-M
264	2014-06-10 22:55:03.935000+00:00	310.82972
727	2014-06-10 23:02:45.206000+00:00	309.59513
992	2014-06-10 23:07:10.237000+00:00	314.40121
1279	2014-06-10 23:11:57.212000+00:00	288.36462
1537	2014-06-10 23:16:15.308000+00:00	305.91341
1854	2014-06-10 23:21:33.946000+00:00	311.86590
2125	2014-06-10 23:26:04.968000+00:00	290.17241
2385	2014-06-10 23:30:23.257000+00:00	321.58828
2667	2014-06-10 23:35:06.338000+00:00	311.88794
2992	2014-06-10 23:40:30.147000+00:00	319.47184
3297	2014-06-10 23:45:35.990000+00:00	333.86803
3622	2014-06-10 23:51:00.630000+00:00	323.85904
3969	2014-06-10 23:56:47.488000+00:00	319.38366
4480	2014-06-11 00:05:18.291000+00:00	322.99924
4785	2014-06-11 00:10:23.382000+00:00	330.07608

	HKLA-M
0	310.82972
1	309.59513
2	314.40121
3	288.36462
4	305.91341
5	311.86590
6	290.17241
7	321.58828
8	311.88794
9	319.47184
10	333.86803
11	323.85904
12	319.38366
13	322.99924
14	330.07608

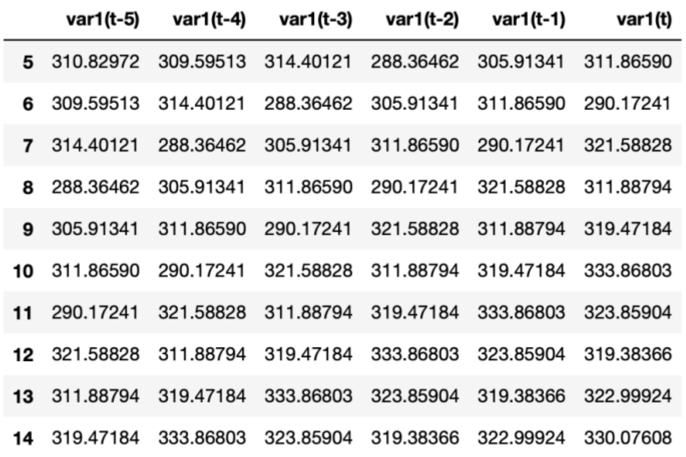
Figure 5-4. Time series to cross-sectional data.

Transform the cross-sectional data into a supervised learning problem

In the second data transformation, supervised learning means learning from data that contains a label or known output. This step involves organizing the cross-sectional data from the previous transformation into an input and output pattern wherein the previous observations predict the next timestep. From this point of this study, one timestep means one stand. This is because each hook load signature is taken from every connection of single stand.

In this study, the past five hook load signatures predict the next hook load signature at time *t* (time *t* means the same with one stand). This provides the model enough stability to make predictions with a reasonably good precision considering the limited amount of data. In this case, the hook load to be predicted serves as the output (also called a label)

From Figure 5-5, var1 stands for the hook load where (*t-5*) means five pipe stands behind time *t*. All the hook load signatures in the previous five stands are used to predict the hook load signature at next time *t*. Each row of data is considered as one data point or instance. Notice that from 15 data points in Figure 5-4, this is reduced to 10. This is because the first five hook are needed to make the first prediction which starts at *t* = 5.

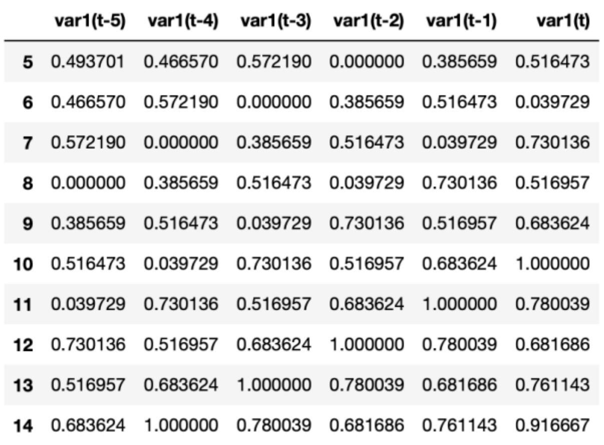


	var1(t-5)	var1(t-4)	var1(t-3)	var1(t-2)	var1(t-1)	var1(t)
5	310.82972	309.59513	314.40121	288.36462	305.91341	311.86590
6	309.59513	314.40121	288.36462	305.91341	311.86590	290.17241
7	314.40121	288.36462	305.91341	311.86590	290.17241	321.58828
8	288.36462	305.91341	311.86590	290.17241	321.58828	311.88794
9	305.91341	311.86590	290.17241	321.58828	311.88794	319.47184
10	311.86590	290.17241	321.58828	311.88794	319.47184	333.86803
11	290.17241	321.58828	311.88794	319.47184	333.86803	323.85904
12	321.58828	311.88794	319.47184	333.86803	323.85904	319.38366
13	311.88794	319.47184	333.86803	323.85904	319.38366	322.99924
14	319.47184	333.86803	323.85904	319.38366	322.99924	330.07608

Figure 5-5. Supervised data.

Transform the observations to have a specific scale

The third transformation involves normalizing the data. When working with ANN, it is problematic to take wildly different ranges of values. Data normalizing allows neural networks to learn easier [49]. For this purpose, we used Scikit-Learn’s [65] transformer MinMaxScaler. This transformer takes the dataset's minimum value, subtracts it from every data point, and divides it by the difference of maximum and minimum value. After normalization, the minimum value in original data becomes 0, the maximum becomes 1, and other values are between the range of 0 and 1.



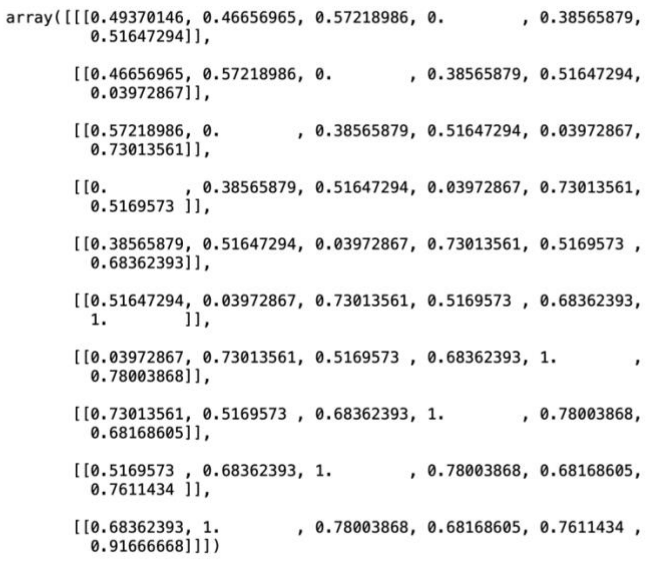
	var1(t-5)	var1(t-4)	var1(t-3)	var1(t-2)	var1(t-1)	var1(t)
5	0.493701	0.466570	0.572190	0.000000	0.385659	0.516473
6	0.466570	0.572190	0.000000	0.385659	0.516473	0.039729
7	0.572190	0.000000	0.385659	0.516473	0.039729	0.730136
8	0.000000	0.385659	0.516473	0.039729	0.730136	0.516957
9	0.385659	0.516473	0.039729	0.730136	0.516957	0.683624
10	0.516473	0.039729	0.730136	0.516957	0.683624	1.000000
11	0.039729	0.730136	0.516957	0.683624	1.000000	0.780039
12	0.730136	0.516957	0.683624	1.000000	0.780039	0.681686
13	0.516957	0.683624	1.000000	0.780039	0.681686	0.761143
14	0.683624	1.000000	0.780039	0.681686	0.761143	0.916667

Figure 5-6. Normalized supervised data using a Scikit-learn [65] MinMaxScaler.

Reshape from 2D array into 3D array

Currently, the data is a normalized 2D data with six columns wherein the last column is the target or to be predicted value, and each row is one instance. However, the LSTM model expects a 3D array input. This means that the data needs to be reshaped from a 2D array (batch size, features) into a 3D (batch size, timestep, features) array. In this context, batch size means the number of samples or instances. For illustration purposes, referring to the transformed and normalized data (Figure 5-6), the batch size is equal to the number of row data. In this case it is 10 (5 to 14). Time step means every row data is one time step. For two time steps, this means two rows of data. Features mean the number of columns, in this case, we have six wherein the first five are the past hook load measurements.

Although when training the LSTM model, we separate the input features from the output. In our case, the LSTM input shape is (10,1,5). This means that the model is trained on 10 data points, wherein each timestep has five features. In this 3D data, the feature means the past hook load measurements. For this purpose, reshape() function in NumPy [75] was used to reshape the 2D array into a 3D array. Figure 5-7 shows the data in the 3D form in Python [15]. Figure 5-8 displays a representation of an LSTM input.



```
array([[[0.49370146, 0.46656965, 0.57218986, 0.        , 0.38565879,
         0.51647294]],

       [[0.46656965, 0.57218986, 0.        , 0.38565879, 0.51647294,
         0.03972867]],

       [[0.57218986, 0.        , 0.38565879, 0.51647294, 0.03972867,
         0.73013561]],

       [[0.        , 0.38565879, 0.51647294, 0.03972867, 0.73013561,
         0.5169573 ]],

       [[0.38565879, 0.51647294, 0.03972867, 0.73013561, 0.5169573 ,
         0.68362393]],

       [[0.51647294, 0.03972867, 0.73013561, 0.5169573 , 0.68362393,
         1.        ]],

       [[0.03972867, 0.73013561, 0.5169573 , 0.68362393, 1.        ,
         0.78003868]],

       [[0.73013561, 0.5169573 , 0.68362393, 1.        , 0.78003868,
         0.68168605]],

       [[0.5169573 , 0.68362393, 1.        , 0.78003868, 0.68168605,
         0.7611434 ]],

       [[0.68362393, 1.        , 0.78003868, 0.68168605, 0.7611434 ,
         0.91666668]]])
```

Figure 5-7. Normalized data in Python 3D array shape.

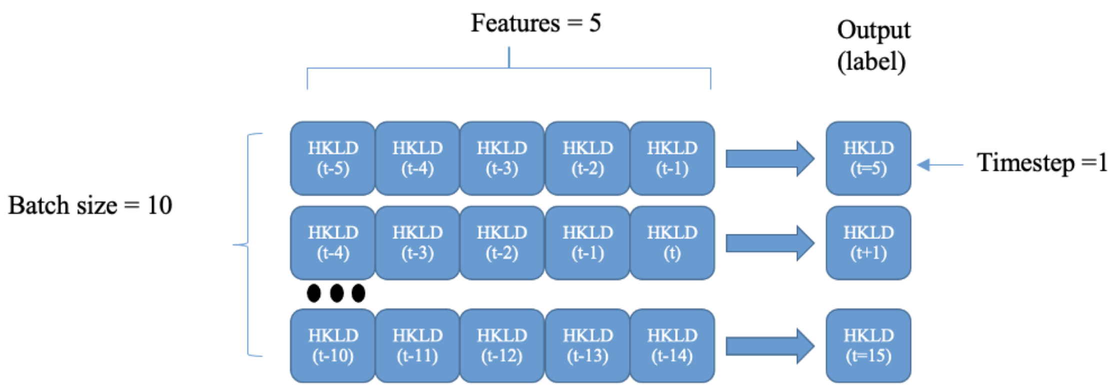


Figure 5-8. LSTM model 3D input with shape (10,1,5)

5.3. Training Long Short Term Memory (LSTM) model

The LSTM model will be used for this study since it is the ML model that handles sequential data (discussed in Section 2.6.2). Exebenus provided a convenience function for training an LSTM model (Appendix C.3.) This LSTM model was implemented using Keras [68]. A total of 55 hook load measurements was used for building the model. This comprises 12 local minimum hook loads from Well A and 43 maximum hook loads combined from Well B and D. As mentioned in Section 2.6, training LSTM is similar to ANN which involves determining the number of layers and neurons in each layer. Aside from the model structure, there is hyperparameters that help the model learn and estimate the model parameters (e.g., weights). Defining the optimal network that simulates the datasets is not an easy task. There are no definite rules when designing neural networks. It generally involves an iterative process [76]. We may use rules of thumb, copying used values from previous problems, or search by trial and error [77]. The convenience function provided by Exebenus already includes default hyperparameter values that guided the author in finding the optimum values. Appendix G shows the hyperparameters for the trained LSTM model and the default values can be found in Appendix C.3. The mathematics behind each hyperparameter is not tackled in this paper.

5.4. Model Testing

After training the model using the training dataset, it was evaluated using the testing data shown in 5.1. The testing data came from Well A that experienced a stuck pipe incident. Only the remaining 53 local minimum hook load comprises the testing data since the first 12 was used for training. These 53 hook loads have undergone the series of data transformations discussed in 5.2. We used the past five measurements to predict the hook load at next time *t*. The LSTM input has a final shape of (48,1,5) which means that the model predicts at each timestep using five past hook load data, 48 times. Figure 5-9 presents the expected value and predicted values using the LSTM model. The model obtained a 7.35 klbm mean absolute error, approximately 2% of the average hook load measurement. Figure 5-10 plots the residual distribution between the expected and predicted values. A more in-depth evaluation of this model's performance is presented in Chapter 6.

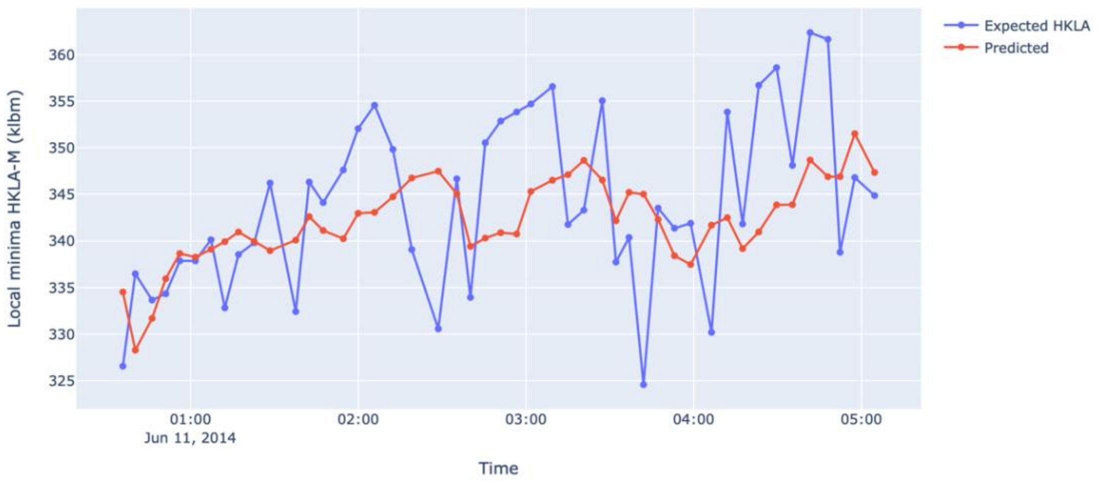


Figure 5-9. LSTM model Predictions on Well A

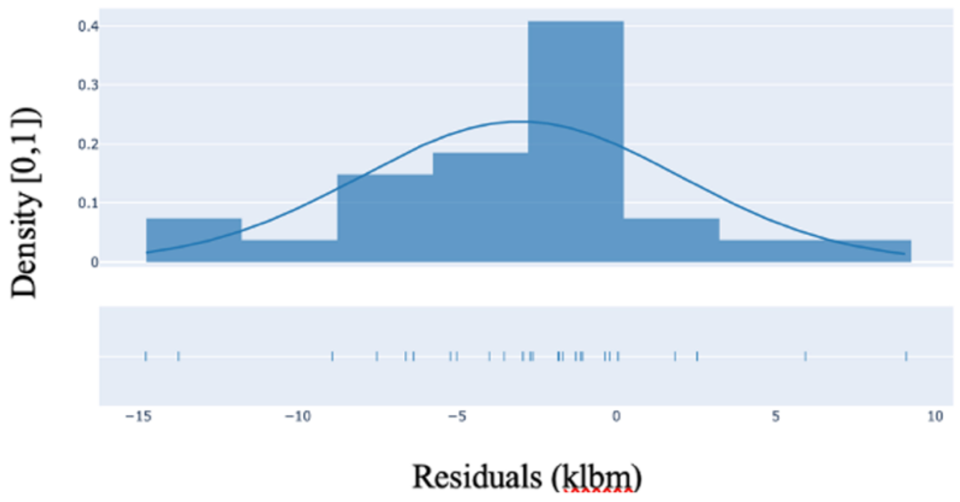


Figure 5-10. Residuals distribution

6 Results and Discussion

6.1. Extracted Hook Load Signatures

Figure 6-1 displays Well D dataset that experienced a stuck pipe incident on the 19th of September at 04:00. On the left plot are the hook load measurements. On its right are the extracted maximum hook loads using Listing 1 in Appendix C. By looking solely at the real-time hook load, the trend is decreasing because joints of pipes are unscrewed during a tripping out operation. However, at a glance, there are no clear indications that a stuck incident will occur. Using the plot to the left, at around 00:00 on 19th of September, it is evident that there is an apparent trend deviation from a decreasing to almost flat until the reported stuck pipe. As discussed in Sections 3.2. and 4.2, this is associated with an increase in static friction. This means that the downhole condition is deteriorating as early as 4 hours before the reported stuck pipe. Considering this early detection, the impending stuck pipe could have been prevented only if the drilling crew was alerted to evaluate the situation.

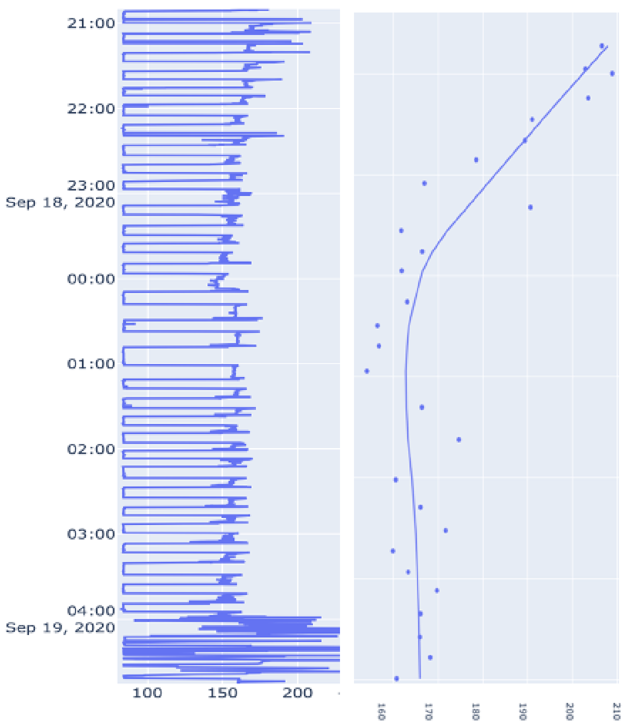


Figure 6-1. Comparative plot of Well D's measured hook load (left) and extracted maximum hook load (right)

Figure 6-2 displays Well A dataset that experienced a stuck pipe incident on the 11th of June at 06:00. On the left are the hook load measurements, and on its right are the extracted local minimum hook loads using the author's proposed algorithms (see Appendix C. Listing 2 and Listing 3). By looking solely at the real-time hook load, the trend is increasing as expected since pipe joints are screwed with the drill string during tripping in operation. However, there are no clear indications that a stuck pipe incident will occur. Using the plot to the right at around 01:30 on the 11th of July, it is evident that there is an apparent change in trend - from an increase to almost flat. As discussed in Sections 3.2. and 4.2, this is associated with an increase in static friction. This means the downhole condition is deteriorating as early as 4 hours and 30 minutes before the reported stuck pipe. Considering this early detection, the impending stuck pipe could have been prevented only if the drilling crew was alerted to evaluate the situation.

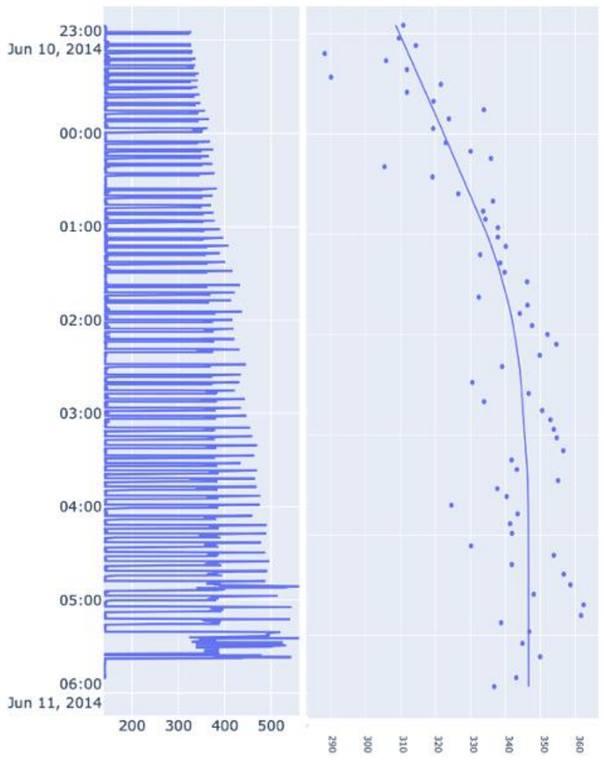


Figure 6-2. Comparative plot of Well A's measured hook load (left) and extracted local minimum hook load (right)

6.2. LSTM Model Performance Analysis

The LSTM model performance was evaluated based on two criteria: first is by the residuals and second according to the trend. In the following, the term expected hook load refers to the extracted hook load signature in the testing data.

As mentioned in Sections 5.3 and 5.4, the model was trained using 43 maximum and 12 local minimum hook loads from Wells B and D, and Well A, respectively. This means that we have 3.5x more data from tripping out operations than tripping in. For testing the model, the remaining 53 local minimum hook loads from Well A were used. We labeled the model predictions in Figure 6-3 with (—◆—) extending up to 01:30, and the (—◆—) starts from 01:30 until the stuck incident. This labeling was based on Figure 6-2 that starting at 01:30, the hook load trend changed from increasing to flat. In this context, we will consider this (—◆—) as the normal condition since it is in line with the expected trend during tripping in operation. Conversely, the (—◆—) is labeled as a deteriorating condition. By focusing on the predicted results during normal conditions, the model performed better with a 5.3 klbm mean absolute error (MAE). While past this normal conditions, MAE was 9.30 klbm which is <3% of the expected hook load. The explanation for this could be that the training data used for building the model includes 12 data points during normal condition from this similar well (Figure 5-3). In addition, due to limited data the model was not trained with local minimum hook load from a deteriorating condition.

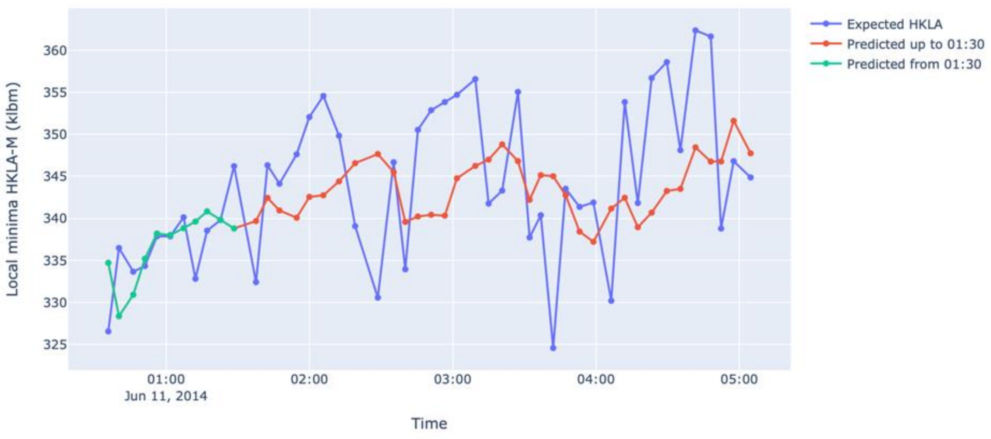


Figure 6-3. Labeled Model Prediction on Well A

Moreover, as mentioned in Section 2.5, it is more sensible to monitor the trend of the hook load rather than the values. Figure 6-4 shows the expected hook load values and below Figure 6-5 shows the predicted hook loads. The boxes contain at least four consecutive hook loads with a downward trend or almost leveled (⬭). It is evident that the model predicted the first box (☐, Figure 6-5) with 30 minutes delay or six hook load measurements to mimic the trend from ☐ in Figure 6-4. If we consider this first box, ☐, as a warning of deteriorating condition, clearly we see that the box ends at time 03:00. At that time, the model will give a warning about 3 hours before the stuck pipe incident. If this first warning was missed, a second trend signature exists. The second box (□ , Figure 6-5) had a delay of 16 minutes or four hook load measurements relative to □ in Figure 6-4. This gives a warning 2 hours before the reported stuck pipe.

Furthermore, using the past five hook load measurements to predict single hook load is insufficient to forecast the trend abnormalities earlier than the measured values. As mentioned earlier, there was a delay of four to six stands to mimic the trend. The model seemed to just average out the previous hook loads to produce the output. This model's design was highly dependent on the amount and quality of data. Out of the seven wells provided, only three were functional, containing at least 0.2 Hz of measurement. Consequently, making a multi-step (hook load) prediction was impossible, which is currently only limited to a single-step. Despite failing to forecast, the model can still detect an upcoming stuck pipe event with reduced warning time. Although, generally evaluating the model on a single well makes it premature to conclude the absolute model performance.

Moreover, these trends (□ and □) observed during abnormal condition was not observed before 01:30 during the normal condition. Thus, the model can classify the well's downhole condition as either normal or deteriorating.

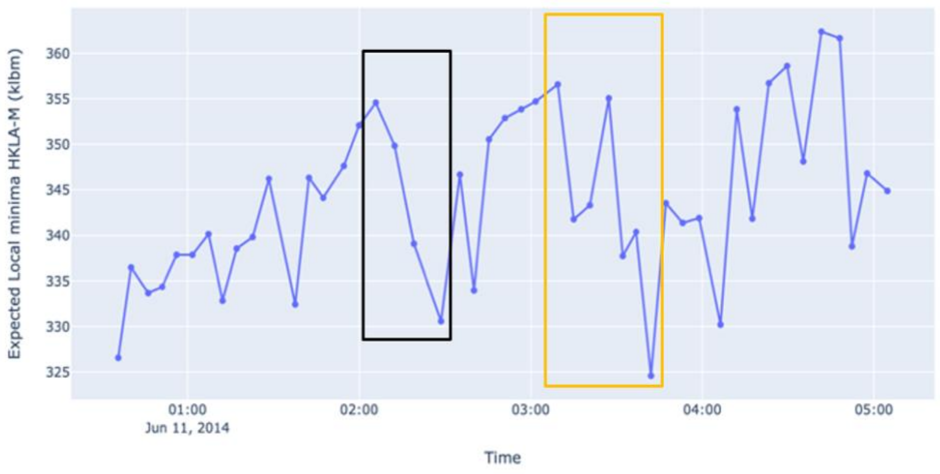


Figure 6-4. Expected local minimum hook load

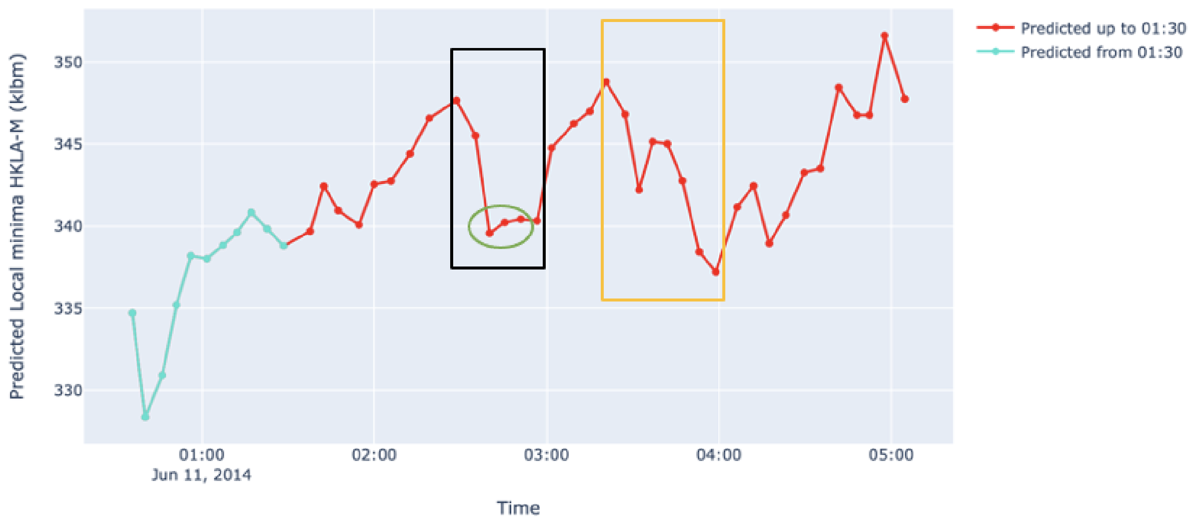


Figure 6-5. Predicted local minimum hook load

7 Conclusions and Future Work

7.1. Conclusions

It was challenging to identify published work in the Oil and Gas industry that has shown a transparent and complete process of building a Machine Learning model – from data collection to model evaluation. As a result, some conclusions are made about the developed LSTM model as well as experiences while working on the project:

- The proposed concept and algorithm in extracting the local minimum hook load accurately identified the data points of interest. Furthermore, it has shown an apparent trend deviation 4 hours and 30 minutes before the reported stuck pipe.
- It was proved that the use of hook load signatures – maximum and local minimum hook loads - provided a better view of the deteriorating downhole condition than relying on the whole hook load measurement. This can be seen in Figure 6-1 and Figure 6-2. Even without a predictive model, this is sufficient in serving as a stuck pipe indicator.
- The model was successfully tested with an acceptable mean absolute error of $< 3\%$. Also, it was able to mimic and produce trend signatures of an impending stuck pipe but with 4 to 6 hook load measurement delays relative to the expected data (see Figure 6-4 and Figure 6-5).
- The majority of the time was consumed for data preparation and feature extraction.
- The two in-house web-based applications developed for data exploration and cleaning were invaluable and paved the way for efficient data analysis.
- A single model capable of predicting hook load signatures during tripping in and tripping out operations was built.
- Reproducible algorithms for this project were all provided.

7.2. Future Work

This study can be used as a stepping stone to further develop Machine Learning models in the Oil and Gas industry, particularly for preventing non-productive time relative to stuck pipe. But before this, it is advisable to consider the following:

- Gather more drilling data with at least 0.2 Hz of measurement frequency.
- With more training data, retrain the model to predict more hook load measurements at each timestep. This will anticipate the trend deviations earlier than the currently developed model.
- Extensive model testing from wells with different configurations.
- Find other parameters that are always available, which can improve hook load prediction.

With a good and reliable multi-step hook load predictive model, it is possible to develop an alarm system to alert the drilling crew of a deteriorating downhole condition that could lead to a stuck pipe. The alarm can be flagged when the trend of consecutive hook load signatures deviates from what is expected.

References

[1] H. H. Elmousalami and M. Elaskary, "Drilling stuck pipe classification and mitigation in the Gulf of Suez oil fields using artificial intelligence," *Journal of Petroleum Exploration and Production Technology,* 2020. [Online]. Available: https://doi.org/10.1007/s13202-020-00857-w.

[2] A. Pant. "Workflow of a Machine Learning project." Towards Data Science. https://towardsdatascience.com/workflow-of-a-machine-learning-project-ec1dba419b94 (accessed May 20, 2021).

[3] G. Press. "Cleaning Big Data: Most Time-Consuming, Least Enjoyable Data Science Task, Survey Says." Forbes. https://www.forbes.com/sites/gilpress/2016/03/23/data-preparation-most-time-consuming-least-enjoyable-data-science-task-survey-says/ (accessed May 20, 2021).

[4] M. A. Muqeem, A. E. Weekse, and A. A. Al-Hajji, "Stuck Pipe Best Practices – A Challenging Approach to Reducing Stuck Pipe Costs," 2012. SPE-160845-MS. [Online]. Available: https://doi.org/10.2118/160845-MS.

[5] A. L. Agbaji, "Optimizing The Planning, Design And Drilling Of Extended Reach And Complex Wells," in *Abu Dhabi International Petroleum Exhibition and Conference*, 2010. SPE-136901-MS. [Online]. Available: https://doi.org/10.2118/136901-MS

[6] C. J. Mason, Igland, Jan Kåre, Streeter, Edward J., Andresen, Per-Arild, "New Real-Time Casing Running Advisory System Reduces NPT," in *SPE Offshore Europe Oil and Gas Conference and Exhibition*, 2013, SPE-166616-MS. [Online]. Available: https://doi.org/10.2118/166616-MS. [Online].

[7] R. J. W. Kucs, H. F. Spoerker, G. Thonhauser, and P. Zoellner, "Automated Real-Time Hookload and Torque Monitoring," *IADC/SPE Drilling Conference,* 2008. SPE-112565-MS.

[8] R. M. Thomas Goebel, Ricardo Vilalta, Kinjal Gupta, "METHOD AND SYSTEM FOR PREDICTING A DRILL STRING STUCK PIPE EVENT," United States of America Patent US 8,752,648 B2 Patent Appl. 13/883,822, 2014.

[9] C. I. Noshi and J. J. Schubert, "The Role of Machine Learning in Drilling Operations; A Review," in *SPE/AAPG Eastern Regional Meeting*, October 10, 2018. SPE- 191823-18erm-ms. [Online]. Available: https://doi.org/10.2118/191823-18ERM-MS

[10] K. R. Holdaway, *Harness oil and gas big data with analytics : Optimize exploration and production with data-driven models.* . ProQuest Ebook Central 2014.

[11] F. Zhang *et al.*, "Real Time Stuck Pipe Prediction by Using a Combination of Physics-Based Model and Data Analytics Approach," in *Abu Dhabi International Petroleum Exhibition & Conference*, November 12, 2019. SPE-197167-MS. [Online]. Available: https://doi.org/10.2118/197167-MS

[12] A. Twin. "Data Mining." https://www.investopedia.com/terms/d/datamining.asp (accessed June 20, 2021).

[13] P. Katiyar. "Difference Between Descriptive and Predictive Data Mining." https://www.geeksforgeeks.org/difference-between-descriptive-and-predictive-data-mining/ (accessed June 20, 2021).

[14] B. R.-K. Thomas Kluyver, Fernando Pérez, Brian Granger, Matthias Bussonnier, Jonathan Frederic, Kyle Kelley, Jessica Hamrick, Jason Grout, Sylvain Corlay, Paul Ivanov, Damián Avila, Safia Ab- dalla, and Carol Willing, F. L. a. B. Schmidt, Ed. *Jupyter Notebooks -- a publishing format for reproducible computational workflows*

(Positioning and Power in Academic Publishing: Players, Agents and Agendas). IOS Press, 2016.
[15] G. V. Rossum and F. L. Drake, *Python 3 Reference Manual*. CreateSpace, 2009.
[16] S. India. "Best language for Machine Learning: Which Programming Language to Learn." https://in.springboard.com/blog/best-language-for-machine-learning/ (accessed June 20, 2021).
[17] "Hoisting system." Petropedia. https://www.petropedia.com/definition/6723/hoisting-system (accessed March 20, 2021).
[18] R. F. Mitchell and S. Z. Miska, *Fundamentals of Drilling Engineering*. Richardson, UNITED STATES: Society of Petroleum Engineers, 2010.
[19] "The Hoisting System." PennState, College of Earth and Mineral Sciences. https://www.e-education.psu.edu/png301/node/725 (accessed March 20, 2021, 2021).
[20] A. T. Bourgoyne, K. K. Millheim, and M. E. Chenevert, *Applied Drilling Engineering*. Richardson, UNITED STATES: Society of Petroleum Engineers, 1985.
[21] "What is a Kelly Rig?" http://www.drillingformulas.com/what-is-kelly-rig/ (accessed February 13, 2021).
[22] "Top Drive System (TDS) Spinning for Oil Drilling Rig." https://www.123rf.com/photo_80732180_top-drive-system-tds-spinning-for-oil-drilling-rig.html (accessed March 20, 2021).
[23] ERITIA. "Drilling Mud Circulation System." https://drillingfluid.org/drilling-fluids-handbook-2/drilling-mud-circulation-system.html (accessed March 20, 2021).
[24] "The Well Control System (Blowout Prevention System)." PennState, College of Earth and Mineral Sciences. https://www.e-education.psu.edu/png301/node/728 (accessed March 20, 2021).
[25] *NORSOK Standard D-001, third edition*, N. O. a. G. Association, Norway, 2012.
[26] J. Vogt, "Automated Racking Board Pipe Handling System for Drilling Rigs Ensures Connection Integrity While Providing Safer Working Conditions and Consistent Tripping Speeds With Minimal Rig Modifications," in *SPE/IATMI Asia Pacific Oil & Gas Conference and Exhibition*, 2015. SPE-176336-MS. [Online]. Available: https://doi.org/10.2118/176336-MS
[27] "MWD/LWD technologies advance to meet industry needs." Offshore. https://www.offshore-mag.com/drilling-completion/article/14038994/measurementwhiledrilling-and-loggingwhiledrilling-advances-to-meet-industry-needs (accessed February 13, 2021).
[28] B. S. Aadnøy, *Modern Well Design*, second ed. P.O. Box 447, 2300 AK Leiden,The Netherlands: CRC Press/Balkema, 2010.
[29] K. A. Bernt S. Aadnøy, "Design of oil wells using analytical friction models," *Journal of Petroleum Science and Engineering,* 2001.
[30] C. A. Johancsik, D. B. Friesen, and R. Dawson, "Torque and Drag in Directional Wells-Prediction and Measurement," *Journal of Petroleum Technology,* 1984. SPE-11380-pa.
[31] M. A. Encinas Quisbert, D. Sui, and A. Mirhaj, "Data Driven ROP Modeling - Analysis and Feasibility Study." Master Thesis. University of Stavanger, Norway, 2020.
[32] M. Belayneh, *Chapter 3B: Drill string mechanics design*. Lecture Notes. University of Stavanger, Norway, 2020.

[33] C. Eric, H. J. Skadsem, and R. Kluge, "Accuracy and Correction of Hook Load Measurements During Drilling Operations," in *SPE/IADC Drilling Conference and Exhibition*, March 18, 2015. SPE-173035-MS. [Online]. Available: https://doi.org/10.2118/173035-MS

[34] Schlumberger, "Hook load," ed, 2012. https://glossary.oilfield.slb.com/en/terms/h/hook_load. (accessed February 13, 2021)

[35] R. Wylie, J. Standefer, J. Anderson, and I. Soukup, "Instrumented Internal Blowout Preventer Improves Measurements for Drilling and Equipment Optimization," in *SPE/IADC Drilling Conference*, 2013. SPE-163475-MS. [Online]. Available: https://doi.org/10.2118/163475-MS

[36] P. l. S. Dipankar Chowdhury, Mohammed Mahbubur Rahman, "PREDICTION OF STAND PIPE PRESSURE USING CONVENTIONAL APPROACH," *Chemical Engineering Research Bulletin,* 2009. [Online]. Available: http://www.ipt.ntnu.no/~pskalle/files/TechnicalPapers/31_SPP.pdf.

[37] Schlumberger, "Equivalent Circulating Density," in *Schlumberger Oilfield Glossary*, ed., 2012. https://glossary.oilfield.slb.com/en/terms/e/ecd (accessed February 13, 2021)

[38] C. Sena. "Get your booty on the drill floor." https://kcacod.wordpress.com/2016/03/27/get-your-booty-on-the-drill-floor/ (accessed February 13, 2021).

[39] L. W. Lake and R. F. Mitchell, *Petroleum Engineering Handbook : Drilling Engineering*. Richardson, UNITED STATES: Society of Petroleum Engineers, 2006.

[40] A. Brankovic *et al.*, "A Data-Based Approach for the Prediction of Stuck-Pipe Events in Oil Drilling Operations," in *Abu Dhabi International Petroleum Exhibition & Conference*, November 12, 2020. SPE-202625-MS. [Online]. Available: https://doi.org/10.2118/202625-MS

[41] F. E. Dupriest, W. C. Elks, and S. Ottesen, "Design Methodology and Operational Practices Eliminate Differential Sticking," *SPE Drilling & Completion,* 2011. SPE-128129-pa.

[42] A. A. Alshaikh and M. Amanullah, "A Comprehensive Review of Differential Sticking, Spotting Fluids, and the Current Testing and Evaluation Methods," in *SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition*, 2018. SPE-192169-MS. [Online]. Available: https://doi.org/10.2118/192169-MS

[43] A. T. Bourgoyne, "Applied drilling engineering," (in English), 1986. [Online]. Available: http://site.ebrary.com/id/10619585.

[44] C. B. R. Procter, *1997 Drillers Stuck pipe Handbook*, Ballater, Scotland, AB35 5UR: Procter & Collins Ltd, 1997.

[45] J. E. Warren, "Causes, Preventions, and Recovery of Stuck Drill Pipe," in *Drilling and Production Practice*, 1940, vol. All Days, API-40-030.

[46] E. Cayeux, B. Daireaux, E. Wolden Dvergsnes, and G. Sælevik, "Early Symptom Detection on the Basis of Real-Time Evaluation of Downhole Conditions: Principles and Results From Several North Sea Drilling Operations," *SPE Drilling & Completion,* 2012. SPE-150422-pa.

[47] M. Awad and R. Khanna, "Machine Learning," in *Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers*. Berkeley, CA: Apress, 2015, pp. 1-18.

[48] E. A. Team, "What is Machine Learning? A Definition.," vol. 2021, ed, 2020. https://www.expert.ai/blog/machine-learning-definition/ (accessed February 13, 2021)

[49] F. Chollet, *Deep Learning with Python*. Manning Publications Co., 2017.

[50] M. M. Meor Hashim *et al.*, "Utilizing Artificial Neural Network for Real-Time Prediction of Differential Sticking Symptoms," in *International Petroleum Technology Conference*, March 29, 2021. IPTC-21221-ms. [Online]. Available: https://doi.org/10.2523/IPTC-21221-MS

[51] C. Siruvuri, S. Nagarakanti, and R. Samuel, "Stuck Pipe Prediction and Avoidance: A Convolutional Neural Network Approach," in *IADC/SPE Drilling Conference*, 2006. SPE-98378-MS. [Online]. Available: https://doi.org/10.2118/98378-MS

[52] A. Murillo, J. Neuman, and R. Samuel, "Pipe Sticking Prediction and Avoidance Using Adaptive Fuzzy Logic Modeling," in *SPE Production and Operations Symposium*, 2009. SPE-120128-MS. [Online]. Available: https://doi.org/10.2118/120128-MS

[53] W. B. Hempkins, R. H. Kingsborough, W. E. Lohec, and C. J. Nini, "Multivariate Statistical Analysis of Stuck Drillpipe Situations," *SPE Drilling Engineering,* 1987. SPE-14181-pa.

[54] A. K. Abbas, H. Almubarak, H. Abbas, and J. Dawood, "Application of Machine Learning Approach for Intelligent Prediction of Pipe Sticking," in *Abu Dhabi International Petroleum Exhibition & Conference*, November 12, 2019. SPE-197396-MS. [Online]. Available: https://doi.org/10.2118/197396-MS

[55] A. Géron, *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow : concepts, tools, and techniques to build intelligent systems*, Second Edition. ed. (Hands-on machine learning with Scikit-Learn and TensorFlow). Sebastopol, CA: O'Reilly, 2019.

[56] V. Jain. "Everything you need to know about “Activation Functions” in Deep learning models." https://towardsdatascience.com/everything-you-need-to-know-about-activation-functions-in-deep-learning-models-84ba9f82c253 (accessed May 20, 2021).

[57] T. N. Activator. "What is An Activation Function?" https://www.neuronactivator.com/blog/what-even-is-activation-function (accessed February 10, 2021).

[58] T. Yiu. "Understanding Neural Networks." https://towardsdatascience.com/understanding-neural-networks-19020b758230 (accessed May 20, 2021).

[59] I. C. Education. "Recurrent Neural Networks." https://www.ibm.com/cloud/learn/recurrent-neural-networks (accessed May 20, 2021).

[60] Y. Bengio, P. Simard, and P. Frasconi, "Learning long-term dependencies with gradient descent is difficult," *IEEE transactions on neural networks / a publication of the IEEE Neural Networks Council,* vol. 5, pp. 157-66, 02/01 1994, doi: 10.1109/72.279181.

[61] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.,* vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[62] B. Thakur and R. Samuel, "Deep Learning for Downhole Data Prediction: A Cost-Effective Data Telemetry Through Data Analytics," in *SPE Western Regional Meeting*,

April 22, 2021. SPE-200870-ms. [Online]. Available: https://doi.org/10.2118/200870-MS

[63] J. Han, Y. Sun, and S. Zhang, "A Data Driven Approach of ROP Prediction and Drilling Performance Estimation," in *International Petroleum Technology Conference*, March 26, 2019. IPTC-19430-ms. [Online]. Available: https://doi.org/10.2523/IPTC-19430-MS

[64] A. Bhandari. "Feature Scaling for Machine Learning: Understanding the Difference Between Normalization vs. Standardization." https://www.analyticsvidhya.com/blog/2020/04/feature-scaling-machine-learning-normalization-standardization/ (accessed May 20, 2021).

[65] F. Pedregosa, Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research,* vol. 12, pp. 2825 - 2830, 2011.

[66] A. Gron, *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly Media, Inc., 2017.

[67] *pandas-dev/pandas: Pandas*. (2020). [Online]. Available: https://doi.org/10.5281/zenodo.3509134

[68] *Chollet, F., & others. (2015). Keras. GitHub. Retrieved from https://github.com/fchollet/keras*.

[69] *TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems*. (2015). [Online]. Available: http://tensorflow.org/

[70] A. T. Tunkiel, T. Wiktorski, and D. Sui, "Drilling Dataset Exploration, Processing and Interpretation Using Volve Field Data," in *ASME 2020 39th International Conference on Ocean, Offshore and Arctic Engineering*, 2020. OMAE2020-18151. [Online]. Available: https://doi.org/10.1115/OMAE2020-18151

[71] *Collaborative data science Publisher: Plotly Technologies Inc.* (2015). Montréal, QC. [Online]. Available: https://plot.ly

[72] D. Kumar. "Introduction to Data Preprocessing in Machine Learning." https://towardsdatascience.com/introduction-to-data-preprocessing-in-machine-learning-a9fa83a5dc9d (accessed May 20,2021).

[73] E. Rençberoğlu. "Fundamental Techniques of Feature Engineering for Machine Learning." https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114 (accessed May 20, 2021).

[74] H. Lim. "7 Types of Data Bias in Machine Learning." https://lionbridge.ai/articles/7-types-of-data-bias-in-machine-learning/ (accessed May 23, 2021).

[75] K. J. M. Charles R. Harris, Stefan J., van der Walt, Ralf Gommers, Stephan Hoyer, Marten H. van Kerkwijk "Numpy," *Nature,* vol. 585, pp. 357-362, 2020. [Online]. Available: https://doi.org/10.1038/s41586-020-2649-2.

[76] M. M. Amer, A. S. DAHAB, and A.-A. H. El-Sayed, "An ROP Predictive Model in Nile Delta Area Using Artificial Neural Networks," in *SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition*, April 25, 2017. SPE-187969-ms. [Online]. Available: https://doi.org/10.2118/187969-MS

[77] J. Brownlee. "What is the Difference Between a Parameter and a Hyperparameter?" (accessed February 13, 2021).

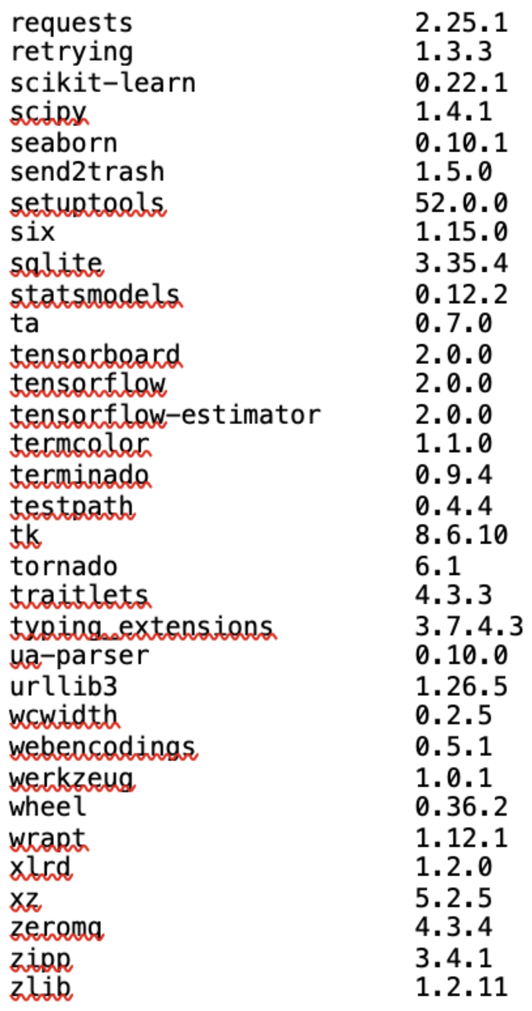
Appendices

Appendix A

Installed Packages

```
# Name                        Version
absl-py                       0.12.0
appnope                       0.1.2
argon2-cffi                   20.1.0
astor                         0.8.1
async_generator               1.10
attrs                         20.3.0
backcall                      0.2.0
bleach                        3.3.0
brotli                        1.0.9
ca-certificates               2021.1.19
cached-property               1.5.2
certifi                       2020.12.5
cffi                          1.14.5
chardet                       4.0.0
chart-studio                  1.1.0
click                         7.1.1
cycler                        0.10.0
dash                          1.20.0
dash-auth                     1.4.1
dash-bootstrap-components     0.12.2
dash-core-components          1.16.0
dash-extensions               0.0.53
dash-html-components          1.1.3
dash-renderer                 1.9.1
dash-table                    4.11.3
decorator                     5.0.5
defusedxml                    0.7.1
entrypoints                   0.3
flask                         1.1.2
flask-caching                 1.10.1
flask-compress                1.9.0
flask-seasurf                 0.3.0
future                        0.18.2
gast                          0.2.2
google-pasta                  0.2.0
grpcio                        1.36.1
h5py                          3.1.0
idna                          2.10
importlib-metadata            3.7.3
importlib_metadata            3.7.3
ipykernel                     5.3.4
ipython                       7.16.1
ipython_genutils              0.2.0
itsdangerous                  1.1.0
jedi                          0.17.0
jinja2                        2.11.3
joblib                        1.0.1
jsonschema                    3.2.0
```

```
jupyter_client                6.1.12
jupyter_core                  4.7.1
jupyterlab_pygments           0.1.2
keras                         2.3.1
keras-applications            1.0.8
keras-preprocessing           1.1.0
kiwisolver                    1.3.1
libcxx                        10.0.0
libffi                        3.3
libsodium                     1.0.18
llvmlite                      0.34.0
markdown                      3.3.4
markupsafe                    1.1.1
matplotlib                    3.3.4
mistune                       0.8.4
more-itertools                8.7.0
nbclient                      0.5.3
nbconvert                     6.0.7
nbformat                      5.1.3
ncurses                       6.2
nest-asyncio                  1.5.1
notebook                      6.3.0
numpy                         1.18.1
openssl                       1.1.1k
opt-einsum                    3.3.0
packaging                     20.9
pandas                        1.0.3
pandoc                        2.12
pandocfilters                 1.4.2
parso                         0.8.2
patsy                         0.5.1
pexpect                       4.8.0
pickleshare                   0.7.5
pillow                        8.2.0
pip                           21.0.1
plotly                        4.14.3
prometheus_client             0.10.0
prompt-toolkit                3.0.17
protobuf                      3.15.7
ptyprocess                    0.7.0
pycparser                     2.20
pygments                      2.8.1
pyparsing                     2.4.7
pyrsistent                    0.17.3
python                        3.6.13
python-dateutil               2.8.1
pytz                          2021.1
pyyaml                        5.4.1
pyzmq                         20.0.0
readline                      8.1
```



```
requests                  2.25.1
retrying                  1.3.3
scikit-learn              0.22.1
scipy                     1.4.1
seaborn                   0.10.1
send2trash                1.5.0
setuptools                52.0.0
six                       1.15.0
sqlite                    3.35.4
statsmodels               0.12.2
ta                        0.7.0
tensorboard               2.0.0
tensorflow                2.0.0
tensorflow-estimator      2.0.0
termcolor                 1.1.0
terminado                 0.9.4
testpath                  0.4.4
tk                        8.6.10
tornado                   6.1
traitlets                 4.3.3
typing_extensions         3.7.4.3
ua-parser                 0.10.0
urllib3                   1.26.5
wcwidth                   0.2.5
webencodings              0.5.1
werkzeug                  1.0.1
wheel                     0.36.2
wrapt                     1.12.1
xlrd                      1.2.0
xz                        5.2.5
zeromq                    4.3.4
zipp                      3.4.1
zlib                      1.2.11
```

Appendix B

Data Preparation Python Code

B.1. Data Visualization Application

In [ ]:

```
import pandas as pd
import dash
import dash_core_components as dcc
import dash_html_components as html
import plotly.graph_objs as go
%config Completer.use_jedi = False
from plotly import tools
import base64
import datetime
import io
from dash.dependencies import Input, Output, State
from plotly.subplots import make_subplots
import flask
from datetime import datetime
import plotly.express as px
```

In [ ]:

```
app = dash.Dash()


app.layout = html.Div([
    html.Div([

            html.H1('Upload and Visualize'),
            html.Br(),
            dcc.Upload(
                        id='upload-data',
                        children=html.Div([
                            'Drag and Drop or ',
                            html.A('Select Files')
                            ]),
                        style={
                        'width': '40%',
                    'height': '60px',
                    'lineHeight': '60px',
                    'borderWidth': '1px',
                        'borderStyle': 'dashed',
                    'borderRadius': '5px',
                    'textAlign': 'center',
                        'margin': '10px'}
                       ),


            html.Br(),


            html.Label('Real-Time Parameters'),
            dcc.Dropdown(id='Columns_option1',
            #options=parameter_options,
            placeholder='X axis columns',
            multi=True,
            style={'width': '80%'}),

            dcc.Dropdown(id='Columns_option2',
            #options=parameter_options,
            placeholder='Y axis',
            multi=False,
            style={'width': '80%'}),



            html.Button(id='my_button',
            n_clicks=0,
            children='Display',
            style={'fontSize':28,'display':'inline-block'})
            ]),

    html.Div([
            dcc.Graph(id='my_graph')
            ])#,style={'width':'10%',height='display':'inline-block'})

            ])



##convert date
def date_convert(date_to_convert):
     return datetime.strptime(date_to_convert,'%H:%M:%S %d-%m-%y')


##function for parsing
def parse_contents(contents, filename, date):
    content_type, content_string = contents.split(',')

    decoded = base64.b64decode(content_string)
    try:
        if 'csv' in filename:
            # Assume that the user uploaded a CSV file
            df = pd.read_csv(
                io.StringIO(decoded.decode('utf-8')))
            return df
        elif 'xls' in filename:
            # Assume that the user uploaded an excel file
            df = pd.read_excel(io.BytesIO(decoded))
            return df
    except:
        None




@app.callback([Output('Columns_option1', 'options'),
              Output('Columns_option2', 'options')],
              Input('upload-data', 'contents'),
              State('upload-data', 'filename'),
              State('upload-data', 'last_modified'))
def update_output(list_of_contents, list_of_names, list_of_dates):
    if list_of_contents is not None:
        df = parse_contents(list_of_contents, list_of_names, list_of_dates)
        df = df.loc[:, ~df.columns.str.contains('^Unnamed')]
        options = [{'label': k, 'value': k} for k in df.columns]
        return [options, options]




@app.callback([Output('my_graph', 'figure')],
              [Input('my_button', 'n_clicks')],
              [State('upload-data', 'contents'),
              State('upload-data', 'filename'),
              State('upload-data', 'last_modified'),
              State('Columns_option1', 'value'),
              State('Columns_option2', 'value')])



def update_figure(n_nlicks,list_of_contents, list_of_names, list_of_dates, params, y_valu
e):

    df = parse_contents(list_of_contents, list_of_names, list_of_dates)

    df = df.loc[:, ~df.columns.str.contains('^Unnamed')]

    for columnn in df.columns:

        try:
            df[columnn] = df[columnn].astype(float)
        except:
            None
        #sometimes the first row is the unit so use '[1:]'
        try:
            df[columnn] = df[columnn][1:].astype(float)

        except:
            None

    #####for datetime####
    #assume first column is always time and date###
    try:
        df[df.columns[0]] = pd.to_datetime(df[df.columns[0]])

    except:
        None

    try:
        df[df.columns[0]] = df[df.columns[0]].apply(date_convert)
    except:
        None

    try:
        df[df.columns[0]] = pd.to_datetime(df[df.columns[0]][1:])

    except:
        None

    try:
        df[df.columns[0]] = df[df.columns[0]][1:].apply(date_convert)
    except:
        None

    try:
        df = df.sort_values(by=df.columns[0])
    except:
        None



    list_of_parameters = df.columns

    if len(params)<8:
            fig = tools.make_subplots(rows=1, cols=len(params),shared_yaxes=True, horizo
ntal_spacing = 0.005)
            for param in params:
                 fig.add_trace(go.Scatter(x =df[param]  , y = df[y_value], mode = 'lines
', name = param),row=1, col=params.index(param)+1)
                 fig.update_xaxes(title_text=param, row=1, col=params.index(param)+1)
                 #fig.update_layout(autosize=True,width=400,height=800)
                 fig.update_layout(height=800)
            fig.update_yaxes(title_text=df.index.name, row=1, col=1)


    if len(params)>7:
            fig = tools.make_subplots(rows=2, cols=5,shared_yaxes=True, horizontal_spaci
ng = 0.005)

            for param in params:
                if params.index(param) < 5:
                     fig.add_trace(go.Scatter(x = df[param] , y = df[y_value], mode = '
lines', name = param),row=1, col=params.index(param)+1)
                     fig.update_xaxes(title_text=param, row=1, col=params.index(param)+1
)
                else:
                     fig.add_trace(go.Scatter(x = df[param] , y = df.index, mode = 'line
s', name = param),row=2, col=params.index(param)-4)
                     fig.update_xaxes(title_text=param, row=2, col=params.index(param)-4
)
            fig.update_yaxes(title_text=df.index.name, row=1, col=1)
            fig.update_yaxes(title_text=df.index.name, row=2, col=1)
        #if len(params)>3:
         #    fig.add_trace(go.Scatter(x = df[params[3]] , y = df.index, mode = 'lines',
name = params[3]),row=1, col=3)
    fig.update_yaxes(title_text=df.index.name, row=1, col=1)
    fig.update_yaxes(autorange="reversed")

    return [fig]





if __name__ == '__main__':
    app.run_server(port=8064)
```

B.2. Data Pre-processing Application

```
In [ ]:
```

```
import pandas as pd
import statistics as stat
import dash_table
import plotly.express as px
import dash
import dash_core_components as dcc
import dash_html_components as html
import plotly.graph_objs as go
from dash.dependencies import Input, Output, State
from plotly.subplots import make_subplots
import json
import numpy as np
%config Completer.use_jedi = False
import base64
import datetime
import io
from dash_extensions import Download
from dash_extensions.snippets import send_data_frame
```

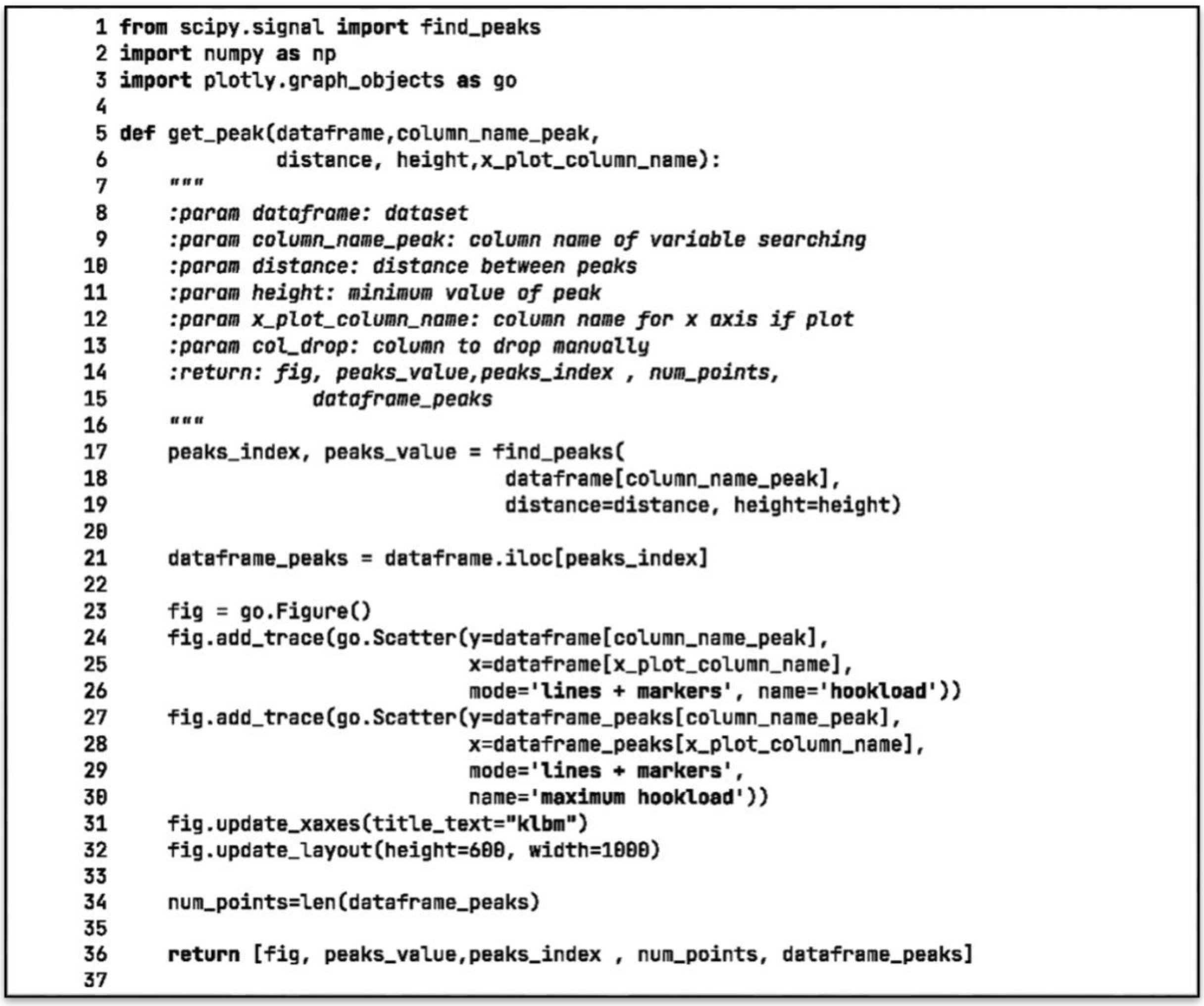
```
In [ ]:
```

```
app = dash.Dash(prevent_initial_callbacks=True)

methods = ['ffill', 'bfill','mean','max','min']

method_dict = []
for method in methods:
    method_dict.append({'label':method , 'value':method})


compare_symbols = ['>', '=', '<', '<=', '>=', '!=']

compare_values_dict = []
for symbol in compare_symbols:
    compare_values_dict.append({'label':symbol , 'value':symbol})




app.layout = html.Div([

            html.H1('Data Sweeper'),
            html.Br(),
            dcc.Upload(
                        id='upload-data',
                        children=html.Div([
                            'Drag and Drop or ',
                            html.A('Select Files')
                            ]),
                        style={
                        'width': '60%',
                    'height': '60px',
                    'lineHeight': '60px',
                    'borderWidth': '1px',
                        'borderStyle': 'dashed',
                    'borderRadius': '5px',
                    'textAlign': 'center',
                        'margin': '10px'
        }#,
        # Allow multiple files to be uploaded
       # multiple=True
    ),#,style={'display':'inline-block'}
    #html.Div(id='output-data-upload'),
                html.H4('Choose Columns'),
                dcc.Dropdown(id= 'Columns_option', multi=True, placeholder='column optio
ns 1',
                          style={'width': '60%'}),
                dcc.Dropdown(id= 'Columns_option2', multi=True,placeholder='column optio
ns 2',
                          style={'width': '60%'}),
                html.H4('Choose Strategy'),
                dcc.Dropdown(id= 'method_option',placeholder='method options 1', options
= method_dict,
                          style={'width': '60%'}),
                dcc.Dropdown(id= 'method_option2', placeholder='method options 2', optio
ns= method_dict,
                          style={'width': '60%'}),

                #input value
                html.H4('Fill in Specified value'),
                dcc.Dropdown(id= 'Columns_option3', multi=True,placeholder='column optio
ns 3',
                          style={'width': '60%'}),
                dcc.Input(placeholder='Type value',id='Fill_value', type='number'),

                #drop na rows
                html.Br(),
                html.H4('Drop rows with NA value'),
                dcc.Dropdown(id= 'Columns_option4', multi=True,placeholder='column optio
ns 4',
                          style={'width': '60%'}),


                ##drop columns
                html.Br(),
                html.H4('Drop columns'),
                dcc.Dropdown(id= 'Columns_option5', multi=True,placeholder='column optio
ns 5',
                          style={'width': '60%'}),

                ##filter values
                html.Br(),
                html.H4('Filter columns'),
                dcc.Dropdown(id= 'Columns_option6', multi=True,placeholder='column optio
ns 6',
                          style={'width': '60%'}),

                dcc.Dropdown(id= 'Columns_option7', multi=False,placeholder='compare_val
ues_dict',
                          options=compare_values_dict, style={'width': '60%'}),
                dcc.Input(placeholder='value',id='compare_value', type='number'),



                html.Br(),
                html.Br(),
                html.Button("Download File", id="btn"),
                       Download(id="download"),

                dcc.Input(placeholder='Enter File Name',id='filename', type='text')


])
##convert date
def date_convert(date_to_convert):
     return datetime.strptime(date_to_convert,'%H:%M:%S %d-%m-%y')

def parse_contents(contents, filename, date):
    content_type, content_string = contents.split(',')

    decoded = base64.b64decode(content_string)
    try:
        if 'csv' in filename:
            # Assume that the user uploaded a CSV file
            df = pd.read_csv(
                io.StringIO(decoded.decode('utf-8')))
            return df
        elif 'xls' in filename:
                # Assume that the user uploaded an excel file
                df = pd.read_excel(io.BytesIO(decoded))
                return df
        except Exception as e:

            return html.Div([
                'There was an error processing this file.'
            ])


    ##callback for column options
    @app.callback([Output('Columns_option', 'options'),
                  Output('Columns_option2', 'options'),
                  Output('Columns_option3', 'options'),
                  Output('Columns_option4', 'options'),
                  Output('Columns_option5', 'options'),
                  Output('Columns_option6', 'options')],
                  Input('upload-data', 'contents'),
                  State('upload-data', 'filename'),
                  State('upload-data', 'last_modified'))
    def update_output(list_of_contents, list_of_names, list_of_dates):
        if list_of_contents is not None:
            #df = [parse_contents(c, n, d) for c, n, d in zip(list_of_contents, list_of_names
    , list_of_dates)]
            df = parse_contents(list_of_contents, list_of_names, list_of_dates)
            options = [{'label': k, 'value': k} for k in df.columns]
            return [options, options, options, options,options,options]

    ##call back to download data
    @app.callback(Output("download", "data"),
                  Input("btn", "n_clicks"),
                  [State('upload-data', 'contents'),
                  State('upload-data', 'filename'),
                  State('upload-data', 'last_modified'),
                  State('method_option', 'value'),
                  State('Columns_option', 'value'),
                  State('method_option2', 'value'),
                  State('Columns_option2', 'value'),
                  State('Columns_option3', 'value'),
                  State('Fill_value', 'value'),
                  State('Columns_option4', 'value'),
                  State('Columns_option5', 'value'),
                  State('Columns_option6', 'value'),
                  State('Columns_option7', 'value'),
                  State('compare_value', 'value'),
                  State('filename', 'value')])

    def func(n_nlicks,list_of_contents, list_of_names, list_of_dates, meth,
             column_chosen, meth2,column_chosen2,column_chosen3,fill_val,column_chosen4,colum
    n_chosen5,
                     column_chosen6, column_symbol, compare_value, filename):
        df = parse_contents(list_of_contents, list_of_names, list_of_dates)


        for columnn in df.columns:
            try:
                df[columnn] = df[columnn][1:].astype(float)

            except:
                None

            try:
                df[columnn] = df[columnn].astype(float)
            except:
                None

        #####for datetime####

        try:
            df[df.columns[0]] = pd.to_datetime(df[df.columns[0]])

        except:
            None

        try:
            df[df.columns[0]] = df[df.columns[0]].apply(date_convert)
        except:
            None

        try:
            df[df.columns[0]] = pd.to_datetime(df[df.columns[0]][1:])

        except:
            None

        try:
            df[df.columns[0]] = df[df.columns[0]][1:].apply(date_convert)
        except:
            None


        try:
            df = df.sort_values(by=df.columns[0])
        except:
            None




        if meth == 'mean':

            df[column_chosen] = df[column_chosen].fillna(df[column_chosen].mean())
        if meth == 'max':

            df[column_chosen] = df[column_chosen].fillna(df[column_chosen].max())
        if meth == 'min':

            df[column_chosen] = df[column_chosen].fillna(df[column_chosen].min())
        if meth == 'ffill':
              df[column_chosen] = df[column_chosen].fillna(method='ffill')
        if meth == 'bfill':

            df[column_chosen] = df[column_chosen].fillna(method='bfill')

            #####part 2####

        if meth2:

            if meth2 == 'mean':

                df[column_chosen2] = df[column_chosen2].fillna(df[column_chosen2].mean())
            if meth2 == 'max':

                df[column_chosen2] = df[column_chosen2].fillna(df[column_chosen2].max())
            if meth2 == 'min':

                df[column_chosen2] = df[column_chosen2].fillna(df[column_chosen2].min())
            if meth2 == 'ffill':

                 df[column_chosen2] = df[column_chosen2].fillna(method='ffill')
            if meth2 == 'bfill':

                df[column_chosen2] = df[column_chosen2].fillna(method='bfill')



        if column_chosen3:
            df[column_chosen3] = df[column_chosen3].fillna(fill_val)

        if column_chosen4:
            df = df.dropna(subset=column_chosen4)

        if column_chosen5:
            df = df.drop(columns=column_chosen5)
        ###filtering values
        if column_chosen6:
            if column_symbol == '>=':
                for col in column_chosen6:
                    df = df[df[col] >= compare_value]

            else:
                None

        return send_data_frame(df.to_csv, filename+'.csv')

    if __name__ == '__main__':
        app.run_server(port=8060)
```

Appendix C

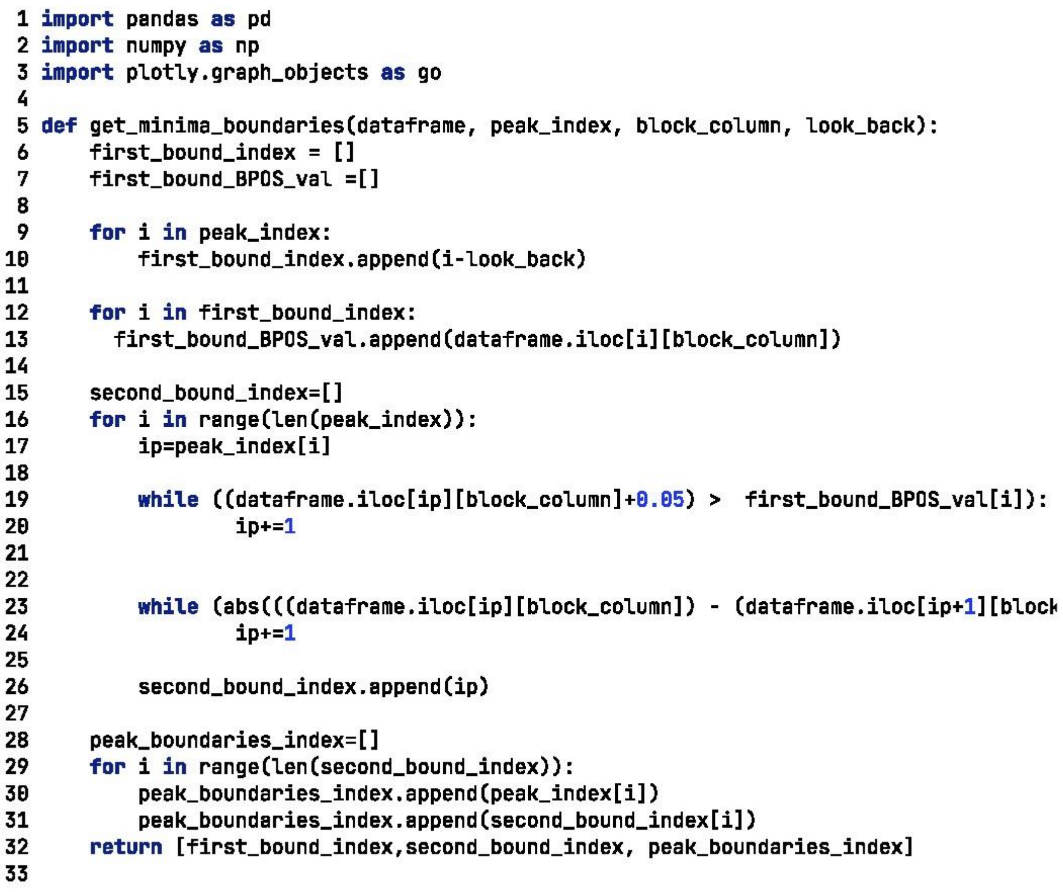
Machine Learning Implementation Functions

C.1. Feature Engineering



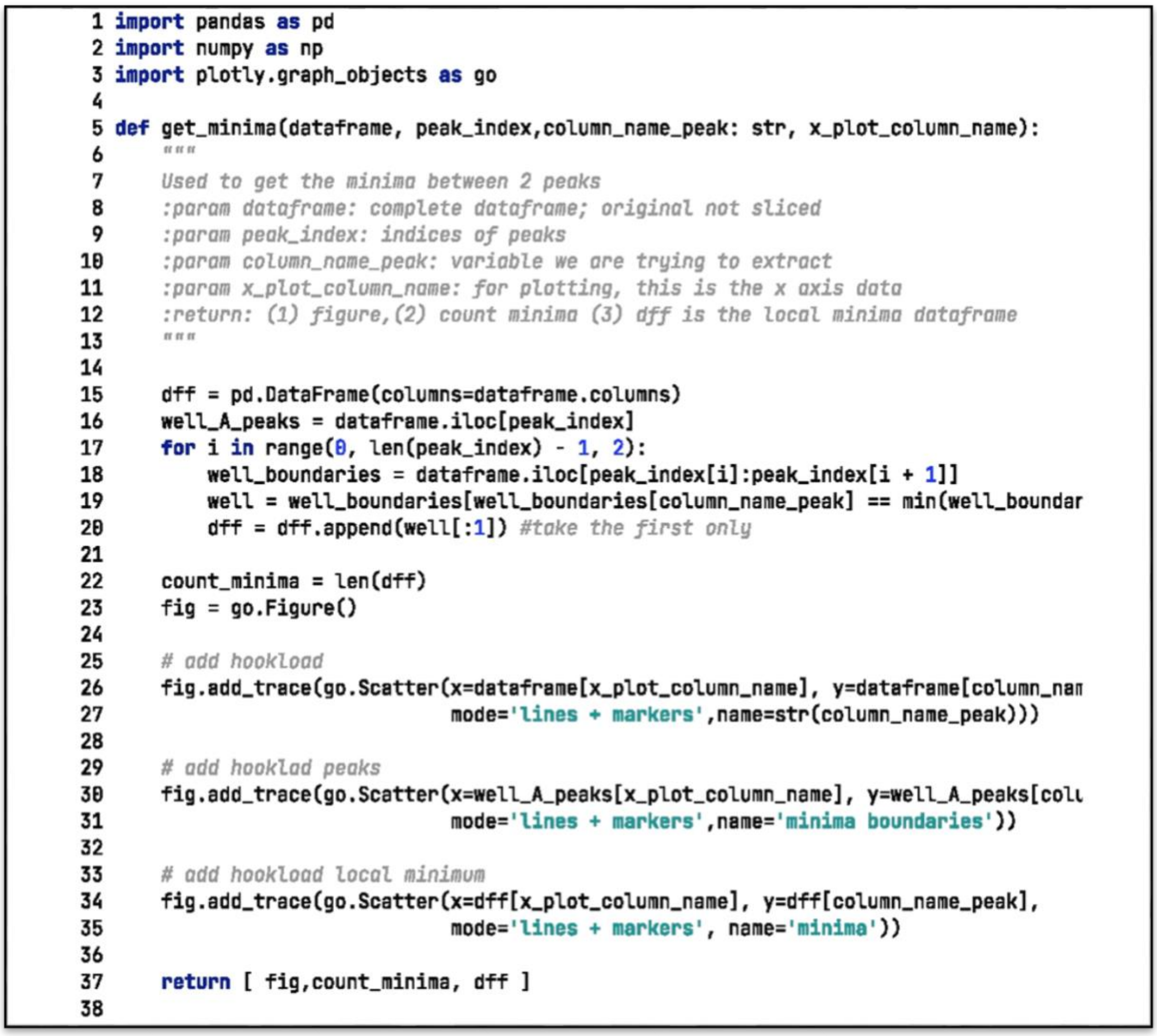
```python
from scipy.signal import find_peaks
import numpy as np
import plotly.graph_objects as go

def get_peak(dataframe,column_name_peak,
             distance, height,x_plot_column_name):
    """
    :param dataframe: dataset
    :param column_name_peak: column name of variable searching
    :param distance: distance between peaks
    :param height: minimum value of peak
    :param x_plot_column_name: column name for x axis if plot
    :param col_drop: column to drop manually
    :return: fig, peaks_value,peaks_index , num_points,
                dataframe_peaks
    """
    peaks_index, peaks_value = find_peaks(
                                dataframe[column_name_peak],
                                distance=distance, height=height)

    dataframe_peaks = dataframe.iloc[peaks_index]

    fig = go.Figure()
    fig.add_trace(go.Scatter(y=dataframe[column_name_peak],
                             x=dataframe[x_plot_column_name],
                             mode='lines + markers', name='hookload'))
    fig.add_trace(go.Scatter(y=dataframe_peaks[column_name_peak],
                             x=dataframe_peaks[x_plot_column_name],
                             mode='lines + markers',
                             name='maximum hookload'))
    fig.update_xaxes(title_text="klbm")
    fig.update_layout(height=600, width=1000)

    num_points=len(dataframe_peaks)

    return [fig, peaks_value,peaks_index , num_points, dataframe_peaks]

```

Listing 1. Function for getting the peak



```python
import pandas as pd
import numpy as np
import plotly.graph_objects as go

def get_minima_boundaries(dataframe, peak_index, block_column, look_back):
    first_bound_index = []
    first_bound_BPOS_val =[]

    for i in peak_index:
        first_bound_index.append(i-look_back)

    for i in first_bound_index:
      first_bound_BPOS_val.append(dataframe.iloc[i][block_column])

    second_bound_index=[]
    for i in range(len(peak_index)):
        ip=peak_index[i]

        while ((dataframe.iloc[ip][block_column]+0.05) >  first_bound_BPOS_val[i]):
                ip+=1


        while (abs(((dataframe.iloc[ip][block_column]) - (dataframe.iloc[ip+1][block
                ip+=1

        second_bound_index.append(ip)

    peak_boundaries_index=[]
    for i in range(len(second_bound_index)):
        peak_boundaries_index.append(peak_index[i])
        peak_boundaries_index.append(second_bound_index[i])
    return [first_bound_index,second_bound_index, peak_boundaries_index]

```

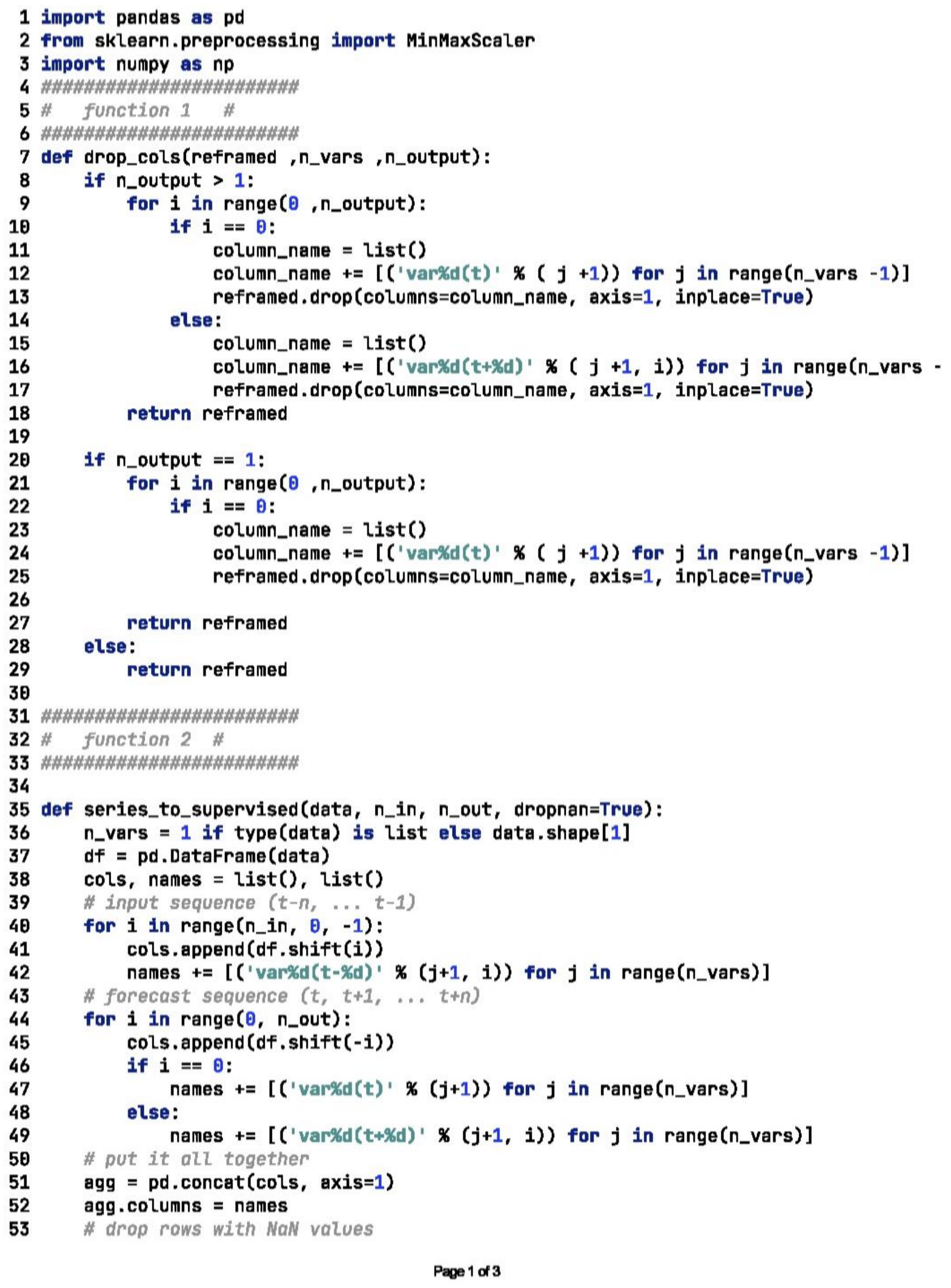
Listing 2. Function for getting local minima boundaries



```python
import pandas as pd
import numpy as np
import plotly.graph_objects as go

def get_minima(dataframe, peak_index,column_name_peak: str, x_plot_column_name):
    """
    Used to get the minima between 2 peaks
    :param dataframe: complete dataframe; original not sliced
    :param peak_index: indices of peaks
    :param column_name_peak: variable we are trying to extract
    :param x_plot_column_name: for plotting, this is the x axis data
    :return: (1) figure,(2) count minima (3) dff is the local minima dataframe
    """

    dff = pd.DataFrame(columns=dataframe.columns)
    well_A_peaks = dataframe.iloc[peak_index]
    for i in range(0, len(peak_index) - 1, 2):
        well_boundaries = dataframe.iloc[peak_index[i]:peak_index[i + 1]]
        well = well_boundaries[well_boundaries[column_name_peak] == min(well_boundar
        dff = dff.append(well[:1]) #take the first only

    count_minima = len(dff)
    fig = go.Figure()

    # add hookload
    fig.add_trace(go.Scatter(x=dataframe[x_plot_column_name], y=dataframe[column_nam
                             mode='lines + markers',name=str(column_name_peak)))

    # add hooklad peaks
    fig.add_trace(go.Scatter(x=well_A_peaks[x_plot_column_name], y=well_A_peaks[colu
                             mode='lines + markers',name='minima boundaries'))

    # add hookload local minimum
    fig.add_trace(go.Scatter(x=dff[x_plot_column_name], y=dff[column_name_peak],
                             mode='lines + markers', name='minima'))

    return [ fig,count_minima, dff ]

```

Listing 3. Function for getting minima

C.2. LSTM Input Preparation

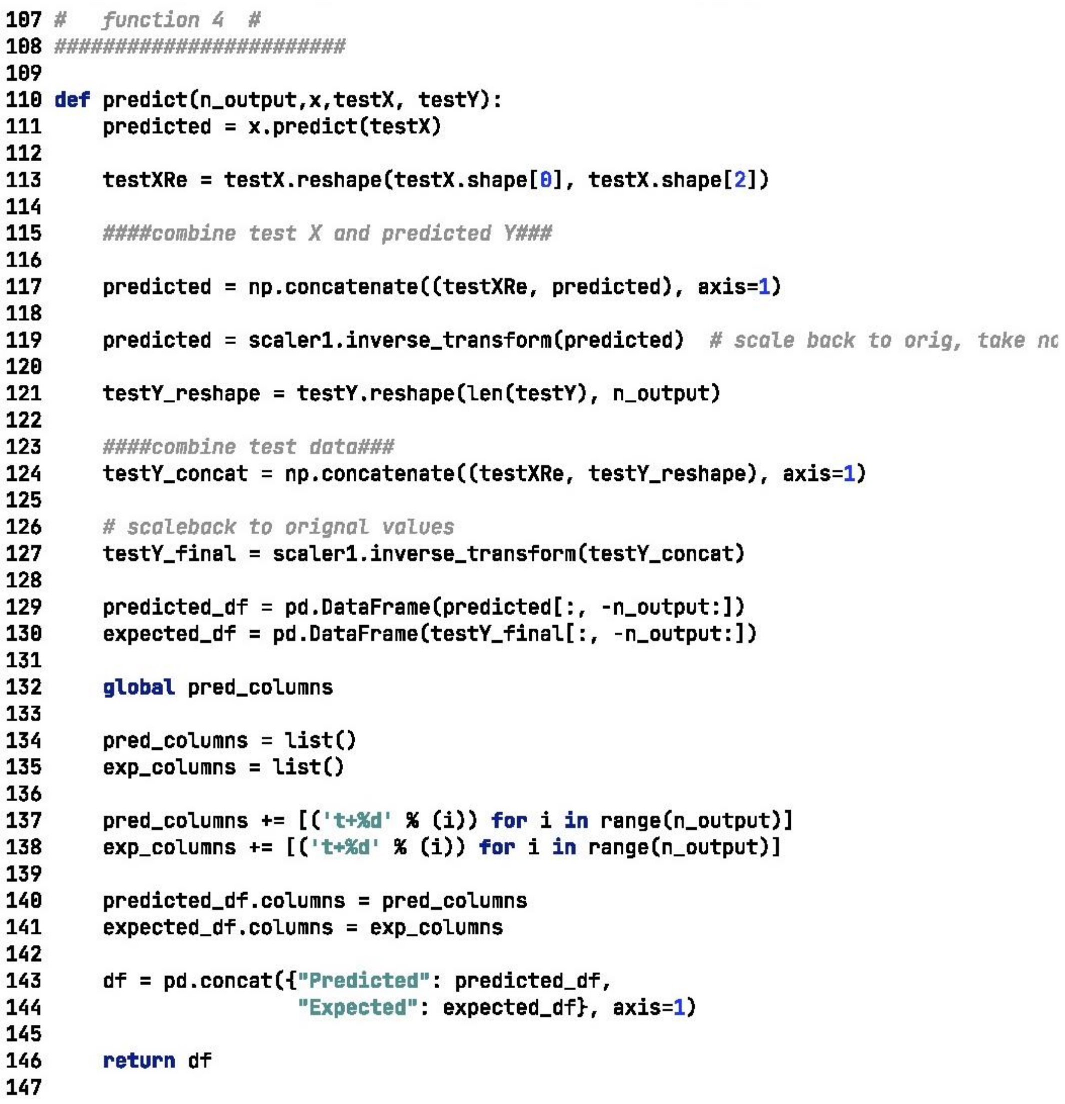


```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import numpy as np
#########################
#   function 1   #
#########################
def drop_cols(reframed ,n_vars ,n_output):
    if n_output > 1:
        for i in range(0 ,n_output):
            if i == 0:
                column_name = list()
                column_name += [('var%d(t)' % ( j +1)) for j in range(n_vars -1)]
                reframed.drop(columns=column_name, axis=1, inplace=True)
            else:
                column_name = list()
                column_name += [('var%d(t+%d)' % ( j +1, i)) for j in range(n_vars -
                reframed.drop(columns=column_name, axis=1, inplace=True)
        return reframed

    if n_output == 1:
        for i in range(0 ,n_output):
            if i == 0:
                column_name = list()
                column_name += [('var%d(t)' % ( j +1)) for j in range(n_vars -1)]
                reframed.drop(columns=column_name, axis=1, inplace=True)

        return reframed
    else:
        return reframed

#########################
#   function 2  #
#########################

def series_to_supervised(data, n_in, n_out, dropnan=True):
    n_vars = 1 if type(data) is list else data.shape[1]
    df = pd.DataFrame(data)
    cols, names = list(), list()
    # input sequence (t-n, ... t-1)
    for i in range(n_in, 0, -1):
        cols.append(df.shift(i))
        names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
    # forecast sequence (t, t+1, ... t+n)
    for i in range(0, n_out):
        cols.append(df.shift(-i))
        if i == 0:
            names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
        else:
            names += [('var%d(t+%d)' % (j+1, i)) for j in range(n_vars)]
    # put it all together
    agg = pd.concat(cols, axis=1)
    agg.columns = names
    # drop rows with NaN values
```

Page 1 of 3

```
    if dropnan:
        agg.dropna(inplace=True)
    return agg

########################
#   function 3   #
########################

def lstm_input(dataframe,
               n_input=1,
               n_output=1,
               dropnan=True,
               test_data_percent=0.70,
               return_framed=False):
    """
    assumptions
        -position of target variable must me on the last column
        -only 1 variable to predict

    :dataframe: original
    :n_input: number of input timestep; if 1, means at time (t-1)
    :n_output: number of output timestep to predict; if 1, means at time (t)
    """
    # number of variables
    n_vars = 1 if type(dataframe) is list else dataframe.shape[1]

    # calling function to convert data into supervised
    reframed = series_to_supervised(dataframe, n_input, n_output)

    #calling function to drop columns not to be predicted
    reframed = drop_cols(reframed, n_vars, n_output)

    if return_framed:
        return reframed

    else:
        global scaler1

        reframed_values = reframed.values
        scaler1 = MinMaxScaler(feature_range=(0, 1))
        scaled = scaler1.fit_transform(reframed_values)
        values = scaled

        n_train = int(len(reframed) * test_data_percent)
        train = values[:n_train]
        test = values[n_train:]
        trainX, trainY = train[:, :-n_output], train[:,-n_output:]  ##only to predi
        testX, testY = test[:, :-n_output], test[:, -n_output:]

        return [trainX, trainY, testX, testY]


########################
```

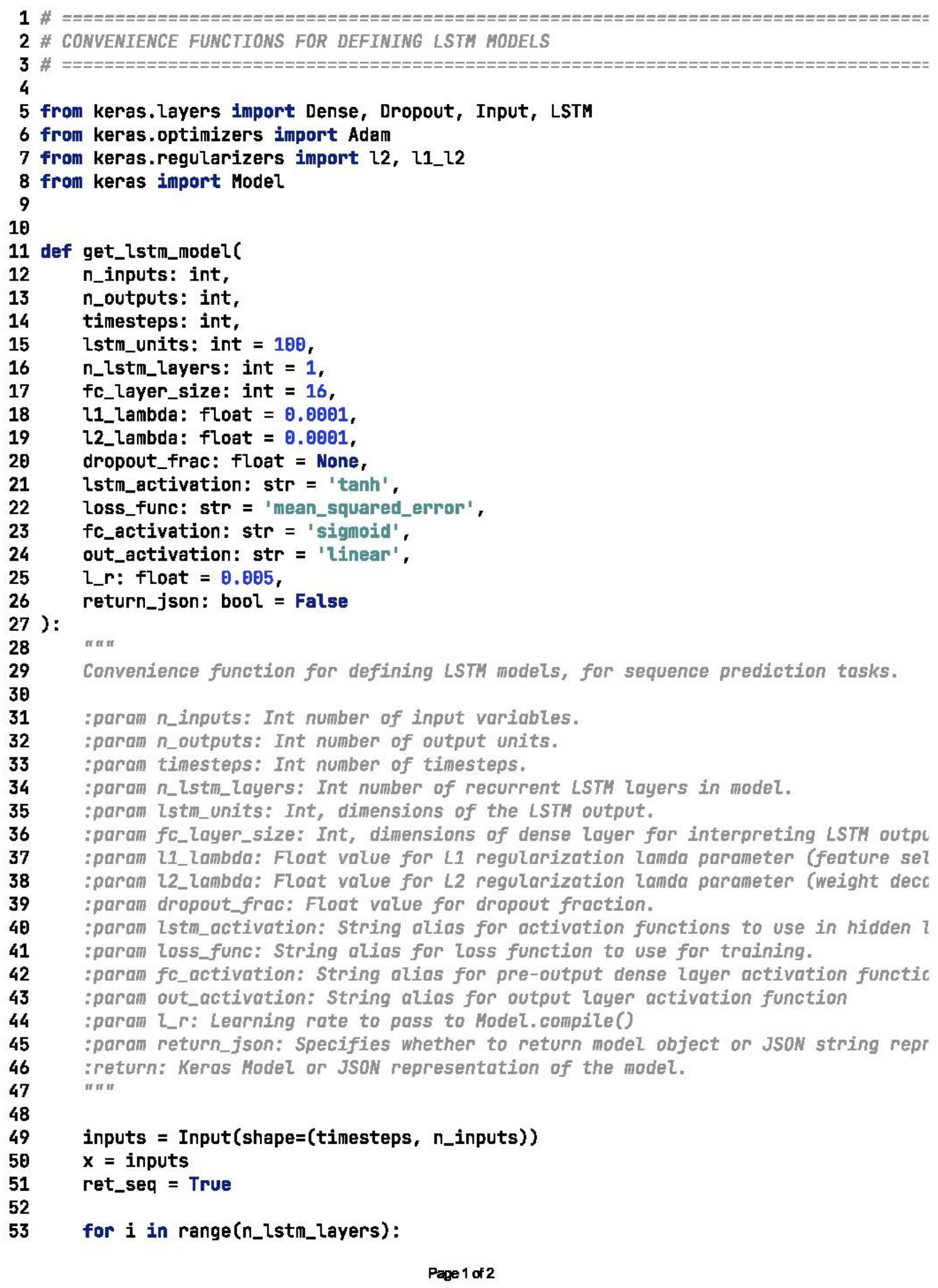
Page 2 of 3



```
#   function 4  #
########################

def predict(n_output,x,testX, testY):
    predicted = x.predict(testX)

    testXRe = testX.reshape(testX.shape[0], testX.shape[2])

    ####combine test X and predicted Y###

    predicted = np.concatenate((testXRe, predicted), axis=1)

    predicted = scaler1.inverse_transform(predicted)  # scale back to orig, take n

    testY_reshape = testY.reshape(len(testY), n_output)

    ####combine test data###
    testY_concat = np.concatenate((testXRe, testY_reshape), axis=1)

    # scaleback to orignal values
    testY_final = scaler1.inverse_transform(testY_concat)

    predicted_df = pd.DataFrame(predicted[:, -n_output:])
    expected_df = pd.DataFrame(testY_final[:, -n_output:])

    global pred_columns

    pred_columns = list()
    exp_columns = list()

    pred_columns += [('t+%d' % (i)) for i in range(n_output)]
    exp_columns += [('t+%d' % (i)) for i in range(n_output)]

    predicted_df.columns = pred_columns
    expected_df.columns = exp_columns

    df = pd.concat({"Predicted": predicted_df,
                    "Expected": expected_df}, axis=1)

    return df

```

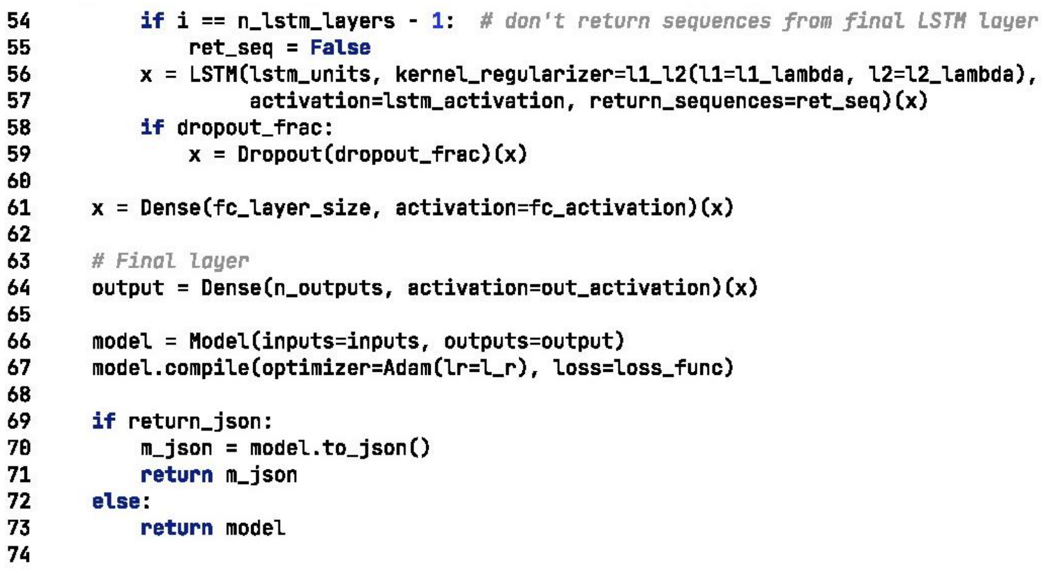
Listing 4. Functions for transforming data into LSTM input

C.3. LSTM model training



```
# ================================================================================
# CONVENIENCE FUNCTIONS FOR DEFINING LSTM MODELS
# ================================================================================

from keras.layers import Dense, Dropout, Input, LSTM
from keras.optimizers import Adam
from keras.regularizers import l2, l1_l2
from keras import Model


def get_lstm_model(
    n_inputs: int,
    n_outputs: int,
    timesteps: int,
    lstm_units: int = 100,
    n_lstm_layers: int = 1,
    fc_layer_size: int = 16,
    l1_lambda: float = 0.0001,
    l2_lambda: float = 0.0001,
    dropout_frac: float = None,
    lstm_activation: str = 'tanh',
    loss_func: str = 'mean_squared_error',
    fc_activation: str = 'sigmoid',
    out_activation: str = 'linear',
    l_r: float = 0.005,
    return_json: bool = False
):
    """
    Convenience function for defining LSTM models, for sequence prediction tasks.

    :param n_inputs: Int number of input variables.
    :param n_outputs: Int number of output units.
    :param timesteps: Int number of timesteps.
    :param n_lstm_layers: Int number of recurrent LSTM layers in model.
    :param lstm_units: Int, dimensions of the LSTM output.
    :param fc_layer_size: Int, dimensions of dense layer for interpreting LSTM outpu
    :param l1_lambda: Float value for L1 regularization lamda parameter (feature sel
    :param l2_lambda: Float value for L2 regularization lamda parameter (weight deca
    :param dropout_frac: Float value for dropout fraction.
    :param lstm_activation: String alias for activation functions to use in hidden l
    :param loss_func: String alias for loss function to use for training.
    :param fc_activation: String alias for pre-output dense layer activation functio
    :param out_activation: String alias for output layer activation function
    :param l_r: Learning rate to pass to Model.compile()
    :param return_json: Specifies whether to return model object or JSON string repr
    :return: Keras Model or JSON representation of the model.
    """

    inputs = Input(shape=(timesteps, n_inputs))
    x = inputs
    ret_seq = True

    for i in range(n_lstm_layers):
```

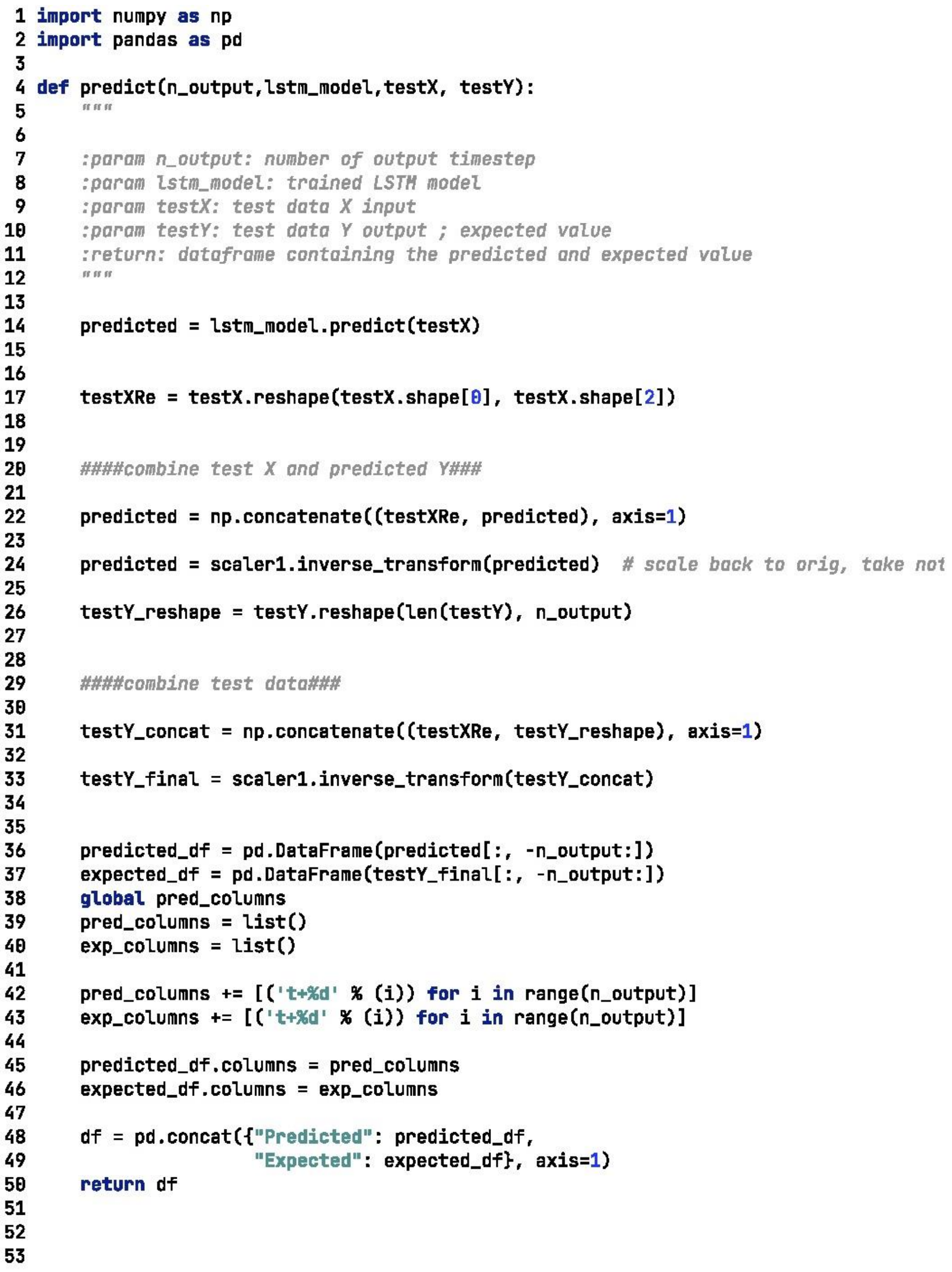
Page 1 of 2



```python
        if i == n_lstm_layers - 1:  # don't return sequences from final LSTM layer
            ret_seq = False
        x = LSTM(lstm_units, kernel_regularizer=l1_l2(l1=l1_lambda, l2=l2_lambda),
                 activation=lstm_activation, return_sequences=ret_seq)(x)
        if dropout_frac:
            x = Dropout(dropout_frac)(x)

    x = Dense(fc_layer_size, activation=fc_activation)(x)

    # Final layer
    output = Dense(n_outputs, activation=out_activation)(x)

    model = Model(inputs=inputs, outputs=output)
    model.compile(optimizer=Adam(lr=l_r), loss=loss_func)

    if return_json:
        m_json = model.to_json()
        return m_json
    else:
        return model

```

Listing 5. Convenience function for training LSTM model

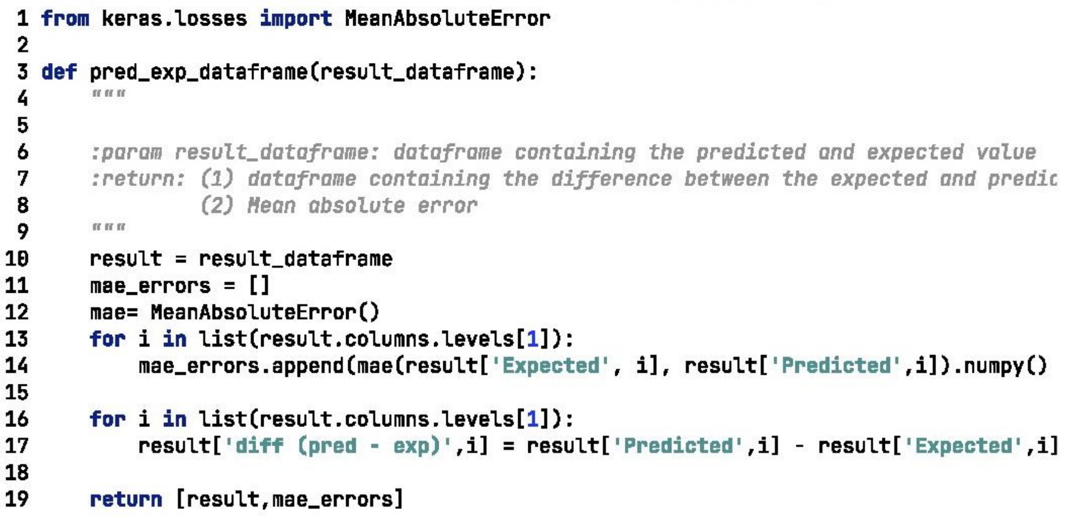
C.4. LSTM model Predict



```python
import numpy as np
import pandas as pd

def predict(n_output,lstm_model,testX, testY):
    """

    :param n_output: number of output timestep
    :param lstm_model: trained LSTM model
    :param testX: test data X input
    :param testY: test data Y output ; expected value
    :return: dataframe containing the predicted and expected value
    """

    predicted = lstm_model.predict(testX)


    testXRe = testX.reshape(testX.shape[0], testX.shape[2])


    ####combine test X and predicted Y###

    predicted = np.concatenate((testXRe, predicted), axis=1)

    predicted = scaler1.inverse_transform(predicted)  # scale back to orig, take not

    testY_reshape = testY.reshape(len(testY), n_output)


    ####combine test data###

    testY_concat = np.concatenate((testXRe, testY_reshape), axis=1)

    testY_final = scaler1.inverse_transform(testY_concat)


    predicted_df = pd.DataFrame(predicted[:, -n_output:])
    expected_df = pd.DataFrame(testY_final[:, -n_output:])
    global pred_columns
    pred_columns = list()
    exp_columns = list()

    pred_columns += [('t+%d' % (i)) for i in range(n_output)]
    exp_columns += [('t+%d' % (i)) for i in range(n_output)]

    predicted_df.columns = pred_columns
    expected_df.columns = exp_columns

    df = pd.concat({"Predicted": predicted_df,
                    "Expected": expected_df}, axis=1)
    return df



```

Listing 6. Function to use the trained LSTM model

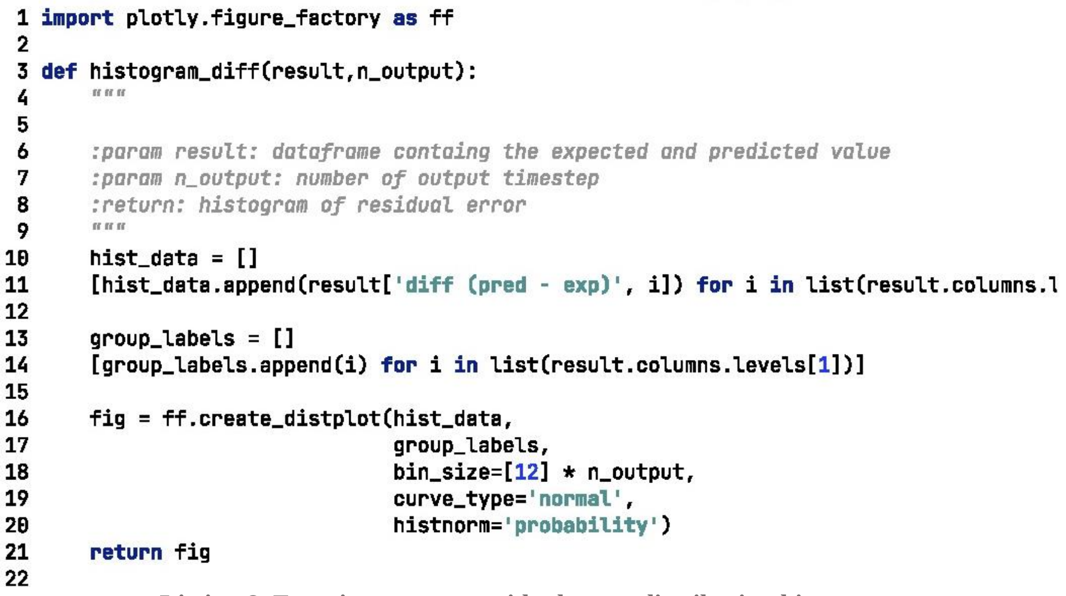
C.5. Mean Absolute Error



```
from keras.losses import MeanAbsoluteError

def pred_exp_dataframe(result_dataframe):
    """

    :param result_dataframe: dataframe containing the predicted and expected value
    :return: (1) dataframe containing the difference between the expected and predic
             (2) Mean absolute error
    """
    result = result_dataframe
    mae_errors = []
    mae= MeanAbsoluteError()
    for i in list(result.columns.levels[1]):
        mae_errors.append(mae(result['Expected', i], result['Predicted',i]).numpy()

    for i in list(result.columns.levels[1]):
        result['diff (pred - exp)',i] = result['Predicted',i] - result['Expected',i]

    return [result,mae_errors]
```

Listing 7. Function for finding the mean absolute error and DataFrame containing the difference between expected and predicted values

C.6. Residual Error Distribution



```
import plotly.figure_factory as ff

def histogram_diff(result,n_output):
    """

    :param result: dataframe containg the expected and predicted value
    :param n_output: number of output timestep
    :return: histogram of residual error
    """
    hist_data = []
    [hist_data.append(result['diff (pred - exp)', i]) for i in list(result.columns.l

    group_labels = []
    [group_labels.append(i) for i in list(result.columns.levels[1])]

    fig = ff.create_distplot(hist_data,
                             group_labels,
                             bin_size=[12] * n_output,
                             curve_type='normal',
                             histnorm='probability')
    return fig

```

Listing 8. Function returns residual error distribution histogram

Appendix D

Data Analysis

D.1. Well A: Tripping In Operation

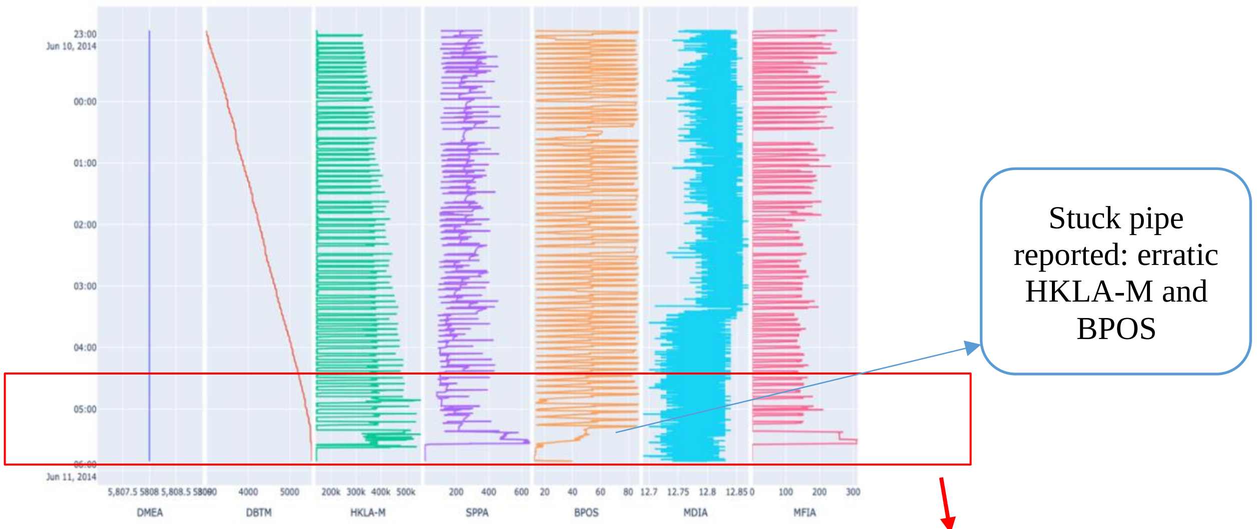
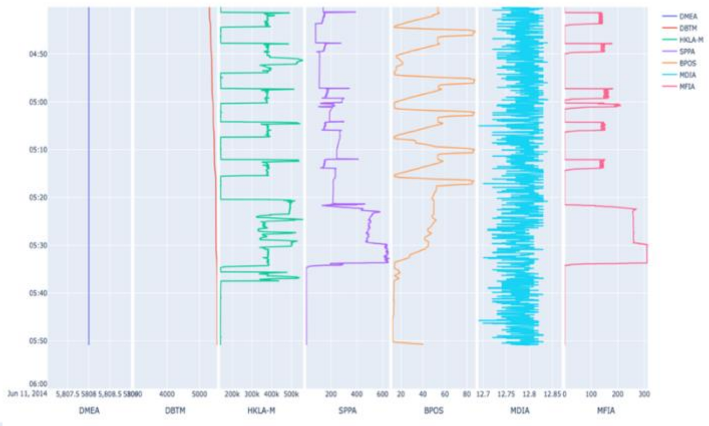


Figure D-0-1. Well A’s DMEA, DBTM, HKLA-M, SPPA, BPOS, MDIA, and MFIA, respectively.



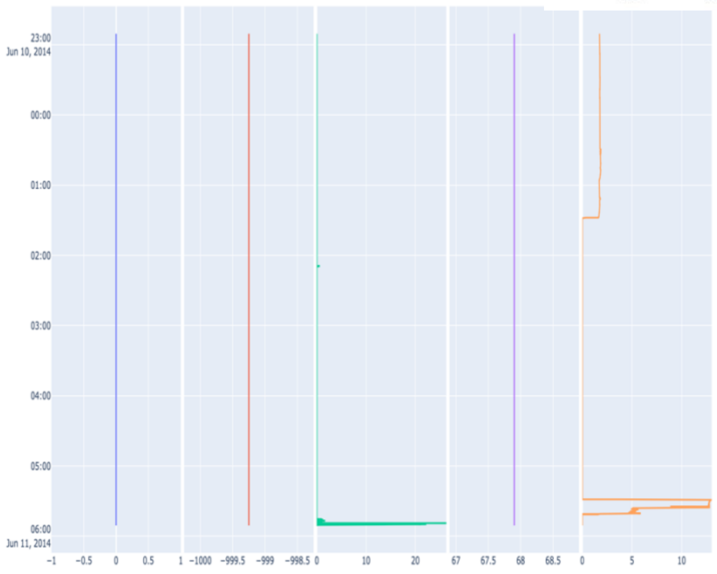


Figure D-0-2. Well A’s TQA, WOB-M, RPMA, ROPA, and MDOA, respectively.

D.2. Well D: Tripping Out Operation (Reaming)

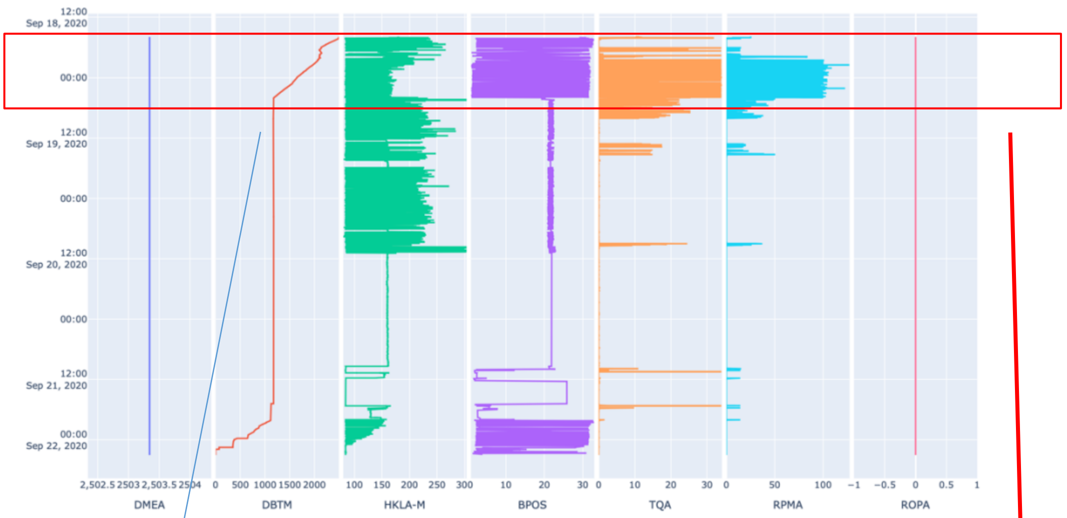
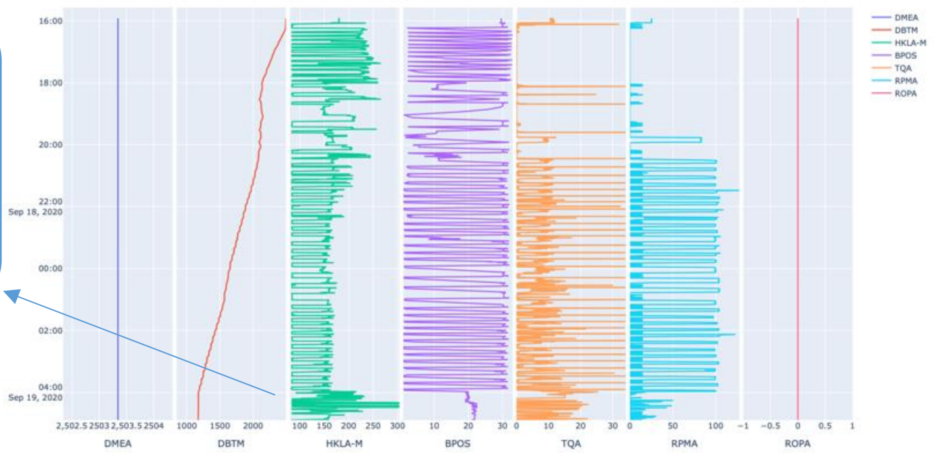


Figure D-0-3. Well D's DMEA, DBTM, HKLA-M, BPOS, TQA, RPMA, and ROPA, respectively.

Stuck pipe reported: erratic HKLA-M and BPOS. DBTM becomes constant.



Appendix E

Hook load Signatures

E.1. Hook load Signatures

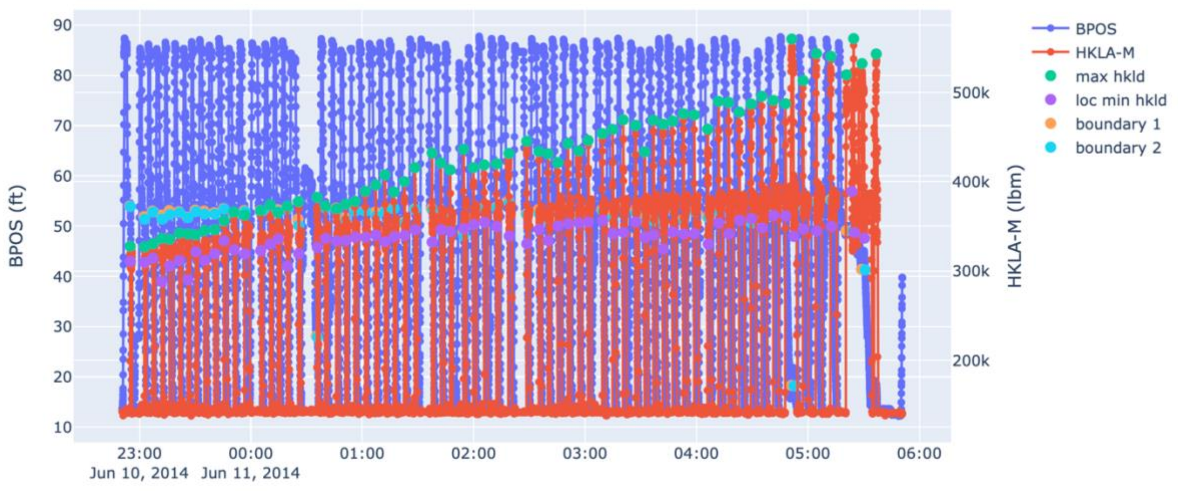


Figure E-0-4. Well A hook load signatures

E.2. Extracted Data Points from Wells A, B, and D

Table 14. First 15 of 65 local minima from Well A

	TIME	HKLA-M
264	2014-06-10 22:55:03.935000+00:00	310.82972
727	2014-06-10 23:02:45.206000+00:00	309.59513
992	2014-06-10 23:07:10.237000+00:00	314.40121
1279	2014-06-10 23:11:57.212000+00:00	288.36462
1537	2014-06-10 23:16:15.308000+00:00	305.91341
1854	2014-06-10 23:21:33.946000+00:00	311.86590
2125	2014-06-10 23:26:04.968000+00:00	290.17241
2385	2014-06-10 23:30:23.257000+00:00	321.58828
2667	2014-06-10 23:35:06.338000+00:00	311.88794
2992	2014-06-10 23:40:30.147000+00:00	319.47184
3297	2014-06-10 23:45:35.990000+00:00	333.86803
3622	2014-06-10 23:51:00.630000+00:00	323.85904
3969	2014-06-10 23:56:47.488000+00:00	319.38366
4480	2014-06-11 00:05:18.291000+00:00	322.99924
4785	2014-06-11 00:10:23.382000+00:00	330.07608

Table 15. 15 maximum hook load from Well B

	TIME	HKLA-M
4391	2020-07-30 13:48:40.241000+08:00	263.23
4670	2020-07-30 14:11:55.302000+08:00	246.35
4930	2020-07-30 14:33:35.484000+08:00	257.45
5202	2020-07-30 14:56:15.723000+08:00	260.06
5514	2020-07-30 15:22:16.069000+08:00	257.17
5814	2020-07-30 15:47:16.328000+08:00	260.30
6095	2020-07-30 16:10:41.438000+08:00	262.41
6318	2020-07-30 16:29:17.698000+08:00	254.28
6544	2020-07-30 16:48:05.847000+08:00	251.72
6767	2020-07-30 17:06:40.857000+08:00	291.42
7120	2020-07-30 17:36:11.028000+08:00	248.46
7336	2020-07-30 17:54:10.987000+08:00	258.69
7546	2020-07-30 18:11:41.099000+08:00	254.77
7762	2020-07-30 18:29:41.191000+08:00	260.92
7981	2020-07-30 18:47:56.286000+08:00	250.19

Table 16. First 15 of 28 maximum hook load from Well D

	TIME	HKLA-M
3461	2020-09-18 20:43:22.060000+08:00	206.58
3625	2020-09-18 20:57:02.133000+08:00	202.88
3658	2020-09-18 20:59:47.080000+08:00	208.88
3833	2020-09-18 21:14:22.149000+08:00	203.49
3985	2020-09-18 21:27:02.255000+08:00	191.00
4136	2020-09-18 21:39:37.272000+08:00	189.38
4273	2020-09-18 21:51:02.390000+08:00	178.52
4441	2020-09-18 22:05:02.327000+08:00	166.93
4612	2020-09-18 22:19:17.310000+08:00	190.59
4778	2020-09-18 22:33:07.382000+08:00	161.79
4928	2020-09-18 22:45:37.515000+08:00	166.46
5064	2020-09-18 22:56:57.487000+08:00	161.89
5286	2020-09-18 23:15:27.596000+08:00	163.07
5455	2020-09-18 23:29:32.663000+08:00	156.42
5600	2020-09-18 23:41:37.758000+08:00	156.77

E.3. Other Training Data

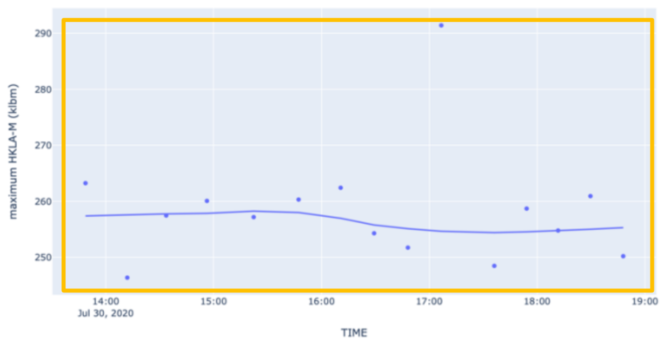


Figure E-0-5. Well B maximum hook load. All points are training data. Only few was extracted from well B due to poor measurement frequency at different time frame

Appendix F

End to End Machine Learning Implementation

In [ ]:

```
import pandas as pd
import numpy as np
import plotly.graph_objs as go
import plotly.express as px
from datetime import datetime
from get_peak import get_peak
from get_minima_boundaries import get_minima_boundaries
from get_minima import get_minima
import statsmodels
import matplotlib
from matplotlib import pyplot as plt
import seaborn as sns
from plotly.subplots import make_subplots
from scipy.signal import find_peaks
import plotly.figure_factory as ff
from lstm_model import get_lstm_model
from keras.losses import MeanAbsoluteError
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from sklearn.metrics import mean_squared_error
from keras.models import Sequential
from keras.callbacks import EarlyStopping
from keras.layers import Dense, Dropout, Input, LSTM, GRU
from keras.optimizers import Adam
from keras.regularizers import l2, l1_l2
from keras import Model
from two_axis_plot import plot_2axis
from lstm_input import lstm_input
from lstm_input import predict
from pred_exp_dataframe import pred_exp_dataframe
from histogram_diff import histogram_diff
```

Well A

In [ ]:

```
well_A_orig = pd.read_csv('Well A filtered.csv')
well_A_orig = well_A_orig.loc[:, ~well_A_orig.columns.str.contains('^Unnamed')]
well_A_orig['HKLA-M'] = well_A_orig['HKLA-M']/1000
well_A = well_A_orig.copy()
well_A['TIME'] = pd.to_datetime(well_A['TIME'])
```

finding peak

In [ ]:

```
fig, peak_value, peak_index, num_points, dff_peaks = get_peak(dataframe=well_A[well_A['BP
OS']>15],
                                                    column_name_peak='HKLA-M',distance=1
80,
                                                  height=250,x_plot_column_name='TIME')
```

finding local minima boundaries

In [ ]:

```
connection_BPOS_index, second_bound_index, boundaries_index = get_minima_boundaries(
                                                                  dataframe = well_A,

                                                                  peak_index = dff_pe
aks.index[:-1].to_list(),
                                                                  block_column = 'BPO
S',
                                                                  look_back = 15)
```

```
n_output=1
n_input =5


trainXbb,trainYbb,testXbb,testYbb = lstm_input(dff_peaks1b,
                              n_input=n_input,
                              n_output=n_output,
                             dropnan=True,
                              test_data_percent=0.80)
trainXbb = trainXbb.reshape(trainXbb.shape[0],1,trainXbb.shape[1])
testXbb = testXbb.reshape(testXbb.shape[0],1,testXbb.shape[1])
```

In [ ]:

```
trainX= np.concatenate((trainXa,trainXdd, trainXbb, trainXaa ), axis=0)
trainY = np.concatenate((trainYa,trainYdd, trainYbb, trainYaa), axis=0)


testX = np.concatenate((testXa,testXdd, testXbb, testXaa ), axis=0)
testY = np.concatenate((testYa,testYdd, testYbb, testYaa ), axis=0)
```

In [ ]:

```
n_vars = 1 if type(dff_peaks1b) is list else dff_peaks1b.shape[1]  ##number of variables
only hookload n_vars=1
```

Training LSTM model

In [ ]:

```
x = get_lstm_model(
    n_inputs= n_input *n_vars ,   ###n_vars* n_input
    n_outputs= n_output,   #number of predicted points
    timesteps= 1,
    lstm_units=23,
    n_lstm_layers =1,
    fc_layer_size = 1,
    l1_lambda= 0.001,
    l2_lambda= 0.001,
    dropout_frac= 0.1,
    l_r = 0.004,
    fc_activation = None)

stop_noimprovement = EarlyStopping(patience=20)
history= x.fit(trainX,
                  trainY,
                   validation_data=(testX,testY),
                   epochs=200,
                   verbose=2,
                   callbacks=[stop_noimprovement],
                   shuffle=False)

plt.plot(history.history['loss'],label='train')
plt.plot(history.history['val_loss'],label='val')
plt.legend()
plt.show()
```

Testing the Model

Prepare data

In [ ]:

```
well_A_results_minima_train2 = well_A_results[['minimum hkld (klbm)']].iloc[12:]
n_output=1
n_input =5
n_vars = 1 if type(well_A_results_minima_train2) is list else well_A_results_minima_trai
```

getting local minima

In [ ]:

```
fig,count_minima, dff  = get_minima(well_A, boundaries_index,'HKLA-M', 'TIME')
```

Extracted hookloads dataframe

In [ ]:

```
well_A_results = pd.DataFrame({'minimum hkld (klbm)': dff['HKLA-M'][:-4]})
well_A_results['Maximum hkld index']= dff_peaks.index[:-5]
well_A_results['Maximum hkld (klbm)']=dff_peaks['HKLA-M'][:-5].to_list()
well_A_results = well_A_results.reset_index()
well_A_results = well_A_results.rename(columns={'index':'minima_index'})
```

In [ ]:

```
well_A_results_minima_train = well_A_results[['minimum hkld (klbm)']].iloc[:12]
well_A_results_maximum_train = well_A_results[['Maximum hkld (klbm)']]
```

well D

In [ ]:

```
well_D_orig = pd.read_csv('well D filtered.csv', low_memory=False)
well_D = well_D_orig.copy()
well_D = well_D.loc[:, ~well_D.columns.str.contains('^Unnamed')]
well_D['TIME'] = pd.to_datetime(well_D['TIME'][:])
```

In [ ]:

```
fig, peak_value, peak_index, num_points, dff_peaks1d = get_peak(dataframe=well_D[5000:800
0][well_D[5000:8000]['BPOS']<3.2],
                                                   column_name_peak='HKLA-M',distance=2
8,
                                                    height=150,x_plot_column_name='TIME
')
dff_peaks1d = dff_peaks1d.copy().reset_index()
dff_peaks1d = dff_peaks1d[['HKLA-M']]
```

In [ ]:

```
fig, peak_value, peak_index, num_points, dff_peaks2d = get_peak(dataframe=well_D[3200:500
0][well_D[3200:5000]['BPOS']<3.2],
                                                   column_name_peak='HKLA-M',distance=3
0,
                                                    height=160,x_plot_column_name='TIME
')
dff_peaks2d = dff_peaks2d.copy().reset_index()
dff_peaks2d = dff_peaks2d[['HKLA-M']]
```

In [ ]:

```
dff_final_peaks_d = pd.concat([dff_peaks2d, dff_peaks1d])
dff_final_peaks_d = dff_final_peaks_d.reset_index(drop=True)
```

well B

In [ ]:

```
well_B_orig = pd.read_csv('well B filtered.csv', low_memory=False)
well_B = well_B_orig.copy()
well_B = well_B.loc[:, ~well_B.columns.str.contains('^Unnamed')]
```

```
well_B['TIME'] = pd.to_datetime(well_B['TIME'][:])
```

In [ ]:

```
well_try = well_B[4000:8000]
fig, peak_value, peak_index, num_points, dff_peaks1b = get_peak(dataframe=well_try[well_t
ry['BPOS']<4.2],
                                                                 column_name_peak='HKLA-M',distance=6
0,
                                                                  height=220,x_plot_column_name='TIME
')
dff_peaks1b = dff_peaks1b.copy().reset_index()
dff_peaks1b = dff_peaks1b[['HKLA-M']]
```

combine data for ML training

Training data from Well A local minima

In [ ]:

```
n_output=1
n_input =5

trainXa,trainYa,testXa,testYa = lstm_input(well_A_results_minima_train,
                                 n_input=n_input,
                                 n_output=n_output,
                                dropnan=True,
                                 test_data_percent=0.80)
print(trainXa.shape,trainYa.shape,testXa.shape,testYa.shape)
trainXa = trainXa.reshape(trainXa.shape[0],1,trainXa.shape[1])
testXa = testXa.reshape(testXa.shape[0],1,testXa.shape[1])
```

Training data from Well D maxima

In [ ]:

```
n_output=1
n_input =5


trainXdd,trainYdd,testXdd,testYdd = lstm_input(dff_final_peaks_d,
                                 n_input=n_input,
                                 n_output=n_output,
                                dropnan=True,
                                 test_data_percent=0.80)
trainXdd = trainXdd.reshape(trainXdd.shape[0],1,trainXdd.shape[1])
testXdd = testXdd.reshape(testXdd.shape[0],1,testXdd.shape[1])
```

Training data from Well B maxima

In [ ]:

```
n_output=1
n_input =5


trainXbb,trainYbb,testXbb,testYbb = lstm_input(dff_peaks1b,
                                 n_input=n_input,
                                 n_output=n_output,
                                dropnan=True,
                                 test_data_percent=0.80)
trainXbb = trainXbb.reshape(trainXbb.shape[0],1,trainXbb.shape[1])
testXbb = testXbb.reshape(testXbb.shape[0],1,testXbb.shape[1])
```

In [ ]:

```
trainX= np.concatenate((trainXa,trainXdd, trainXbb), axis=0)
```

```
trainY = np.concatenate((trainYa,trainYdd, trainYbb), axis=0)


testX = np.concatenate((testXa,testXdd, testXbb), axis=0)
testY = np.concatenate((testYa,testYdd, testYbb), axis=0)
```

In [ ]:

```
n_vars = 1 if type(dff_peaks1b) is list else dff_peaks1b.shape[1]  ##number of variables
only hookload n_vars=1
```

Training LSTM model

In [ ]:

```
x = get_lstm_model(
    n_inputs= n_input *n_vars ,   ###n_vars* n_input
    n_outputs= n_output,   #number of predicted points
    timesteps= 1,
    lstm_units=23,
    n_lstm_layers =1,
    fc_layer_size = 1,
    l1_lambda= 0.001,
    l2_lambda= 0.001,
    dropout_frac= 0.1,
    l_r = 0.004,
    fc_activation = None)

stop_noimprovement = EarlyStopping(patience=20)
history= x.fit(trainX,
                  trainY,
                   validation_data=(testX,testY),
                   epochs=200,
                   verbose=2,
                   callbacks=[stop_noimprovement],
                   shuffle=False)

plt.plot(history.history['loss'],label='train')
plt.plot(history.history['val_loss'],label='val')
plt.legend()
plt.show()
```

Testing the Model

Prepare data

In [ ]:

```
well_A_results_minima_train2 = well_A_results[['minimum hkld (klbm)']].iloc[12:]
n_output=1
n_input =5
n_vars = 1 if type(well_A_results_minima_train2) is list else well_A_results_minima_trai
n2.shape[1]

trainX,trainY,testX,testY = lstm_input(well_A_results_minima_train2,
                              n_input=n_input,
                              n_output=n_output,
                             dropnan=True,
                              test_data_percent=1)
trainX = trainX.reshape(trainX.shape[0],1,trainX.shape[1])
testX = testX.reshape(testX.shape[0],1,testX.shape[1])
```

Use the trained model to predict

In [ ]:

```
result_3, mae = pred_exp_dataframe(predict(n_output,x,trainX, trainY)) #pred, exp, and di
```

```
ff
print(mae)
```

Residual Distribution

In [ ]:

```
histogram_diff(result,n_output).show()
```

Expected and Predicted Dataframe

In [ ]:

```
result_3['nth casing'] = list(range(17,65))
result_3 = result_3.set_index('nth casing')
result_3_plot = result_3['Predicted']
result_3_plot['TIME'] = minima_data[17:65][['TIME']]
```

Expected vs Predicted Plot

In [ ]:

```
fig = go.Figure()

fig.add_trace(go.Scatter(x=minima_data.TIME[:-4], y=minima_data['HKLA-M'][:-4], name='Ex
pected HKLA', mode='lines+markers'))
fig.add_trace(go.Scatter(x=result_3_plot.TIME , y=result_3_plot['t+0'],name='Case 1 Pred
icted',mode='lines+markers'))

fig.update_layout(title='Hookload')
fig.update_yaxes(title_text="HKLA-M (klbm)")
fig.update_xaxes(title_text="Time")

fig.show()
```

Appendix G

Model Hyperparameters

Table 17. LSTM model hyperparameters

Hyperparameter	Python Variable	Value
n_lstm_layers	number of recurrent LSTM layers in model.	1
lstm_units	dimensions of the LSTM output	23
l1_lambda	value for L1 regularization lamda parameter (feature selection)	0.001
l2_lambda	value for L2 regularization lamda parameter (weight decay)	0.001
dropout_frac	value for dropout fraction	0.1
lstm_activation	alias for activation functions to use in hidden layers	tanh
loss_func:	alias for loss function to use for training	mean_square_error
l_r	Learning rate	0.004