Chair of Drilling and Completion Engineering

Master's Thesis

Application of Data Mining to Predict and Assess the ROP Response

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dpe DEPARTMENT PETROLEUM ENGINEERING

MONTAN UNIVERSITÄT

To my family, my kids and my dear friends.

Abstract

Performance enhancement is the main wish in any industry. In the drilling process, the challenge lies in finding the right conditions to reach a desired depth faster, while balancing the operational complexities with the associated risks. In this regard, drilling operations generate enormous quantities of data and metadata with the main goal of providing detailed visualization of operations accessible remotely and in real time. This aligns with the existent big-data time, where data mining techniques appear as means to drive proficiencies in data processing to generate new and valuable information. From this perspective, the ultimate goal of this thesis is to assess the application of data mining software to transform commonly acquired drilling data into actionable data with possible impact in well planning and during later operations. In order to achieve the prime goal of the thesis the Rate of Penetration (ROP) was selected to be the focus of the study.

The ROP, known as one of the contributors in time estimation for operations, is the variable of interest for the analysis and prediction. This work applies data mining techniques to examine pre-existing data sets of previously drilled wells looking for meaningful information about the measured ROP. Then Machine-learning models are used for its predictions to serve as a reference to evaluate any deviation and its possible causes, by testing the prediction in a new data set.

This thesis is divided into four main parts. Starting by exploring data mining functionalities and its applications, including specific examples related to the Oil & Gas (O&G) industry. The following part involves understanding drilling data, its origins in measurements, its data type, and some of the challenges faced during its acquisition process. The ROP measurement is discussed in detail during this stage as well. With a general overview of the resources, the third part is dedicated to the methodology by developing a workflow including Pre-processing and Processing of the data using a commercial data mining software to implement a model for ROP prediction. In the last part, the Data Analysis and Model Evaluation are performed using different visualization tools, reinforced by descriptive statistics. A discussion of the model implementation and testing process is presented as well, based on the obtained results.

The outcome of this work, drawn a road for further research on ROP deviation causes. It offers an insight for data mining applications for practical analysis and prediction derived from drilling data. It endorses its application when objectives are clearly defined and with no resources constraints.

Zusammenfassung

Effizienzsteigerung ist eines der Hauptziele in allen Industriezweigen. Während des Bohrprozesses besteht die Herausforderung darin, die Bohrparameter so anzupassen, dass die geplante Teufe möglichst schnell erreicht wird und die mit dem Bohrprozess verbundenen Risiken und operativen Schwierigkeiten gleichzeitig geringgehalten werden. Im Zusammenhang mit der Bohrtätigkeit werden enorme Mengen an Daten und Metadaten generiert, mit dem Hauptziel, eine detaillierte Visualisierung der Vorgänge zu ermöglichen, auf die von überall aus und in Echtzeit zugegriffen werden kann. Diese Entwicklung geht Hand in Hand mit dem vorherrschenden Trend zu Big Data, in dem Data Mining-Methoden eingesetzt werden um die Effizienz in der Datenverarbeitung zu steigern und neue und wertvolle Informationen zu gewinnen. Davon ausgehend ist es das Ziel dieser Arbeit, die Anwendung von Data Mining-Software auf standardmäßig aufgezeichnete Bohrdaten zu bewerten, um aus ihnen verwertbare Informationen zu erhalten, die möglicherweise Einfluss in der Planungsphase und dem späteren operativen Verlauf von Bohrungen haben können. Dazu wurde in dieser Arbeit die Bohrfortschrittsrate (ROP) als Studienschwerpunkt ausgewählt.

Die Bohrfortschrittsrate stellt bekannterweise einen Faktor in der Zeitplanung von Bohrungen dar und dient hier also zu untersuchende Variable für die Analyse und Vorhersage. Die Arbeit wendet Data-Mining Methoden auf bereits existierende Datensätze von abgeteuften Bohrungen an um diese auf aussagekräftigen Informationen über die gemessene Bohrfortschrittsrate zu prüfen. Anschießend werden maschinelle Lernmethoden genutzt um die Bohrfortschrittsrate vorherzusagen. Diese dienen als Referenz um Abweichungen und deren mögliche Gründe zu evaluieren, indem die Vorhersagen auf neue Datensätze angewandt werden.

Die Arbeit gliedert sich in vier Hauptteile, beginnend mit Funktionsweisen des Data Mining und deren Anwendung, einschließlich spezifischer Beispiele für die Öl- und Gasindustrie. Darauffolgend werden Bohrdaten und die Ursprünge ihrer Aufzeichnung, ihr Datenformat sowie die Schwierigkeiten im Zusammenhang mit ihrer Aufzeichnung behandelt. Dies beinhaltet eine detaillierte Diskussion der Messung der Bohrfortschrittsrate. Der dritte Teil behandelt die Methodik, mit einer allgemeinen Übersicht über die Ressourcen in dem ein Workflow erarbeitet wird der die Vorverarbeitung und Verarbeitung der Daten mit einer kommerziellen Data Mining-Software umfasst, um ein Modell für die Vorhersage der Bohrfortschrittsrate zu implementieren. Im letzten Teil werden die Datenanalyse und die Modellbewertung mit verschiedenen Visualisierungswerkzeugen durchgeführt und durch beschreibende Statistk gestützt. Anhand der erzielten Ergebnisse werden Modellimplementierungs- und Testprozesse diskutiert.

Das Ergebnis der Arbeit zeigt einen Weg für die weitere Erforschung der Ursachen von Abweichungen der Bohrfortschrittsrate auf. Es bietet einen Einblick in Data Mining-Anwendungen zur praktischen Analyse und Vorhersagen die von Bohrdaten abgeleitet werden. Die Anwendung von Data Mining ist aufgrund der Ergebnisse zu befürworten, wenn die Ziele klar definiert sind und keine Ressourcenbeschränkungen bestehen.

Acknowledgements

Primarily I want to thank my thesis advisor Dipl.-Ing. Asad Elmgerbi for his support and guidance during my studies, and particularly for the culmination of this work. He has been a true mentor for my professional and personal growth.

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Special thanks to my family who gave me their love and unconditional support during the highs and lows of this journey.

Finally yet importantly, I want to thank to my favourite person, my beloved sister, who made many sacrifices for me. Without your support this would not be possible, love you Kiki!

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Chapter 1 Introduction

1.1 Overview

There is no doubt that it is a data–driven time, where scientific data, medical data, financial data, and practically every daily interaction inside a system is being registered and stored in some kind of format as data. Only understanding what to do or how to use this vast amount of data can open the possibilities to knowledge.

In this regard, data mining appears to provide the resources to handle this big amount of data. It brings promising solutions as a dynamic, breadth, and multidisciplinary field founded in statistics, data visualization, artificial intelligence, and machine learning along with database technology and high-performance computing. In brief, its focus is on finding insights, regardless of the methods, yet it commonly uses machine-learning algorithms to build models, but its focus is knowledge discovery.

Drilling data is not exempted, with a trend of growing constantly accelerating in volume and type, but still in the process of being explored to its theoretical potential.

Knowing that ROP is one of the parameters of concern during drilling operations, its proper understanding and prediction have become of great interest for optimization, where data mining and machine learning techniques, directly related with data analysis and prediction, appear as a positive alternative for this purpose. Particularly when so much theoretical research has been done regarding ROP, usually under limited conditions that ends preventing its applicability. Data mining, on the other hand, opens the possibility of insights and predictions based on real drilling data generated under operations with tangible and, in many cases, repetitive conditions.

1.2 Motivation and Objectives

With the increase of automatic processes during drilling operations, an increment of data sources is expected with more and different type of sensors installed to accomplish all kind of tasks.

In addition to this increment, Figure 1 shows the number of wells drilled until 2018 in the US shale sector, with a projection to drill and complete more than 20,000 wells for 2019. A tendency of growing is estimated until 2022 reflecting how drilling data is expected to continue growing tremendously in the upcoming years. Handling such a big amount of data demands the application of data mining, covering all the aspects from data preparation to analysis, particularly when it has been already successfully applied in several fields.

Thus, the challenge consists in boosting data mining functionalities in the direction of drilling performance. Therefore, this work represents an opportunity to combine drilling engineering with data mining by applying some of its techniques to a set of drilling data.

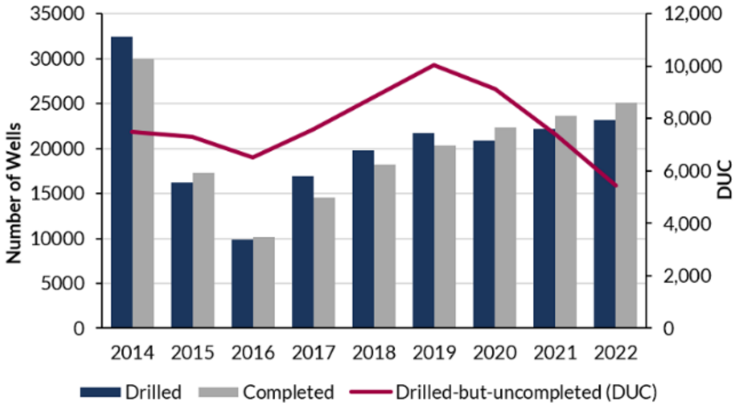


Figure 1 Wells drilled, completed, and drilled-but-uncompleted per year until 2018. Projection until 2022 (Jacobs, Journal of Petroleum Technology 2019)

The main objective is to improve the understanding of ROP behaviour, and when possible identify the factors affecting its expected performance, with the creation of a model to predict its response. The mean for this purpose are sensor data collected constantly during normal drilling operations, along with geographical well position data in one specific field.

In order to achieve the intended goal, a comprehensive workflow was created, and its main phases are showed in Figure 2.

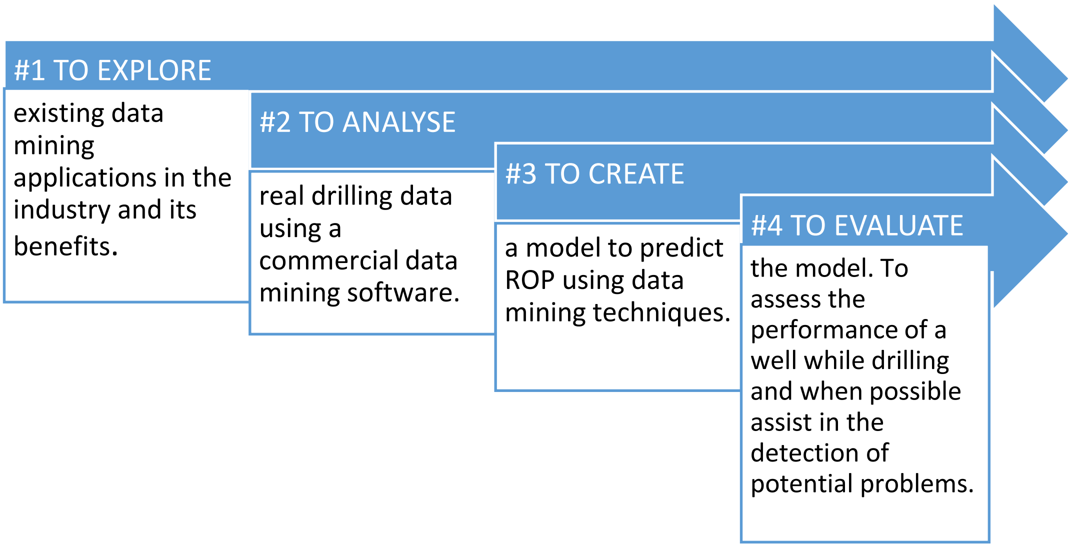

#1 TO EXPLORE
existing data mining applications in the industry and its benefits.
#2 TO ANALYSE
real drilling data using a commercial data mining software.
#3 TO CREATE
a model to predict ROP using data mining techniques.
#4 TO EVALUATE
the model. To assess the performance of a well while drilling and when possible assist in the detection of potential problems.

Figure 2 Workflow divided in four specific phases

The two initial phases, involved literature review, and research associated with the topic to support the proposal for methodology, by studying existing data mining applications along with more detailed examples directly related to the O&G industry. In addition, the second phase includes the use of a commercial data mining software to process and analyse drilling data. Then, the last two phases evoke for the implementation of a predictive model for ROP using data mining techniques, to finally evaluate the model and its applicability for drilling performance.

Chapter 2 Data Mining

2.1 Overview

Data mining emerged during the late 1980s, with important advances through the next decade and until today. It refers to the application of science to extract useful information from large data sets or databases, focusing on issues relating to their feasibility, usefulness, effectiveness, and scalability. In other words, a person, under a particular situation, working with specific data sets and pursuing well-defined objectives, executes it. (Gung 2016)

There is a lot of discussion around the proper definition of data mining and how it differs from machine-learning. Many authors and researchers in the area are still in some level of disagree. However, data mining researchers Jiawei Han and Micheline Kamber, in their book *Data Mining: Concepts and Techniques*, provide a formal definition:

"Data mining also popularly referred to as knowledge discovery from data (KDD), is the automated or convenient extraction of patterns representing knowledge implicitly stored or captured in large databases, data warehouses, the Web, other massive information repositories, or data streams." (Han and Kamber 2006)

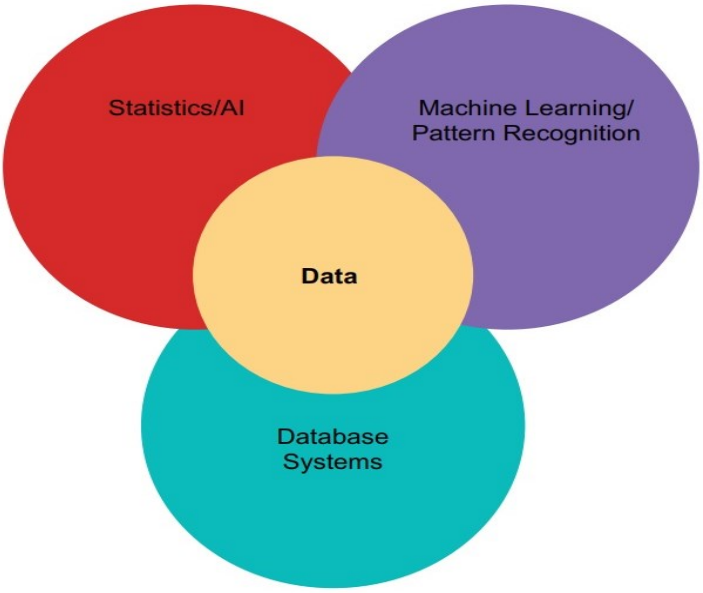


Figure 3 Data Mining system (Abou-Sayed 2012)

Considering that every time vast amounts of data are being created, transmitted and stored on more frequent time basis, data mining serves the purpose of providing a description of the observed data regardless its volume or type. Research and commercial interest align with this demand with the development of software solutions designed and dedicated exclusively to handle massive amount of data, including algorithms and tools to simplifier its process.

The term is not yet commonly used in the O&G industry; for that reason, some of its functionalities and common applications should be shallow discussed to recognize its value for the industry. There are two main tasks that can be performed using data mining: descriptive and predictive. Descriptive tasks characterize the main features or general properties of the data in a convenient way. The objective is to derive patterns, which summarize the relationships in the data. On the other hand, predictive tasks interpret the current data to model a future behaviour for some variables based on values of other known variables.

To perform any of the tasks, a suite of techniques are employed. The selected approach is highly depended on the nature of the task and the availability of the data. Some of the techniques include Statistics, Artificial Intelligence (AI), Pattern Recognition, Machine Learning, and Data Systems analysis.

2.2 Functionalities

In order to be familiar with the terminology used in the framework of data mining, it is important to properly segregate some common terms like model and pattern. A model is a global concept that provides a full description of the data and can be apply to all points in the database. On the other hand, a pattern corresponds to a local description of some subset of the data that can hold for some variables, but not for all of them. Patterns are used to extract unusual structures within the data and are valuable for both main mining tasks. Then data mining techniques can be classified based on different criteria like: the type of database to be mined, the type of knowledge to be discovered, and the types of methods to be used. (Platon and Amazouz 2007)

Because it is a field in constant change, there are sort of best algorithms for certain problems, and with pragmatic rules of thumb about when to apply each technique to make it highly effective. Usually, a data mining system consists of a set of elements for tasks such as characterization, association and correlation analysis, classification, prediction, cluster analysis, outlier analysis, and evolution analysis. In addition, there are a several variations of those tasks, resulting in new algorithms, considered in some cases as “new techniques.” For the purpose of this thesis, only the broad classes of data mining algorithms will be discussed. (Pinki, Prinima and Indu 2017)

2.2.1 Concept/Class Description: Characterization and Discrimination

Class/Concept description refers to the advantage of associating data with classes or concepts for summaries of individual descriptions based on these precise terms.

There are three techniques used to derive this description:

- Data Characterization: the class of interest, also referred as target class, is summarized in general terms or, based on its features.
- Data Discrimination: the general features of the class under study are compared with the general features of one or more comparative classes, to obtain a contrast between them.
- Combination of both data characterization and discrimination.

The methods used for characterization and discrimination include summaries and output presentations based on statistical measures, generalized relations, in rule forms and descriptive plots like: bar charts, curves, pie charts, multidimensional tables, and so on.

2.2.2 Frequent Patterns, Associations, and Correlations

Frequent Patterns corresponds to one of the most basic techniques and is about learning to recognize frequent patterns in data sets. It is usually based on distinguishing aberrations in data happening at regular intervals over time. Different kinds of frequent patterns include:

- Frequent item-sets: denote a set of items that recurrently appear together in a transactional data set.
- Frequent sequential pattern: refer to a pattern occurring in a sub-sequential trend, one after another, repeatedly.
- Frequent sub-structured pattern: occur when different structural arrangements take place on a regular basis. The form of those arrangements can be graphs, trees or lattices, and may be combined with sub-sequences or item-sets.

Associations and correlations occur when frequent patterns within the data are tracked in a more specific way to dependently link variables. In the association analysis, two groups can be distinguished related to the number of attributes/dimensions:

- Single-dimensional association rule: Involves a single attribute or predicate that repeats (i.e., buy)
- Multidimensional association rule: Consists of more than one attribute or predicate (i.e., age, income, and buy).

When certain association rules are considered interesting, statistical correlations can be applied to show whether and, how strongly associated attribute–values pairs relate.

2.2.3 Classification and Prediction

A more complex and commonly applied mining technique is classification, where a model is created to describe and differentiate data classes/concepts and then collect them together into discernable categories. The final aim is to use the model, derived from the known data, also known as 'training data', to make predictions of the data labelled as unknown.

There are a number of forms to represent the model, for example using:

- Classification rules: with the function IF – THEN.
- Decision trees: creating a flow chart via an algorithm based on the "information gain" of the attributes. Basically, each node is tested on an attribute value, where the tree brands represent the outcome and the leaves denote the class distribution.
- k-nearest neighbour (k-NN) classification: uses the data to determine the model structure by not making assumptions on the original data distribution (non-parametric) but learning based on feature similarity. Hence, it does not do

generalization based on the training data rather it utilizes the training data for the testing phase.

- Neural networks: structurally consist of many small units called neurones, and it is a powerful mathematical tool for solving problems. The neurons are linked to each other into layers, and cooperate to propagate the inputs using weighted connections through 'activation functions'. Then the Bias values are converted mathematically to continue the transformation of the inputs into outputs in the best possible manner. (Solesa 2017)
- Support Vector Machine: combines linear modelling and instance-based learning to overcome the limitations of linear boundaries. It relies in selecting a small number of critical boundary instances, called support vectors from each class, and build a linear discriminant function that separates them as widely as possible. The result permits the inclusion of extra nonlinear terms in the function, in order to form higher-order decision boundaries. (Witten and Frank 2005)
- Naïve Bayesian: it's based on the Bayes's rule (named after Rev. Thomas Bayes 1702-1761) and is mainly appropriate when the dimensionality of the inputs is high, i.e., in a simplistic way, it assumes independency between attributes. This technique works well when combined with procedures to eliminate redundancy (non-independent attributes). The algorithm output will be a function of the prior probability, based on previous experience, and the likelihood for a new object to be classified in a certain class. Naïve Bayes miscarries if a particular attribute value does not occur in the training set along with every class value. (Witten and Frank 2005)

Though conventionally the term prediction is used in reference to numeric prediction as class label prediction, more precisely, classification is used for categorical predictions labels (discrete, unordered), and prediction to emphasize models describing continuous-valued functions. In this context, regression analysis appears as a statistical methodology, commonly used for numeric prediction. However, other methods exist and could also provide a good performance.

2.2.4 Outlier Detection

In many cases, data sets may include anomalies, or outliers, i.e., data that do not comply with the general behaviour or model of the data, data that need to be identified and demand investigation to get a clear understanding of the data set. In general, data mining offers algorithms to discard outliers as noise or exceptions. This type of data could affect data analysis and therefore, needs to be excluded.

This functionality can also serve other purpose, when anomalies can provide information of interest, like for example, in cases of fraud detection using credit cards to purchase extremely large amounts compare to regular transactions.

Outlier detection is possible conventionally through statistical tests, where a certain type of distribution is assumed, or by using probability models to discard anomalies. Other methods include the use of distance or density measures, where examples substantially far or with less data density from any other cluster are identified as outliers. On the other hand, deviation-based methods, compare the main characteristics between examples and by examining the differences set apart outliers.

2.2.5 Cluster Analysis

Clustering seems similar to classification, but involves grouping amounts of data without a specific known class label, using only their similarities. Clustering, can in fact, be used to generate the necessary labels.

The principle used to group the data search for examples to maximize their intraclass similarities within the group, and at the same time, to minimize the intraclass similarities with other groups. The final result is different groups (clusters) in a way that examples in the same group are similar to each other but different from examples in other groups. Groups are clearly distinguished and can be used to derive rules. (Han and Kamber 2006)

Different techniques are used for clustering, where the most common examples are hierarchical clustering and *k*-means clustering. (Abou-Sayed 2012)

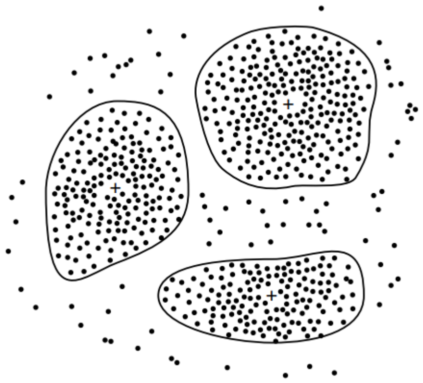


Figure 4 Plot of customer data in relation to its location in a city. Three data clusters are clearly identified (Han and Kamber 2006)

2.2.6 Regression

It is a statistical method used to approximate the given data primarily as a form of planning and modelling continues values. There are different types of regression analysis, but the principle consist in evaluating the influence of one or more independent variables on a dependent variable. It allows examining the likelihood of a certain variable, in the presence of other variables, providing a way to uncover the exact relationship between two or more variables in a certain data set.

The simplest form is called linear regression, where the response variable can be modelled as a linear function of another variable. In the event when two or more variables have a linear relationship with the dependent variable, the regression is then known as multiple linear regression. Linear regression is very sensitive to outliers, which can distort the calculation.

Multiple regression is an extension of the simple form, used to predict a relationship between multiple variables, which increases the complexity of the prediction.

Some of the most popular types of Regression are Logistic Regression, Polynomial Regression, Stepwise Regression, Ridge Regression, Lasso Regression, among others. Each one following specific conditions to better suits problems (Ray 2015).

2.3 Common Applications

Data mining is widely popular in credit risk applications and in cases of fraud detection. The common technique applied is Classification, where a model is developed employing pre-classified examples and then categorize the records through decision tree or neural network-based classification algorithms. Outlier detection is also used for fraud detection, where the outliers become the data of interest. In general, during the process, it is necessary to include records of valid and fraudulent activities to properly train the model on how to determine the required parameters to do the discrimination. (Pinki, Prinima and Indu 2017)

Data mining is also being used successfully in industrial process applications, in areas that include process monitoring, fault detection and diagnosis, process-related decision-making support to improve process understanding, soft sensors, process parameter inference, and many others. Each application demands different techniques along with different types of data bases. However, one of the most popular techniques for prediction modelling is based on neural network approaches due to its well-known predictive capabilities. In some cases, a combination of various methods can also be used to create hybrid models and overcome individual limitations to achieve the proposed objective. (Platon and Amazouz 2007)

Retailer analysis of buying patterns is another classical application of data mining, where its solving problems proficiency of analysing long time stored databases full of data of customer actions and loyalty represents an open door for the marketplaces. In every transaction, customers expose their choices, along with some of their profile data, that when properly processed results in patterns of customer behaviour. This information allows to identify distinguishing characteristics related to their loyalty and churn likelihood to certain products. The results provide client’s profile identification and clients preferences that can be worked as inputs for marketing strategies, market predictions, to serve a customer oriented economy where increasing sales is the final aim. As an example, the giant Wal-Mart can be cited, which transfers all its relevant daily transactions to a data warehouse collecting terabytes of data, that is also accessible to its suppliers enabling them to extract the information regarding customer buying patterns and shopping habits, as well as most shopped days, most sought for products, and so on.

There are many other specific applications. Like screening images with a hazard detection system to identify oil slicks from satellite images and give an earlier warning of ecological disasters. For the forecast of the load for the electricity supply industry based on historical records of consumption. In the medicine field, for best treatment selection and in human in vitro fertilization where over 60 recorded features of the embryos need to be analysed simultaneously; and countless more applications. (Witten and Frank 2005)

2.4 Applications in the Industry

It has been estimated that a large offshore field delivers more than 0.75 terabytes of data weekly, and a large refinery 1 terabyte of raw data per day. References have been made to input/output points somewhere between 4000 and 10000 per second. (Abou-Sayed 2012) With this amount of data flowing constantly, the key lies in ensuring that the right information reaches the right people at the right time.

The industry's emphasis has been normally on monitoring and assurance of production; therefore, some Operators and Service Companies recognizing the potential of data mining have started to make important investments in that direction. Some examples of the potential of data mining that are already applied to optimize solutions are related to:

- Predict well productivity, reservoir recovery factors, and decline rate.
- Identify key drivers for performance of producers and water injectors subjected to multiple factors like high pressures and temperature.
- Defining best practices in completion.
- Minimizing production downtime and well intervention costs.
- Extend production life of wells.

Data Mining scope is still uncertain. Therefore some interesting advances are further discussed showing it application in three different disciplines. The first example refers to Reservoir Management and how supported on seismic data it is possible to identify and advice regarding sweet spots. The second example is related to Wellbore stability, and how data can be used to prevent some of the causes and the associated risks. In the last case, an application for Formation Evaluation predictions is presented as an alternative to reduce completion costs.

2.4.1 Example 1 - Reservoir Management

British Petroleum (BP) along with Beyond Limits are working on a project to absorb the learnings of petrotechnical experts, like geologists and petroleum engineers, using cognitive computing to imitate their decision-making processes as they work on subsurface challenges.

The first joint program is already running since July-2018 with a group of BP's upstream engineering team aiming that their expertise train the system and remain longer digitally. It was meant to be used on the job, in a way that a number of Artificial Intelligent (AI)-agents constantly interact with members of the team to start building experience, learn the art of solving problems and store knowledge further. It starts as a design tool, with a process of learning to become a recommendation tool that with experience can build trust, to later be used as a control system. In a glimpse of the early stage of the project, BP is expecting from the system answers on how to mitigate the impact of sand production with prediction and advice with asphaltene buildups in a well.

A cognitive computing system involves self-learning technologies that use basic analytics, deep learning, data mining, pattern recognition, and natural language processing to solve problems the way humans solve problems, by thinking, reasoning and remembering. It can combine data from different information sources, weigh its context, and solve conflicts using the evidence to propose the best possible answers. Through deep learning, the information is processed in layers where the output from one layer becomes the input for the next one, improving the result. (Jacobs, Journal of Petroleum Technology 2018)

BP's interest on Beyond Limits arose due to its work with Jet Propulsion Laboratory (JPL) on the real Mars rovers Curiosity. One of their principals was the author of a distinctive AI program in charge of managing one of the rover's battery. The outstanding was that when the program detected that the solar panels were suffering from dust storms, it autonomously accessed data from pressure and temperature sensors with the purpose of building a weather model in order to understand how to properly orient its solar panels to prevent dust from storms. This aligns with the definition of AI as "the science of making computers do things that require intelligence when done by humans" (Evans 2017). In the Curiosity mission, the program was capable to execute a task that was not designed in its model.

Beyond Limits is relatively new and not exclusive to the Oil & Gas industry, therefore unknown. However, it is developing a system, referred as Reservoir Management advisor, that will learn from geologists and reservoir engineers as they search for sweet spots in offshore seismic data to recommend probable well locations, and the more suitable well designs to maximize the recovery of hydrocarbons. It is supported on another software called Sherlock IQ, born from the experience on the rover program and based on machine cognition to autonomously shift through different paths of data to discover specific details and scenarios that ultimately will allow it to assess risks. It is expected to become reliable, faster, and capable to appraise more data in a period of just few hours, to complement the work of real experts, which usually can take months.

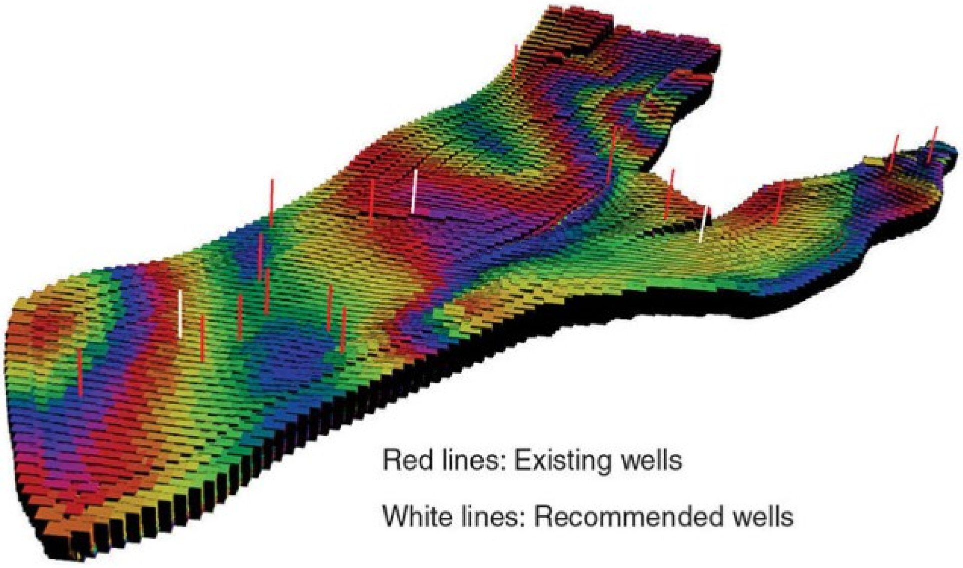


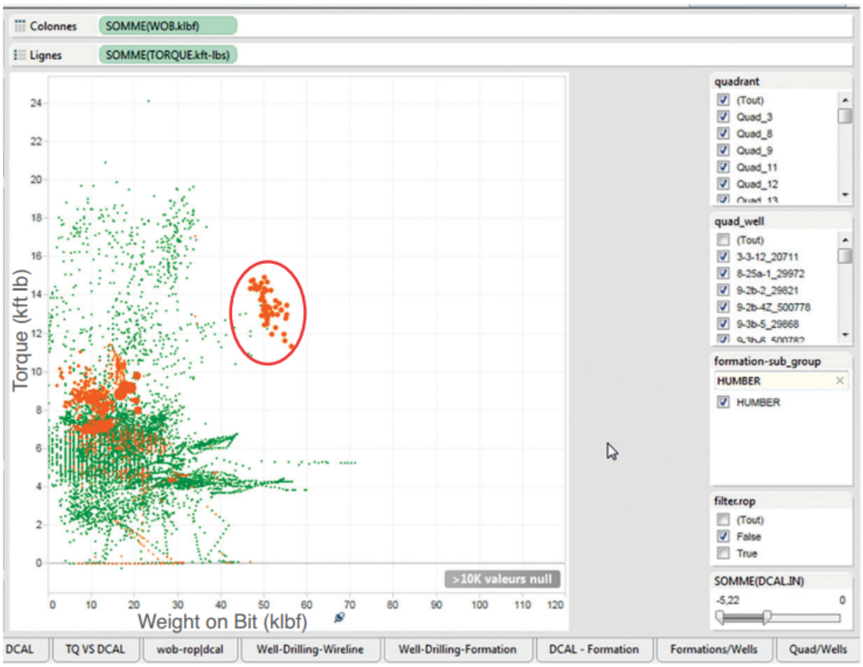
Figure 5 Beyond Limits Reservoir Management advisor (Jacobs, Journal of Petroleum Technology 2018)

2.4.2 Example 2 – Data Mining to Understand Drilling Conditions.

Lately terminologies like "intelligent wells" or "digital oilfields" are becoming more and more oft used, according to how data use is changing in the industry. The usual approach of established workflows using only specific set of relationships between variables, like linking core data to well logs, has become obsolete.

Data mining functionality along with the proper technology allow to work with disparate data types structured and unstructured, and with different degrees of accuracy and granularity. The combination enables rapid associations between data that normally would be assumed not linked. This perspective was tested by the UK Department of Energy & Climate Change, with a project together with CGG as the official UK Continental Shelf data release agent. The study purpose was to improve drilling results using data mining main tasks: descriptive modelling and predictive relationships. More specifically the project's aim was to find out the optimum conditions for drilling efficiency and identify the high-risk situations.

A total of 350 wells located in the UK North Sea were used for the study in the form of 20000 files with different formats but including data from Well logs, well geographical locations, drilling parameters, geological reports, and well deviations. All data was thoroughly loaded, quality controlled and finally used for the analysis. The caliper reading was determined as the main reference, to identify poor hole conditions, by normalizing it with the bit size. Other drilling parameters in detail used were: Torque, Weight on Bit (WOB), and ROP. The visualization tool allowed to combine and contrast the inputs/variables in order to understand how its variations affect borehole quality. (Johnston and Aurelien 2015)



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☑ False
☐ True

SOMME(DCAL.IN)
-5,22 0

Figure 6 Anomaly Detection: A high risk situation was identified (Johnston and Aurelien 2015)

Data mining revealed its functionality working with big amount of data and performing better than the usual approach and in very short period. Figure 6, is an example of how anomaly detection was possible using one of the visualization tools. It showed the case of a single well well where an increase of WOB, ended in poor hole conditions and affecting the reading of the caliper measurement. Subsequently, it was found that the well faced logging stuck issues and forced an extra wiper trip. In conclusion, a high risk situation was identified.

There were more discoveries as result of the study, which included some predictive statistics meant to provide valuable information to drill future wells in the same area hopefully with less problems.

2.4.3 Example 3 – Predictions of Formation Evaluation Measurements to Replace Logging Tools used in Lateral Sections.

The shale revolution growth over the past two decades positioned United States in the top of oil producers worldwide, competing with Saudi Arabia and Russia (Donnelly 2019). However, the threat of the low oil price market after the crisis at the end of 2014, forced producers to become extremely efficient, to cut costs, and to look for innovation. In this regard, in the Eagle Ford Shale in Texas, the EOG Resources reported a decrease of 70% in the average drilling days from 14.2 during 2012 to 4.3 in 2015. The curios side of this improvement in efficiency relates to the overall cost per well, which only decreased a 20%, from USD 7.2 million to USD 5.7 million. The discrepancy is due to the completion cost, being the major contributor and independent of any possible improvement in efficiency during operations (Parshall 2015). Innovation was on demand.

It is important to bear in mind that to provide smart completions, the location of stages and perforation clusters is essential and currently engineering designed using formation evaluation technology. This technology, known by being costly, must be add to the already considerable cost per stage, where experience has shown that between 30% and 50% of the perforation clusters do not even produce. This situation caught the attention of Quantico Energy Solutions, a data driven company, understanding the need of more and better information about the reservoirs and its geological complexity without the investment required by conventional logs.

The necessity of innovation became stronger due to the way shale fields are developed where operators can afford to log few appraisal wells but not all the subsequent wells, which ideally should be smartly completed too. Therefore, data mining became an alternative, considering a scenario where already thousands of wells in the area have been drilled, collecting not just important geological data from logging tools and cutting samples, but also a huge amount of data regarding drilling parameters, completion and production.

After a two years research, Quantico Energy Solutions, supported by several major shale operators, along with industry specialist in neural networks and openhole logging tool designers, developed a source of formation evaluation characteristics, called QLog. It is a commercial logging system based on machine-learning software that trained neural networks models using the drilling and logging data from horizontal wells collected for years by operators. It is capable to simulate compressional, shear, and density logs on horizontal wells to prevent the use of expensive logging tools. With the results, it is possible to derive elastic properties such as Young's modulus, Poisson's ratio, horizontal stress, and brittleness, fundamental to engineer the completions. Actually, later on, the company developed QFrac software, which using the simulated results, is able to recommend engineered stage locations.

The success of the system, requiring less investment compared to the actual design and test of physical logging tools, created a network effect where more operators decided to step in, providing more data. In consequence, a real time simulator service was developed, QDrill, to assist drillers with well placement operations too. It is a software based on artificial intelligence, that provides petrophysical properties of a reservoir. The algorithm was developed using several hundred wells for many basins that have the measured well logs along with the drilling data. It was designed to use as input, gamma ray logs and drilling dynamics parameters, like ROP, WOB, torque, and so on.

There are several advantages in using data mining to simulate formation evaluation logs. Starting with the reduction of capital expenses, with savings up to 80% of conventional logging costs. Other benefits include no nuclear or acoustic sources in the well (Quantico Energy 2019). In fact, models for specific fields can be generated in few days. However, the main advantage is the elimination of the risks of running expensive logging tools with the latent possibility of being stuck, or in the worse scenario lost-in-hole. Specially, when the results of simulations have shown repeatable accuracy consistent with the one obtained by logging tools in both deep-water and land wells.

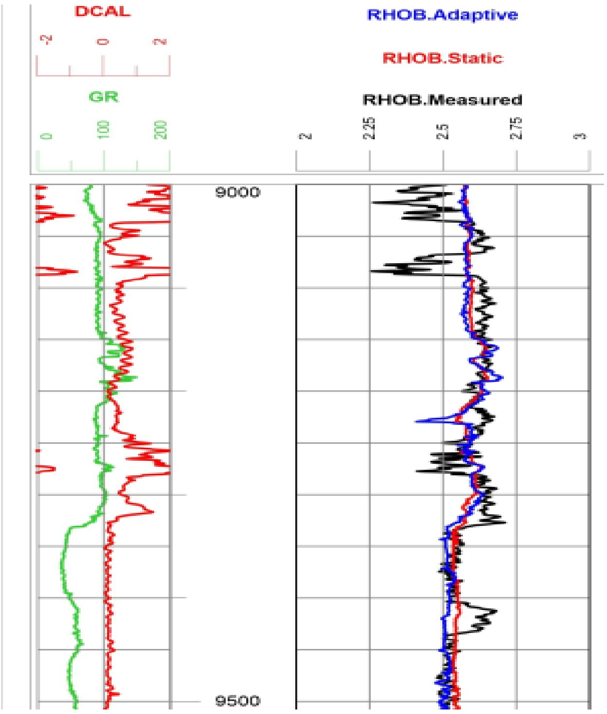


Figure 7 Differences were less than the precision of the logging tools, where Real Time measuremets are highly depended of the hole conditions and largely affected by hole washouts (Zhang 2018)

Figure 7, refers to a case study in the Midcontinent region of the U.S., where the target was a formation with a clastic laminated/layered sandstone reservoir. The AI model was prepared and the client drilled two laterals sections using Quantico logs for real time geosteering interpretations to place completion stages in areas with higher porosity intervals and equalizing minimum horizontal stress across stages. To compare predicative accuracy and repeatability of the model with the real time measurements, two models were used: one static, based on information from proprietary database, and one adaptive, constantly incorporating in the training set the data acquired from logging tools. The results showed negligible differences between the bulk densities from both models in relation to the one measured by logging tools (Zhang 2018).

Chapter 3 Measurements and Data

The first step in data mining consist in gathering all relevant data for the study, which might not be an obvious task. This is why it is important to state a clear objective to identify the necessary data. In this regard and, as earlier mentioned, the aim for this work looks for a better understanding of the ROP measurement, which in operations is the reflection of the drilling conditions, and include among others, the drilling parameters set while drilling. Thus, prior to mining the data, it is key to understand which are the main measurements and sensors involved during drilling operations and providing the data, as well as some relevant concepts and considerations regarding the data itself.

3.1 Sensors and Rate of Penetration

3.1.1 Sensors Measurements

There are different number and type of sensors involved during normal drilling operations. This is highly related to the nature of the rig, the sort of operation, and the available budget. Sensors are used in the process to measure parameters, and their outputs are the values that provide these parameters' descriptions.

It is important to distinguish how some measurements are originated with sensors installed on surface while others come from downhole sensors included in the tools used in the Bottom Hole Assembly (BHA). In addition, there are different types of measurements, some are direct and others indirect. Finally, two domains are working in parallel, so data measurements are acquired in Time and Depth.

In general, there are more less 10 key measurements obtained from surface sensors. However, due to the scope of the present work, only some of the main and most common measurements will be discussed, as they provide input for further analysis and modelling. Table 1 summarizes the surface sensor measurements, normally acquired by the mud logging service provider during daily drilling operations, with a brief description for each attribute (Nguyen 1996).

As previously mentioned, data is acquired in two domains, being DEPTH one of them; for that reason, this attribute is by far the most important one regarding measurements. Nevertheless, concerning rig operations, there are three measurements that are indispensable for operations: hook load, rotation and pump discharge pressure.

Besides, the majority of these measurements are indirect, demanding a certain level of interpretation along with regular on site calibration and thus more susceptible to human error.

Attributes	Description
Hole Depth [DEPTH]	Permits depth tracking and refers to the most recent position of the Bit while drilling along the trajectory.
Hook load [WOH]	Correspond to the average value of the weight/load on the Hook.
Rate of Penetration [ROPins]	Calculate the rate of movement of the Bit while drilling in a certain interval.
Rotation per Minute [RPM]	Provides the average revolutions transmitted to the drill-string by the Top Drive.
Standpipe Pressure [SPP]	Indicates the average Pressure delivered by the pumps. Usually measured at the Standpipe.
Weight on Bit [WOB]	Calculated as the difference between the weight on the hook while off bottom and on bottom.
Torque [TRQ]	Average torque in the drill-string.
Flow Rate [FLOW]	Average flow rate delivered by mud pumps, usually referred as Flow in.

Table 1 Summary of Attributes coming from surface sensors

Downhole measurements are also indirect, but in most of the cases, its calibration process is more rigorous and normally performed only in the workshop and under specific conditions, i.e., yearly, once per job, etc. Downhole measurements are mainly used for wellbore positioning, directional work, and formation evaluation. Table 2 shows the attributes related to the directional work and obtained from downhole sensors. It includes DEPTH, which is measured on surface and adjusted to the offset of the downhole sensors position in the BHA. It is necessary as point of reference.

Attributes	Description
Depth [DEPTH]	Corresponds to the depth position of the sensor in the borehole while taking the measurement.
Inclination [Inclination]	Provides the deviation of the borehole in relation to the vertical.
Azimuth [Aimuth]	Gives the position of the borehole regarding the North and projected onto a horizontal plane.
Build Rate [BR]	Refer to the incremental increase or decrease in inclination angle from vertical, specified in degrees per 100 ft. or per 30 m. (Azar and Samuel 2007)
Turn Rate [TR]	Provides a measurement of the incremental change in azimuth per 100 ft. or per 30 m (Azar and Samuel 2007).
Dogleg Severity [DLS]	Describe the amount of change in the inclination and/or direction of a wellbore. Also expressed in degrees per 100 ft. or per 30 m (Carden 2007)

Table 2 Attribute related to the directional work

With a first glimpse of the measurements involved in this study, it is important to discuss one in further detail: ROP. During normal drilling operations, this parameter is of main concern due to its influence in drilling performance and efficiency, and therefore in drilling costs.

3.1.2 Rate of Penetration (ROP)

The ROP is defined as the "advancement in unit time, while the drill bit is on bottom and drilling ahead" and the factors affecting it are categorized in three main groups (Mensa-Wilmot, et al. 2010):

1. Planning.
2. Environment.
3. Execution.

The first group, is defined during the planning stage and includes: Hole size and casing depths, well profile, drive mechanism selected to drill (Motor, RSS, etc.), BHA configuration, bit selection (aggressiveness of the design), bit hydraulic horse power per square inch (HSI), flow rate, drilling fluid type and rheology properties and hole cleaning. From the listed factors, it is important to notice that hole size, bit selection, HSI, drive mechanism, and BHA are constant for a run, i.e., since the BHA is running in hole until it is pulled out of hole again.

The environment category refers to the lithology of the area, the formation drillability (rock strength, abrasiveness, etc.), the pressure conditions (differential and hydrostatic) and the deviation tendencies, among others. The differential pressure and deviation tendencies are in constant change during well construction. However, the formation related factors could be considered constant for a specific area or field.

Last, but not least, are the execution factors: Weight-on-bit (WOB), RPM, drilling dynamics, etc. (IADC 2014). These factors also change constantly and are an essential part of the drilling parameters set on surface to construct a well in order to follow a trajectory previously planned. It is important to consider that some technical limitations exist in this regard. For example, the bit selection usually determined the maximum WOB applicable. In the same way, the maximum RPM are limited by rig capability; also in relation to the BHA configuration, the motor bent housing in case of its use as deflection tool, the resulted torque, the well profile, vibrations, and many others.

For instances, it is necessary to differentiate between the two main types of ROP, the average and the instantaneous. The average is used as a description of the measurement over a certain interval or in relation to a particular BHA. The concept of instantaneous ROP, on the other hand, refers to the measurement over a finite time or distance and offers a reference in real time (Mensa-Wilmot, et al. 2010).

3.2 Data Type

Working with data usually represents a challenge because the majority of the data is collected in an unstructured way, which means it does not involve a pre-defined data model or it is simply not organized in a pre-defined manner. Therefore, it becomes important to understand how to work with different data sets based on the final aim. By definition "an attribute is a property or characteristic of an object, that may vary, either from one object to another or from one time to another" (Tan, Steinbach and Kumar 2006). The description of data is done by using different attributes, which not only differ in its values but might also vary in its type.

At the most basic level, the physical value for different attributes are mapped as numbers or symbols, where the values used to represent an attribute may have properties that are not properties of the attribute itself, and vice versa. A way to differentiate the types of attributes is to recognise the properties of numbers associated to the properties of the attribute. Four main operations are used to distinguish between attributes:

1. Distinctness.
2. Order.
3. Addition.
4. Multiplication.

Resulting in four types of attributes, with specific properties and operations clearly defined and valid for each type (Tan, Steinbach and Kumar 2006):

1. Nominal: Provide enough information to distinguish one object from another (=, ≠). For example, gender, ID numbers, etc.
2. Ordinal: Based on the information objects can be ordered with a logic criteria (<, >). For example, grades, costs, quality, etc.
3. Interval: The differences between values are meaningful (+, -). For example, temperature in Celsius or Fahrenheit, where a unit of measurement exists.
4. Ratio: The differences and ratios between values are meaningful. For example, monetary quantities, age, length, etc.

The first and second type of attribute are commonly denoted as categorical or qualitative, and cannot be treated as numbers, even if represented by numbers, because of its absence of the properties of numbers. In contrast, the last two types of attributes are usually referred to as quantitative or numeric, and are not only represented by numbers but actually, those numbers have direct meaning as measurement and have most of the properties of numbers.

In addition, attributes can also be classified based on their numeric values, which can be discrete or continuous. Discrete attributes are usually represented using integer variables and have a finite set of values, i.e., can only take certain values. A special subgroup of discrete attributes is binary attributes, where only two values are possible (0 or 1, True or False, etc.) and often represented as Boolean variables. Continuous attributes are essentially real numbers, can occupy any value over a continuous range and are represented as floating-point variables. Normally, categorical attributes are discrete, while numeric attributes are continuous.

3.3 Data Issues, Limitations and Resource Constraints

The most time consuming stage during any application of data mining corresponds to the preparation of the data for processing. This includes collecting and cleaning the data. Surveys show that between 60 to 80% of the time is designated to this purpose.

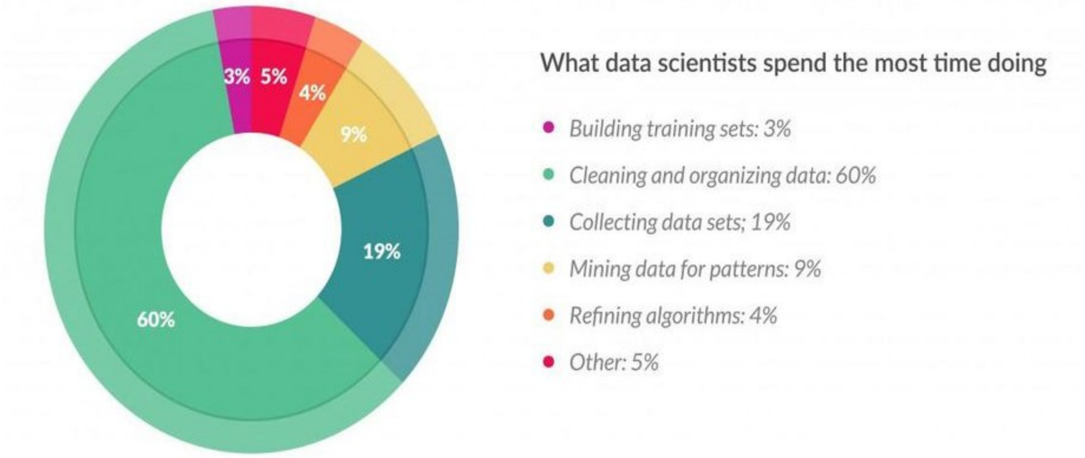


Figure 8 Results of survey between data scientists showing the time needed to massage the data prior its use (Press 2016)

There are several measurements and data collection issues. Mainly, related to human error, limitation of measuring devices, or defects in the data collection process, which includes inappropriate sensor installation or poor understanding of the physics involved behind the measurement (Maidla, et al. 2018). Therefore, it is very common to find missing data, duplicate objects, outliers, and inconsistent values.

Typical errors during the measurement process result in differences between the recorded value and the true value, which is known as discrepancy. This can happen due to several reasons like a sensor defect, the used of wrong calibrations or an inadequate installation. Other common problems involve facing noise in the signal or simply lack of maintenance, allowing debris or humidity to affect the measurement. Signal noise is normally associated with spatial or temporal components that result in spiking signals distorting the measurement (Tan, Steinbach and Kumar 2006).

Errors concerning the data collection process include omitting relevant data or the inappropriate inclusion of data, which is not suitable for the analysis. Moreover, lack of availability of data. Finally, yet importantly, data frequency and range must as well be considered, because it can affect the granularity of the data, having an impact on the results.

Some illustrations in this regard can be found in Figure 9, where the standpipe pressure measurement correspond to the reading of a pressure transducer installed in the manifold. When the sensor is wrong placed, with a plausible closed valve in the fluid path, the reading could suggest a false pumps off. Figure 10, on the other hand, shows the mounting of a Hookload sensor (Clamp Line Tensor - CLT Type) on the drill line about 6-8 ft. above the dead line anchor. It's reading could be affected by drill line vibrations when not properly adjusted or when installed too far from the anchor. Finally, debris and humidity are a concern in all sensor connections, which are constantly exposed to the environmental conditions.

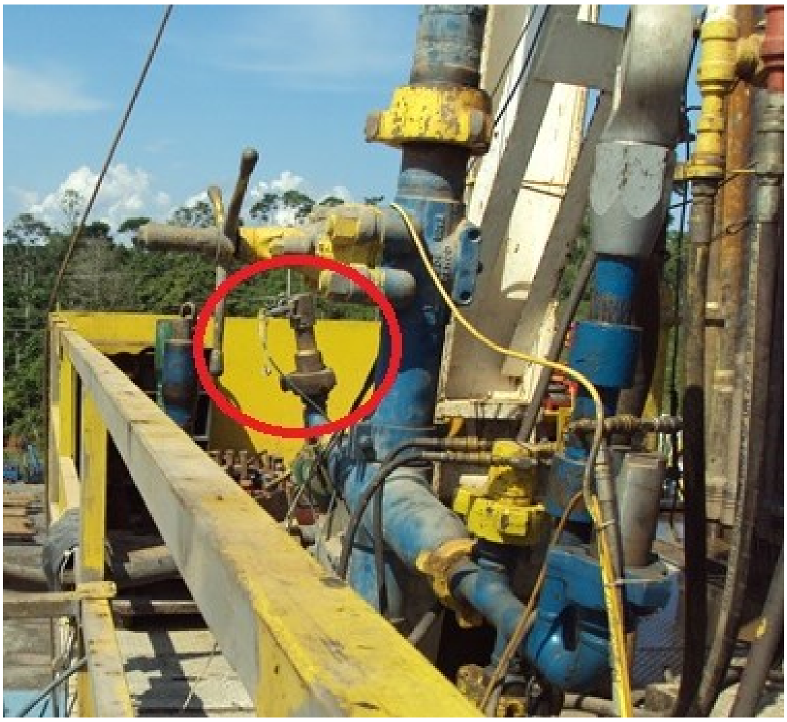


Figure 9 Pressure Transducer installed in manifold on the rig floor

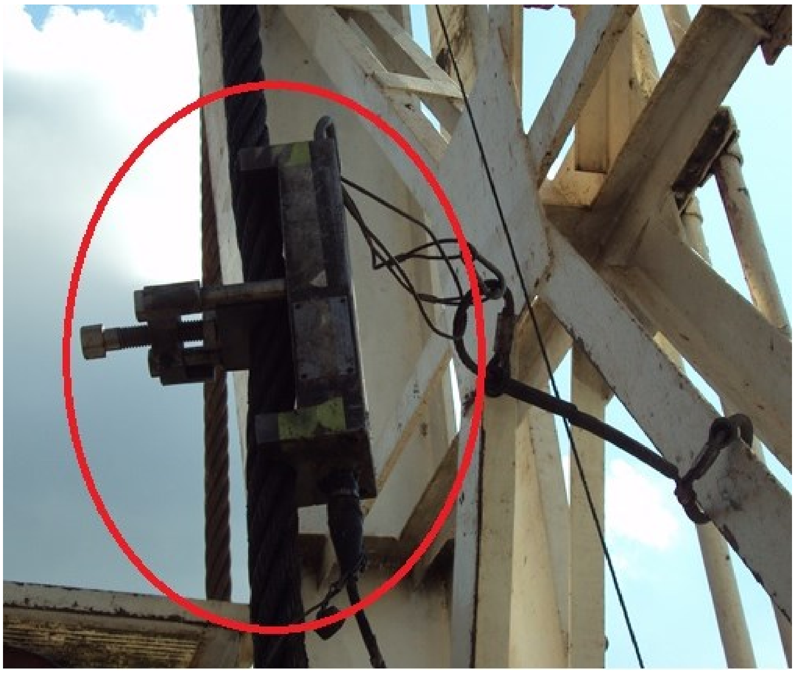


Figure 10 Hookload sensor installed in the drill line

Chapter 4 Methodology

With the clear objective of modelling the ROP response based on drilling data and considering all the factors influencing it, along with the data available for the project, the following general structure was developed:

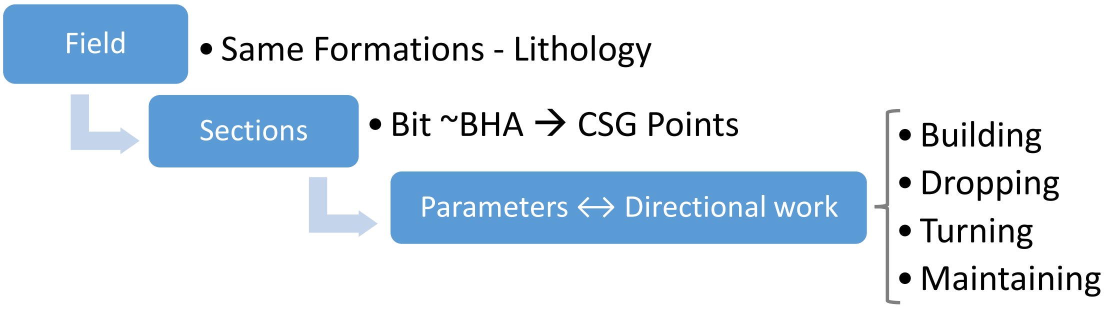


Figure 11 General structure for the methodology

It was clear that the starting point was to gather data from the same field. Wells drilled in the same field, normally share the same geology, lithology, formation drillability and even face similar issues while drilling. The second important point relates the well schematic. Yet again, wells drilled in the same field are prone to share similar well schematics, i.e., hole sizes, CSG depths, fluid type, bit selection, well profiles, etc.

Then, the last point refers to the drilling parameters. Ideally, in this context, the same rig would be used to drill all the wells in the field. Therefore the technical limitations would be the same. In addition, a relation between the directional work and the drilling parameters is posed, as they are linked and usually defined between the Directional Driller, the Bit engineer and the Company Man. By gathering enough data, data mining techniques can be used to train the model that allows predicting the ROP, providing a point of reference to assess the performance of a new well, hoping for insights of potential factors affecting its result.

Based on the general structure, Figure 12 shows the specific phases defined to cover all aspects involved in the methodology workflow.

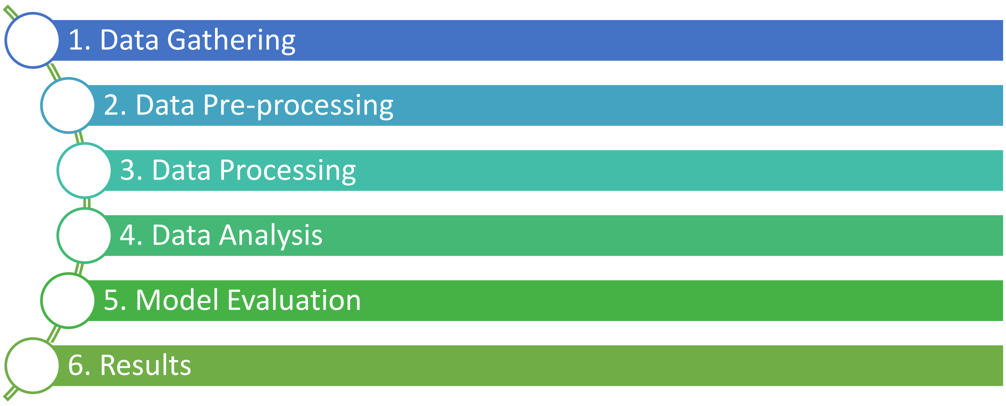


Figure 12 Phases for the workflow

In the following sections, only the first four phases of the workflow will be explained in detail, and the other ones will be covered in the next chapter.

4.1 Data Gathering

Data confidentiality is the most important clause in any company, especially when there is so much in gamble with high monetary investments and considerable environmental associated risks. Therefore, obtaining data is the first challenge.

In this regard, drilling operations are described using different means in the form of reports. For this project, it was possible to collect a limited amount of data to work with. The data set consisted of different files, with different formats and granularity, from four wells drilled onshore, and in the same field with the same rig.

Parameter	Well_1	Well_2	Well_3	Well_4
TD MD/TVD	11250 / 10838	12330 / 10600	11660 / 10800	11455 / 10823
VS	2794	3188	3553	3204
Section1 MD/TVD	6490 / 6267.4	6280 / 6247.15	6502 / 6225.1	6520 / 6253.18
Section2 MD/TVD	10387 / 9988.02	10493 / 10010.93	10820 / 10001.53	10627 / 10011.60
Section3 MD/TVD	11250 / 10838.22	11950 / 10587.33	11660 / 10800.66	11455 / 10823.34
Section4 MD/TVD		12330 / 10600.12		
Max. Inc/VSA [°]	18.476 / 136.087	88.794 / 98.375	30.993 / 35.682	25.66 / 158.608
Well Type	S / 2D	Horizontal / 3D	S / 2D	S / 2D

Table 3 Well candidates' basic details. All units related to distances are in feet [ft]

Following the main objective of this work along with the general structure described in Figure 11 for the methodology, only the reports available for this thesis and with potential impact on the ROP are further explained:

- Survey Listing: refers to the well profile, which is the result of the drilling parameters used to build the trajectory, and therefore influencing the ROP.
- BHA Report: includes information about the Bit size (i.e. hole size), its type (cutting mechanism), position of the stabilizers and the deflection tool used. Component affecting the resulted ROP.
- LAS Files: presents a list of all sensors measurements taken on surface, including the ROP, in other words, summarizing with different granularities and domains, the parameters used during operations. The number of sensors installed varies according to the mud logging company contract.
- Geological Topes List: provides a simple description of the different formations from the surface to the target. It usually states the names used to identify each formation tope in relation to its MD and TVD. Formation names vary according to the geographical location. This document differs from the Geological Report, which is a much more detailed description of the cuttings and its composition. In this case, the geological topes list was included with the Survey Listing.

In relation to the well candidates, the following files were shared for this project:

Files	Well_1	Well_2	Well_3	Well_4
Survey Listing	✓	✓	✓	✓
No. BHA's	5	11	4	6
BHA Template	✓	✓	✓	✓
Depth LAS File	✓	✓	✓	✓
Time LAS File	×	×	×	×
Geological Topes	✓	✓	✓	✓

Table 4 (✓) Available file, (×) Unavailable file

4.1.1 LAS Files

A Log ASCII Standard (LAS) file is an industry standard, used for storing wellbore log information. The Canadian Well Logging Society was its creator in an effort to standardize well log data storage (Optima 2017). The format is divided into two main parts:

1. Header Sections: provides metadata, i.e., company name, drilling location, date, column names, units, etc.
2. ASCII log data: contains all data points in a tubular form and in the corresponding sequence following the column names.

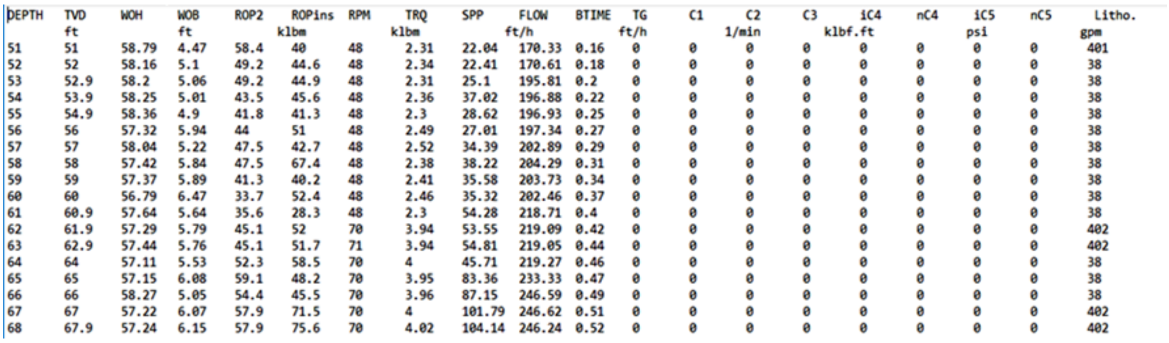
The emblematic value used to represent null values is -999.25, i.e., data is not available. Furthermore, LAS files are usually generated in two domains depending on the necessity:

1. Time base: provides information of drilling progress as a reference for optimization. Particularly important to register events off bottom, for example, tight spots while tripping, increments in pressure while circulating, etc. The granularity in this domain is restricted to the frequency of acquisition. In other words, data can be acquired every 1 second or every 10 seconds, which is equivalent to 1 Hz or 0.1 Hz respectively. Naturally, the ideal scenario would use the highest frequency possible to detect every single event.
2. Depth base: Storage data only on bottom and while drilling. The granularity of the data can be customized. Some typical values used for sampling are every 0.5 ft. or every 1 ft. of data. Nevertheless, for logging, it is usually recommended to have at least two data points per foot.

The difference between these two domains is representative in terms of quantity, and therefore in the demand of databanks and data processors (computers). Considering as an example, a well with a TD of 20,000 ft. If data sets have a granularity per foot, there would be 20,000 data points, just talking about data, called also examples (rows). This need to be multiplied by the number of sensors transmitting, as well known as properties or attributes (columns) available. As a general number, there would be at least 10 sensors providing the data in a rig, and then in total, there would be 200,000 data points to work with for one single well.

When the data has a time domain, like a 5 seconds sampling, which is a conventional acquisition rate of 0.2 Hz. Just in one day, the amount of data collected would be 17,280 data points for one single property. Like in the previous example, assuming 10 measurements, the amount of data for one day would be 172,800 examples. Then the duration of a well needs to be included in the final calculation and using a conservative value of 15 days, the final amount of data per well would be approximately 2'592,000 data points. To sum up, when the file domain is time, data points are roughly estimated as 10 times higher than when using a depth domain.

For this project, it was possible to gather data sets for 4 wells from a mud logging service company. The files are depth based LAS files with a granularity of 1 foot and include data for 20 properties between drilling parameters, Natural Gas Liquid (NGL) components, etc. Table 1, earlier presented, provides a description of the main parameters considered for this thesis.

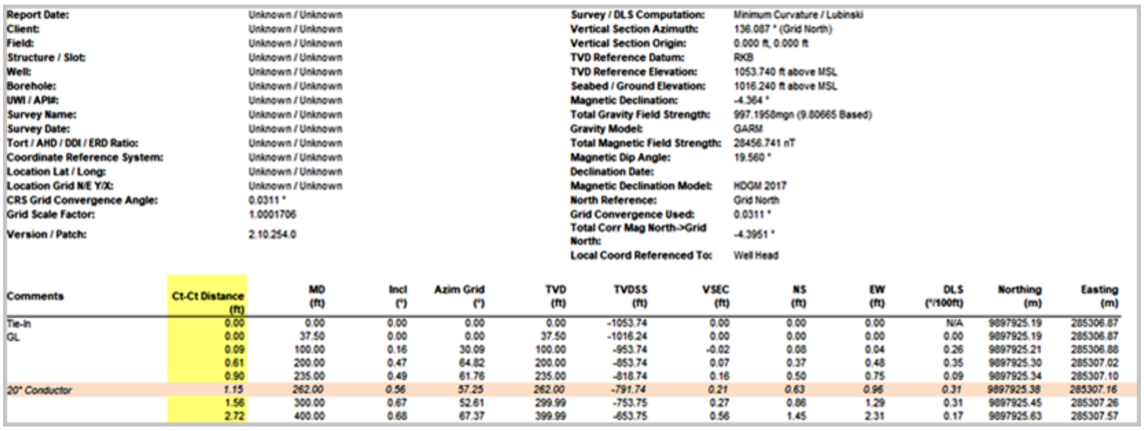


```
DEPTH  TVD    WOH    WOB    ROP2   ROPins  RPM   TRQ    SPP     FLOW    BTIME  TG     C1     C2     C3     iC4    nC4    iC5    nC5    Litho.
       ft            ft            klbm          klbm           ft/h           ft/h          1/min         klbf.ft              psi           gpm
51     51     58.79  4.47   58.4   40      48    2.31   22.04   170.33  0.16   0      0      0      0      0      0      0      0      401
52     52     58.16  5.1    49.2   44.6    48    2.34   22.41   170.61  0.18   0      0      0      0      0      0      0      0      38
53     52.9   58.2   5.06   49.2   44.9    48    2.31   25.1    195.81  0.2    0      0      0      0      0      0      0      0      38
54     53.9   58.25  5.01   43.5   45.6    48    2.36   37.02   196.88  0.22   0      0      0      0      0      0      0      0      38
55     54.9   58.36  4.9    41.8   41.3    48    2.3    28.62   196.93  0.25   0      0      0      0      0      0      0      0      38
56     56     57.32  5.94   44     51      48    2.49   27.01   197.34  0.27   0      0      0      0      0      0      0      0      38
57     57     58.04  5.22   47.5   42.7    48    2.52   34.39   202.89  0.29   0      0      0      0      0      0      0      0      38
58     58     57.42  5.84   47.5   67.4    48    2.38   38.22   204.29  0.31   0      0      0      0      0      0      0      0      38
59     59     57.37  5.89   41.3   40.2    48    2.41   35.58   203.73  0.34   0      0      0      0      0      0      0      0      38
60     60     56.79  6.47   33.7   52.4    48    2.46   35.32   202.46  0.37   0      0      0      0      0      0      0      0      38
61     60.9   57.64  5.64   35.6   28.3    48    2.3    54.28   218.71  0.4    0      0      0      0      0      0      0      0      38
62     61.9   57.29  5.79   45.1   52      70    3.94   53.55   219.09  0.42   0      0      0      0      0      0      0      0      402
63     62.9   57.44  5.76   45.1   51.7    71    3.94   54.81   219.05  0.44   0      0      0      0      0      0      0      0      402
64     64     57.11  5.53   52.3   58.5    70    4      45.71   219.27  0.46   0      0      0      0      0      0      0      0      38
65     65     57.15  6.08   59.1   48.2    70    3.95   83.36   233.33  0.47   0      0      0      0      0      0      0      0      38
66     66     58.27  5.05   54.4   45.5    70    3.96   87.15   246.59  0.49   0      0      0      0      0      0      0      0      38
67     67     57.22  6.07   57.9   71.5    70    4      101.79  246.62  0.51   0      0      0      0      0      0      0      0      402
68     67.9   57.24  6.15   57.9   75.6    70    4.02   104.14  246.24  0.52   0      0      0      0      0      0      0      0      402
```

Figure 13 The majority of the Header Section was not provided due to confidentiality reasons

4.1.2 Survey Data

The survey report is the formal document describing the actual trajectory of a well station by station (Knezevic 2017). It is a list that specifies the positioning of the well through several measurements and for different views (2D - vertical view and plan view, 3D), and it is normally provided by the surveying or directional drilling company.



Report Date:	Unknown / Unknown	**Survey / DLS Computation:**	Minimum Curvature / Lubinski
Client:	Unknown / Unknown	**Vertical Section Azimuth:**	136.087 ° (Grid North)
Field:	Unknown / Unknown	**Vertical Section Origin:**	0.000 ft, 0.000 ft
Structure / Slot:	Unknown / Unknown	**TVD Reference Datum:**	RKB
Well:	Unknown / Unknown	**TVD Reference Elevation:**	1053.740 ft above MSL
Borehole:	Unknown / Unknown	**Seabed / Ground Elevation:**	1016.240 ft above MSL
UWI / API#:	Unknown / Unknown	**Magnetic Declination:**	-4.364 °
Survey Name:	Unknown / Unknown	**Total Gravity Field Strength:**	997.1958mgn (9.80665 Based)
Survey Date:	Unknown / Unknown	**Gravity Model:**	GARM
Tort / AHD / DDI / ERD Ratio:	Unknown / Unknown	**Total Magnetic Field Strength:**	28456.741 nT
Coordinate Reference System:	Unknown / Unknown	**Magnetic Dip Angle:**	19.560 °
Location Lat / Long:	Unknown / Unknown	**Declination Date:**	
Location Grid N/E Y/X:	Unknown / Unknown	**Magnetic Declination Model:**	HDGM 2017
CRS Grid Convergence Angle:	0.0311 °	**North Reference:**	Grid North
Grid Scale Factor:	1.0001706	**Grid Convergence Used:**	0.0311 °
Version / Patch:	2.10.254.0	**Total Corr Mag North->Grid North:**	-4.3951 °
		Local Coord Referenced To:	Well Head

Comments	Ct-Ct Distance (ft)	MD (ft)	Incl (°)	Azim Grid (°)	TVD (ft)	TVDSS (ft)	VSEC (ft)	NS (ft)	EW (ft)	DLS (°/100ft)	Northing (m)	Easting (m)
Tie-In	0.00	0.00	0.00	0.00	0.00	-1053.74	0.00	0.00	0.00	N/A	9897925.19	285306.87
GL	0.00	37.50	0.00	0.00	37.50	-1016.24	0.00	0.00	0.00	0.00	9897925.19	285306.87
	0.09	100.00	0.16	30.09	100.00	-953.74	-0.02	0.08	0.04	0.26	9897925.21	285306.88
	0.61	200.00	0.47	64.82	200.00	-853.74	0.07	0.37	0.48	0.35	9897925.30	285307.02
	0.90	235.00	0.49	61.76	235.00	-818.74	0.16	0.50	0.75	0.09	9897925.34	285307.10
20" Conductor	*1.15*	*262.00*	*0.56*	*57.25*	*262.00*	*-791.74*	*0.21*	*0.63*	*0.96*	*0.31*	*9897925.38*	*285307.16*
	1.56	300.00	0.67	52.61	299.99	-753.75	0.27	0.86	1.29	0.31	9897925.45	285307.26
	2.72	400.00	0.68	67.37	399.99	-653.75	0.56	1.45	2.31	0.17	9897925.63	285307.57

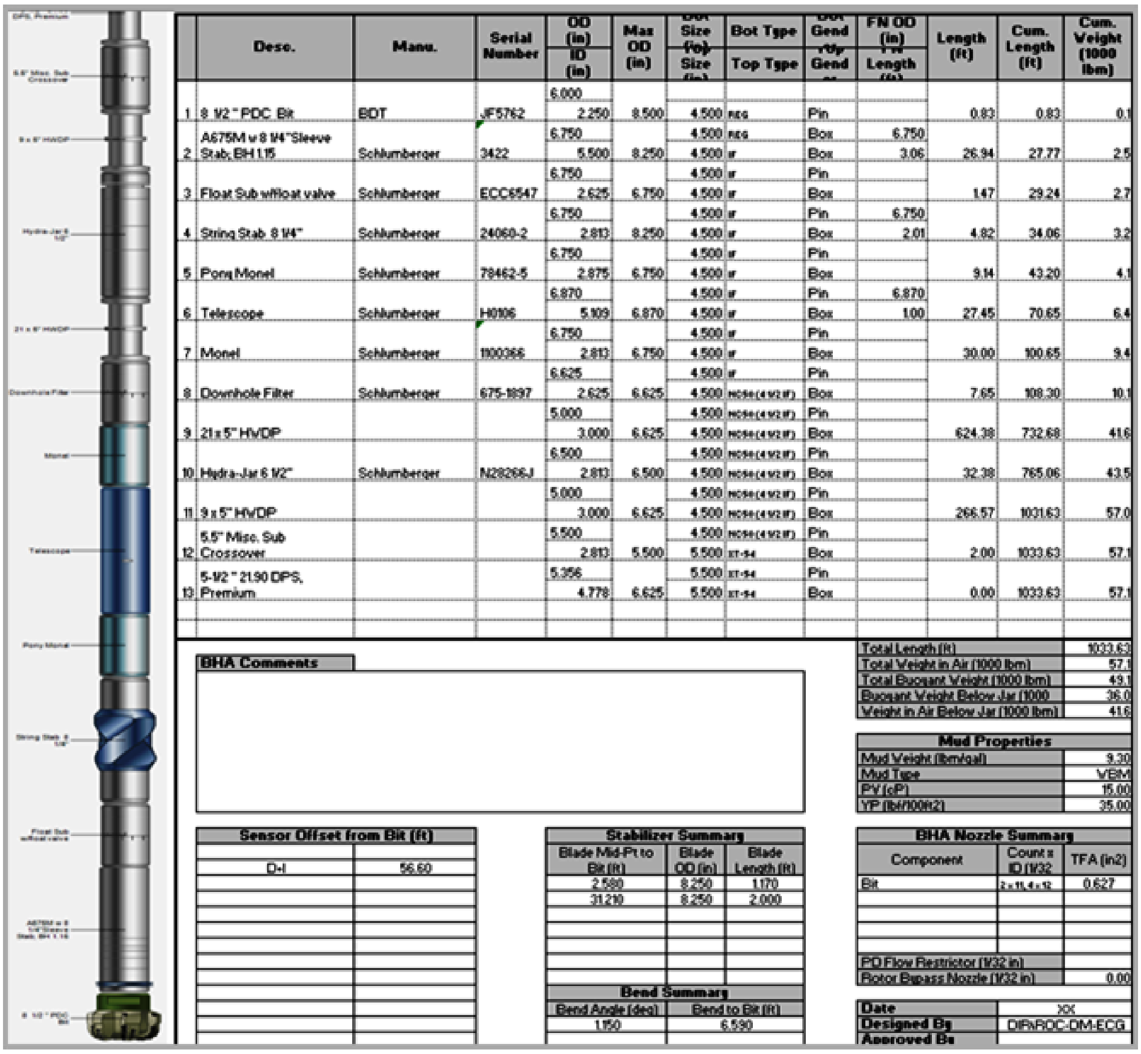
Figure 14 Example of a Survey Report

Surveys are downhole measurements, typically taken when drilling stops to make a connection. The result of a survey measurement will basically include, Inclination and Azimuth, for the measured depth where the station was taken. This data then serves as input to calculate additional properties relevant for trajectory construction. Table 2, presented in chapter 3, provides a brief description for the parameters considered in this work. The format of a Survey Report might vary from client to client, but it usually includes at least those three measurements. For this assignment, the survey reports for the candidate wells included the geological tops information along with the casing points' depths.

4.1.3 Bottom Hole Assembly (BHA) Configuration

The BHA is an essential document in the rig during drilling operations. It provides a sketch of the components in the lowest part of the drill string. In other words, the components that will be ran in the wellbore with a detailed description regarding its dimensions, weights, technical specifications, etc. starting from the bit until the drill pipe (Economides M. J. 1997).

Its design, under normal conditions, must ensure proper weight transfer to the bit as well as directional control in balance with sufficient Rate of Penetration (ROP).



	Desc.	Manu.	Serial Number	OD (in) ID (in)	Max OD (in)	Bot Size (in) Top Size (in)	Bot Type Top Type	Bot Gend Top Gend	FN OD (in) FN Length (ft)	Length (ft)	Cum. Length (ft)	Cum. Weight (1000 lbm)
1	8 1/2 " PDC Bit	BDT	JF5762	6.000	8.500					0.83	0.83	0.1
				2.250		4.500	REG	Pin				
2	A675M w 8 1/4"Sleeve Stab, BH 1.15	Schlumberger	3422	6.750	8.250	4.500	REG	Box	6.750	26.94	27.77	2.5
				5.500		4.500	IF	Box	3.06			
3	Float Sub w/float valve	Schlumberger	ECC6547	6.750	6.750	4.500	IF	Pin		1.47	29.24	2.7
				2.625		4.500	IF	Box				
4	String Stab 8 1/4"	Schlumberger	24060-2	6.750	8.250	4.500	IF	Pin	6.750	4.82	34.06	3.2
				2.813		4.500	IF	Box	2.01			
5	Pony Monel	Schlumberger	78462-5	6.750	6.750	4.500	IF	Pin		9.14	43.20	4.1
				2.875		4.500	IF	Box				
6	Telescope	Schlumberger	H0106	6.870	6.870	4.500	IF	Pin	6.870	27.45	70.65	6.4
				5.109		4.500	IF	Box	1.00			
7	Monel	Schlumberger	1100366	6.750	6.750	4.500	IF	Pin		30.00	100.65	9.4
				2.813		4.500	IF	Box				
8	Downhole Filter	Schlumberger	675-1897	6.625	6.625	4.500	IF	Pin		7.65	108.30	10.1
				2.625		4.500	NC50(4 1/2 IF)	Box				
9	21 x 5" HWDP			5.000	6.625	4.500	NC50(4 1/2 IF)	Pin		624.38	732.68	41.6
				3.000		4.500	NC50(4 1/2 IF)	Box				
10	Hydra-Jar 6 1/2"	Schlumberger	N28266J	6.500	6.500	4.500	NC50(4 1/2 IF)	Pin		32.38	765.06	43.5
				2.813		4.500	NC50(4 1/2 IF)	Box				
11	9 x 5" HWDP			5.000	6.625	4.500	NC50(4 1/2 IF)	Pin		266.57	1031.63	57.0
				3.000		4.500	NC50(4 1/2 IF)	Box				
12	5.5" Misc. Sub Crossover			5.500	5.500	4.500	NC50(4 1/2 IF)	Pin		2.00	1033.63	57.1
				2.813		5.500	XT-54	Box				
13	5-1/2 " 21.90 DPS, Premium			5.356	6.625	5.500	XT-54	Pin		0.00	1033.63	57.1
				4.778		5.500	XT-54	Box				

BHA Comments

Total Length (ft)	1033.63
Total Weight in Air (1000 lbm)	57.1
Total Buoyant Weight (1000 lbm)	49.1
Buoyant Weight Below Jar (1000	36.0
Weight in Air Below Jar (1000 lbm)	41.6

Mud Properties	
Mud Weight (lbm/gal)	9.30
Mud Type	WBM
PV (cP)	15.00
YP (lbf/100ft2)	35.00

Sensor Offset from Bit (ft)	
D+I	56.60

Stabilizer Summary		
Blade Mid-Pt to Bit (ft)	Blade OD (in)	Blade Length (ft)
2.580	8.250	1.170
31.210	8.250	2.000

Bend Summary	
Bend Angle (deg)	Bend to Bit (ft)
1.150	6.590

BHA Nozzle Summary		
Component	Count x ID (1/32	TFA (in2)
Bit	2 x 11, 4 x 12	0.627
PD Flow Restrictor (1/32 in)		
Rotor Bypass Nozzle (1/32 in)		0.00

Date	XX
Designed By	DIPAROC-DM-ECG
Approved By	

Figure 15 Example of a BHA Configuration Report.

4.2 Data Pre-processing

Pre-processing is the immediate and an essential step after collecting the data, where data is ultimately prepared for processing and it involves three main steps:

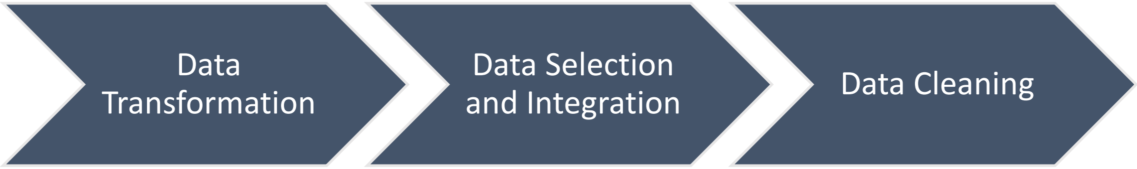
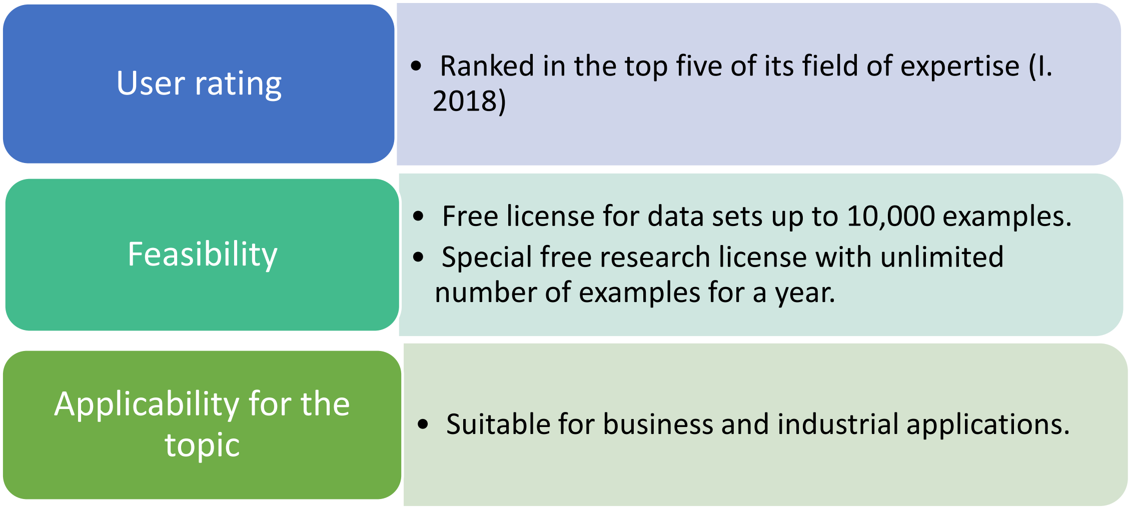


Figure 16 Steps of the Pre-processing stage

To continue describing the stages followed, it is necessary to become familiar with the data mining software used to prepare the data.

4.2.1 Rapidminer Studio Software

In order to decide which data mining software to use, there were three primary criteria, which resulted in the selection of Rapidminer Studio Software, because of its:



User rating	• Ranked in the top five of its field of expertise (I. 2018)
Feasibility	• Free license for data sets up to 10,000 examples. • Special free research license with unlimited number of examples for a year.
Applicability for the topic	• Suitable for business and industrial applications.

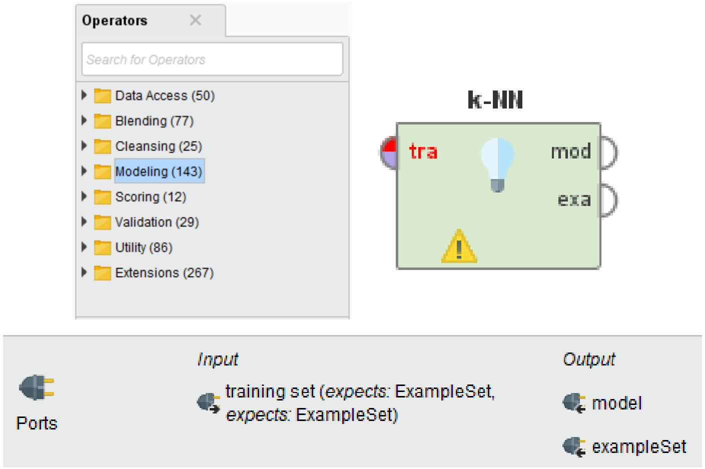
Figure 17 Software selection criteria

Rapidminer (RM) is a data science platform with a user-friendly visual design that provides an integrated environment for data preparation, machine learning, deep learning, text mining, and predictive analytics workflows. Compatible with other alternatives in the market like R and Python code, it also provides pre-built extensions to assist in any possible task.

In the last version release, additional emphasis has been taken to provide users with tools to facilitate the data cleanse process and its analysis. The efforts are gambling for a less specific design to a more familiar interaction, with tables of data somehow evoking excel experience but with much more powerful tools and capabilities.

Nevertheless, RM working principal consist in a succession of individual work steps to define analysis processes. Some important terminology regarding the software needs to be mention at this stage:

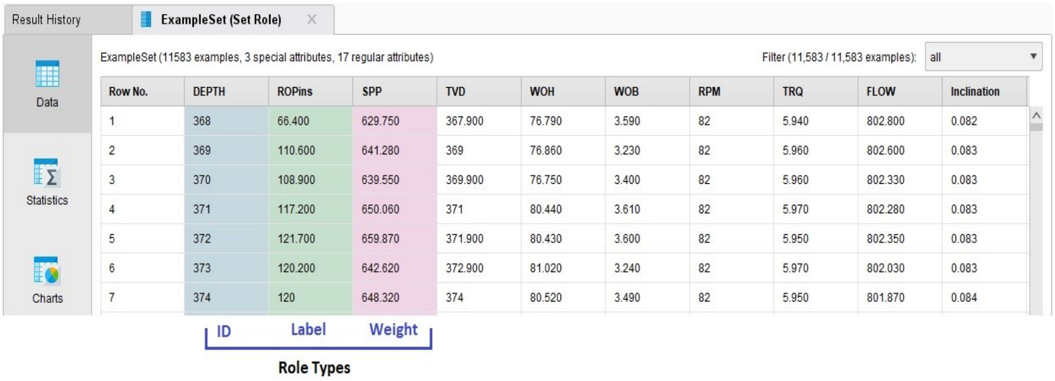
- Operators: Are basically process components in the shape of blocks. In general, operators are defined by a description of the expected input, a description of the delivered output, the action performed through the operator and the parameters that control the previous mentioned action. The software counts with an extended library composes of hundreds of operators, ready-to-use as well as operators that can be modified, combined, personalized or build by the user. In an upper level operators can be classified in two groups, the normal ones and the super operators, where the last ones contain one or more sub processes.
- Input / Output: Input refers to the data used to feed an operator and output is the result after the data has passed through the operator process.



training set (*expects:* ExampleSet, *expects:* ExampleSet)

Figure 18 Rapidminer Studio Operators Library classification. Example of an Operator along with the Input/Output descriptions

- Examples: It denote the rows of a data set, i.e., the data itself.
- Attributes: Also known as parameters, properties or characteristics, i.e., the columns of a data set. In RM the attributes can be distinguish as special or regular. Regular attributes are the default status; special notation is used for attributes with specific roles.
- Roles: Attributes can be distinct based on their role as ID, Label or Weight. ID is the short name for an attribute that serves as an identifier. Label is used for the attributes of interest, which characterize the examples in a certain manner and which want to be known/ predicted for new examples. Finally, Weight is the name for the attributes with a designated weight regarding the Label (Rapidminer 2014)



ExampleSet (11583 examples, 3 special attributes, 17 regular attributes)

Filter (11,583 / 11,583 examples): all

Row No.	DEPTH	ROPins	SPP	TVD	WOH	WOB	RPM	TRQ	FLOW	Inclination
1	368	66.400	629.750	367.900	76.790	3.590	82	5.940	802.800	0.082
2	369	110.600	641.280	369	76.860	3.230	82	5.960	802.600	0.083
3	370	108.900	639.550	369.900	76.750	3.400	82	5.960	802.330	0.083
4	371	117.200	650.060	371	80.440	3.610	82	5.970	802.280	0.083
5	372	121.700	659.870	371.900	80.430	3.600	82	5.950	802.350	0.083
6	373	120.200	642.620	372.900	81.020	3.240	82	5.970	802.030	0.083
7	374	120	648.320	374	80.520	3.490	82	5.950	801.870	0.084

Figure 19 Data view through Examples, regular and special attributes

- Data type: also known as Value Type, because it is an indication of the value of the attribute. There are different value types, and they can also be transformed into other type when necessary. Still, the main groups are text in the case of free text, numerical when numbers are involved and nominal when only few values are possible (Rapidminer 2014). Regarding this work, the following table summarize the values types used and automatically selected by RM when reading the data:

Integer	A positive or negative number which no fractional part.
Real	A number that represent any quantity along a number line. Can be positive or negative. (Page 2011)
Polynominal	Special case of nominal type. Attributes can have more than two different non-numerical values.

Table 5 Summarize of the value types used in the data sets.

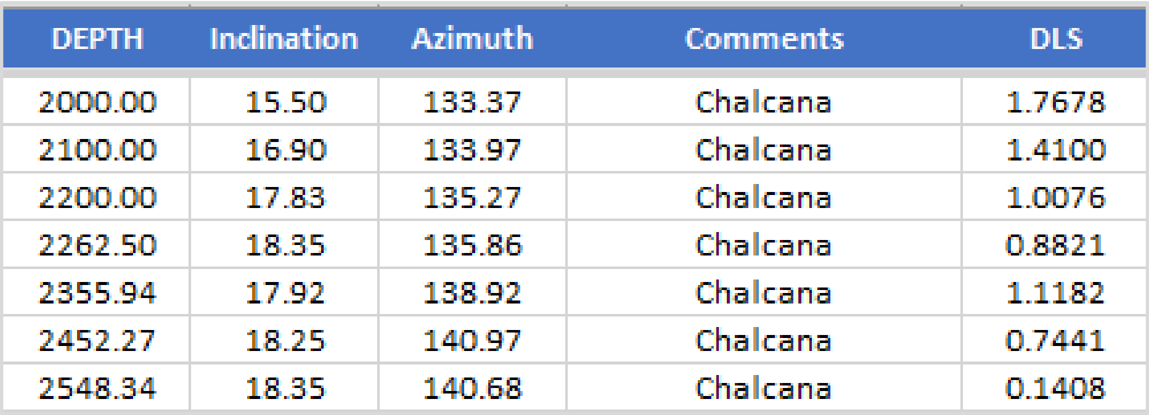
With a general overview of the software chosen, it is important to mention that basically all the data analysis and simulations were done using it. Nevertheless, part of the data preparation was done using Excel in combination with Visual Basic Script (VBS) and can be reviewed in detail in the Appendix A.1.

4.2.2 Data Transformation

As previously described, two files are the main source of data: the depth based LAS files and the survey listings. It is necessary to consider that both files have different granularities; the LAS files provide data every 1 foot while the survey report provide data at different fixed depths. In addition, the BHA Reports are per drilling run.

To follow the proposed methodology and asses the functionality of data mining, all data must be imported in the RM software and be comparable too. The LAS files are already with the appropriate base, but the survey listing demands additional attention as well as the BHA reports, which need to be transform to the same base.

As the Survey Report is commonly exported in Excel, it was decided to use VBS to develop a tool to make the calculation and the coding process automatically, based on the necessary inputs, allowing for the transformation of the data given at specific depths to data per foot including hole sizes and drilling tool used.



DEPTH	Inclination	Azimuth	Comments	DLS
2000.00	15.50	133.37	Chalcana	1.7678
2100.00	16.90	133.97	Chalcana	1.4100
2200.00	17.83	135.27	Chalcana	1.0076
2262.50	18.35	135.86	Chalcana	0.8821
2355.94	17.92	138.92	Chalcana	1.1182
2452.27	18.25	140.97	Chalcana	0.7441
2548.34	18.35	140.68	Chalcana	0.1408

Figure 20 Example of the content of the Survey Report, showing only the attributes of interest at specific depths

The first step was to calculate the variation between stations for the main directional attributes:

- Depth
- Inclination
- Azimuth

Knowing the variation delta (Δ) in Inclination and Azimuth for a certain distance (Δ depth) the increments could be obtained per foot.

Besides, a depth range was entered in order to include data regarding the Hole Size and the drilling Tool used to deviate the wells, which later could be distributed per foot as well. Figure 21, shows the Workflow followed for this purpose.

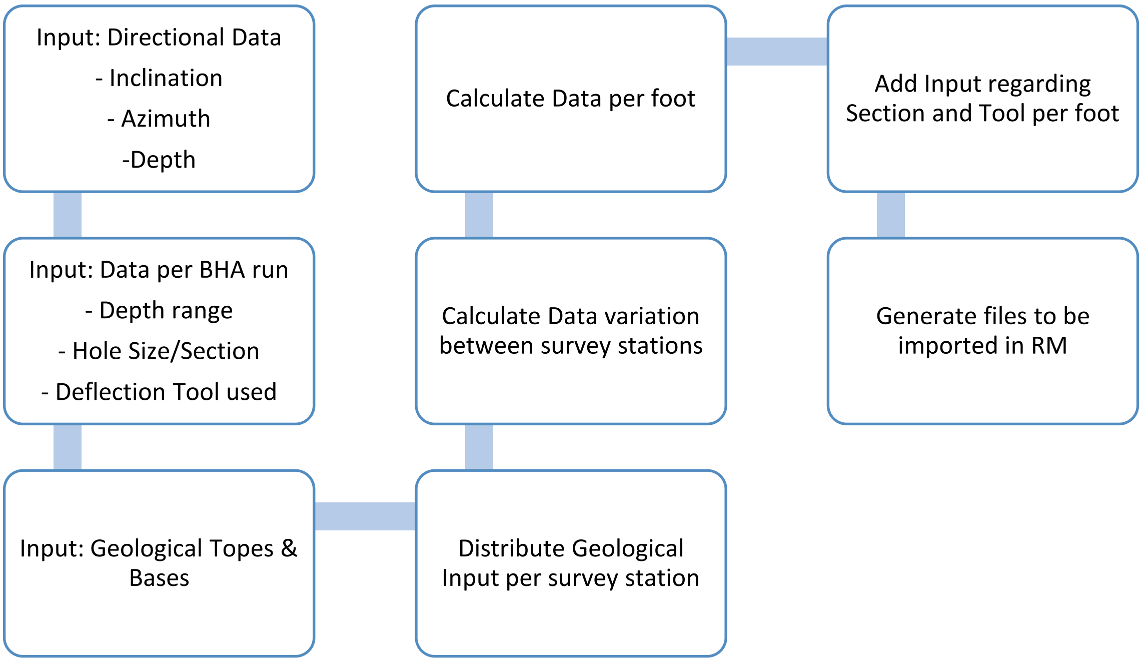

Input: Directional Data
- Inclination
- Azimuth
-Depth
Input: Data per BHA run
- Depth range
- Hole Size/Section
- Deflection Tool used
Input: Geological Topes & Bases
Distribute Geological Input per survey station
Calculate Data variation between survey stations
Calculate Data per foot
Add Input regarding Section and Tool per foot
Generate files to be imported in RM

Figure 21 Workflow implemented in VBS to transform the data into the desired granularity

The result is showed in Directional and Geological Data per foot.Figure 22 providing Directional Data, Geological topes, Hole Size and Drilling Tool used per foot. Furthermore, other directional attributes were calculated as well:

- Dogleg Severity (DLS): It is a measure of the amount of change in the inclination and azimuth of a borehole, expressed in degrees per 100 feet or per 30 meters course length. It's calculation is based on the Minimum Curvature Method as it is the standard method used in the Industry (Asad 2016).

$$DLS = \frac{100}{ds} cos^{-1}\{sinI_1 sinI_2 \cos(A_2 - A_1) + cosI_1 cosI_2\} \tag{1}$$

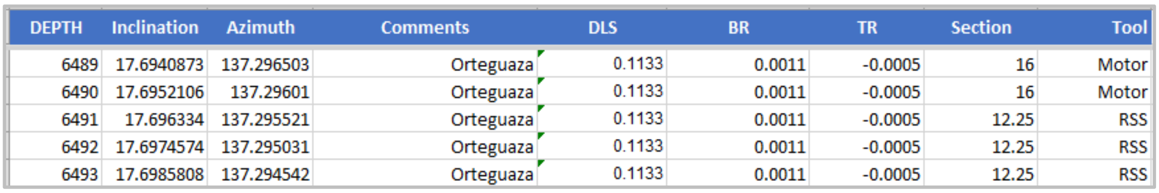
Where *ds* is the course length between survey stations 1 and 2
*I*1, *I*2 are the Inclinations in survey stations respectively
*A*1, *A*2 are the Azimuths in survey stations respectively.

- Build-rate angle (BR): refers to the increase or decrease in Inclination from vertical per 100 ft. or 30 m.

$$BR = \frac{dI(s)}{ds} = \Delta I \tag{2}$$

- Turn-rate angle (TR): is the degree of change in the Azimuth per 100 ft. or 30 m.

$$TR = \frac{dA(s)}{ds} = \Delta A \tag{3}$$



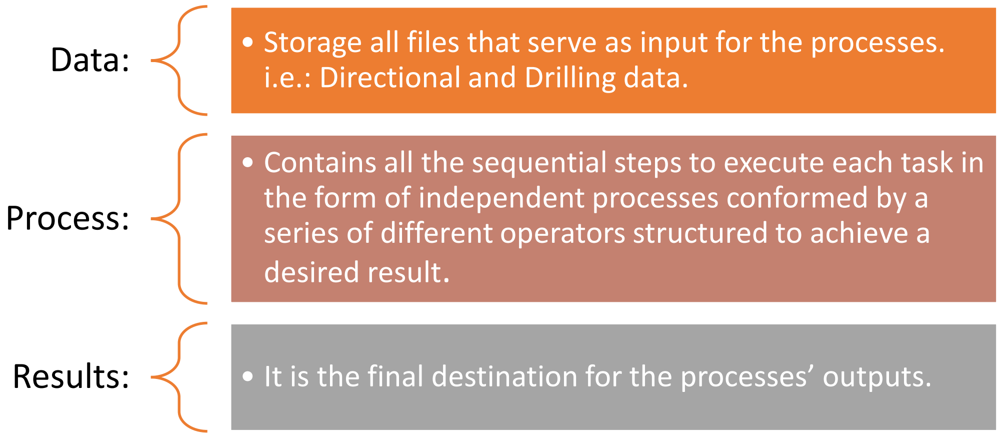
DEPTH	Inclination	Azimuth	Comments	DLS	BR	TR	Section	Tool
6489	17.6940873	137.296503	Orteguaza	0.1133	0.0011	-0.0005	16	Motor
6490	17.6952106	137.29601	Orteguaza	0.1133	0.0011	-0.0005	16	Motor
6491	17.696334	137.295521	Orteguaza	0.1133	0.0011	-0.0005	12.25	RSS
6492	17.6974574	137.295031	Orteguaza	0.1133	0.0011	-0.0005	12.25	RSS
6493	17.6985808	137.294542	Orteguaza	0.1133	0.0011	-0.0005	12.25	RSS

Figure 22 Directional and Geological Data per foot.

4.2.3 Project creation and Data Loading

With the files ready to be imported into RM, it was necessary to create the project and get familiar with the kind of operators suitable for the task. Appendix A.2 contains a list of the main operators used to create the different processes which are also detailed in the Appendix A.3. During the following steps, all RM processes will be referenced by their process' names in parenthesis for its further reference in the mentioned appendix.

The first step was to create the Repository with the desire folders to keep a clean and clear structure of the work:



Data:

- Storage all files that serve as input for the processes. i.e.: Directional and Drilling data.

Process:

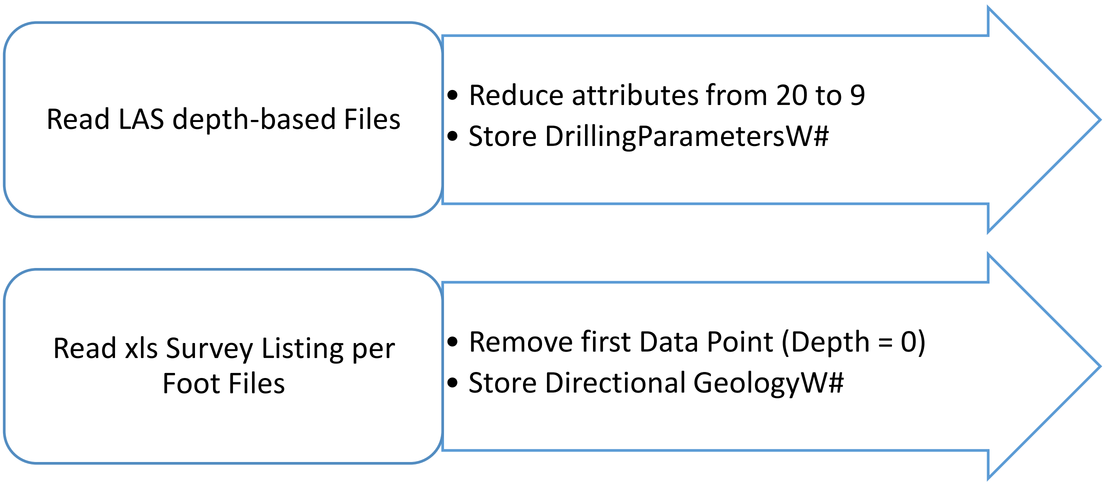
- Contains all the sequential steps to execute each task in the form of independent processes conformed by a series of different operators structured to achieve a desired result.

Results:

- It is the final destination for the processes' outputs.

Figure 23 Project structure in RM

With the project created, the next step is to load the data as showed in Figure 24.



Read LAS depth-based Files

- Reduce attributes from 20 to 9
- Store DrillingParametersW#

Read xls Survey Listing per Foot Files

- Remove first Data Point (Depth = 0)
- Store Directional GeologyW#

Figure 24 Flowchart to load Drilling, Directional and Geological parameters

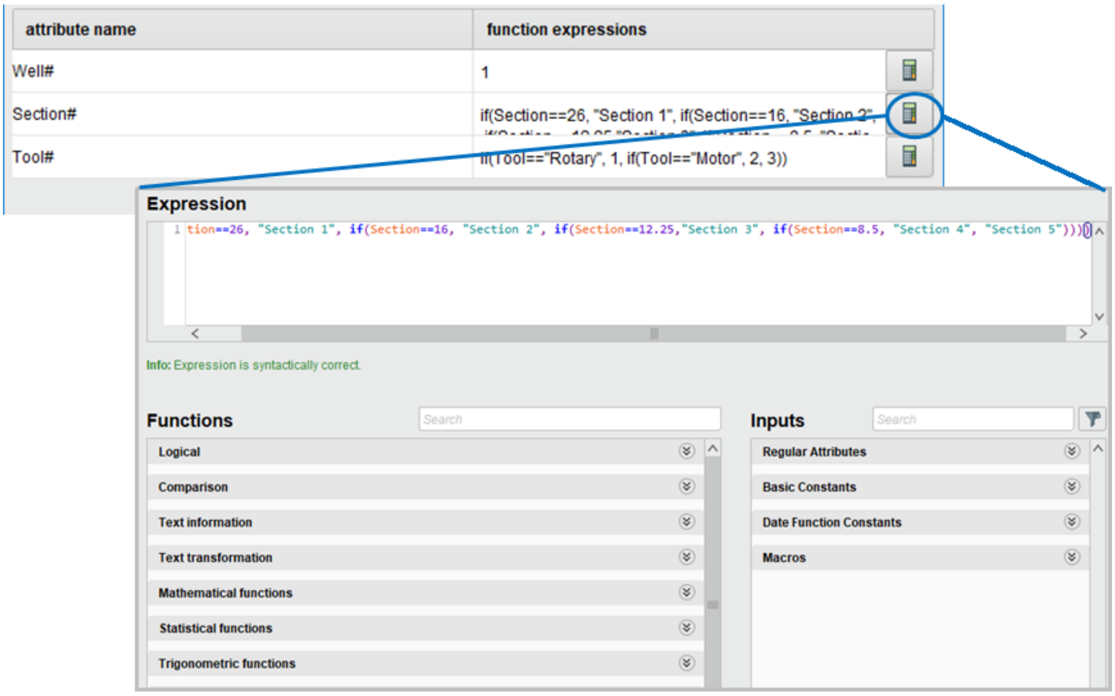
During this stage (Process: 001DataLoadDP), the LAS files are read using the CSV read operator. Then only the relevant attributes related to common drilling parameters were selected and stored in the Data Folder with the corresponding nomenclature per well (DrillingParametersW#). A similar procedure (Process: 001DataLoadDG) was followed to import the transformed survey listing file but using a XLS read operator. In addition, the first example was removed as it corresponded to Depth = 0. Then data is stored in the Data Folder with the corresponding nomenclature per well (DirectionalGeologyW#).

4.2.4 Data Integration

Data Integration is the corresponding next step to handle the data per well. For the Data Integration (Process: 002DataPerWell), the previous generated Drilling Parameters files along with the Directional Geology files are restored from the Data repository and combined using a Join operator in a sub process based on the common attribute: Depth.

In addition, a well identification (Well ID) is generated, along with an attribute called Section# corresponding to the Hole Size data, both as a polinominal attribute to finally store the data in the Result folder with the corresponding nomenclature (AllDataW#).

The generation of those two additional attributes, Well ID and Section#, was possible using the Generate Attribute operator, which allows for different entries, to transform or generate new ones. It offers too "function expressions" with a pre-defined selection that includes but are not limited to logical functions, comparison functions, mathematical and statistical functions, etc. Functions that can be used to define Expressions/user-defined codes to achieve specific tasks. In this case, it was mainly used to improve the work with the data by coding it differently.



attribute name	function expressions
Well#	1
Section#	if(Section==26, "Section 1", if(Section==16, "Section 2",
Tool#	if(Tool=="Rotary", 1, if(Tool=="Motor", 2, 3))

Expression

```
tion==26, "Section 1", if(Section==16, "Section 2", if(Section==12.25,"Section 3", if(Section==8.5, "Section 4", "Section 5"))))
```

Info: Expression is syntactically correct.

Figure 25 Attribute Generator operator applications

The final set of the selected attributes includes all examples per foot per well with 20 regular attributes:

Attribute	Unit	Type
Depth	Ft	Real
TVD	Ft	Real
WOH	Klbm	Real
WOB	Klbm	Real
ROPins	Ft/hr	Real
RPM	1/min	Integer
TRQ	Klbf.ft	Real
SPP	Psi	Real
FLOW	Gpm	Real
Inclination	Degrees [°]	Real
Azimuth	Degrees	Real
Comments	N.A.	Polynominal
DLS	°/100ft.	Real
BR	°/100ft.	Real
TR	°/100ft.	Real
Section	In.	Real
Tool	N.A.	Polynominal
Well#	N.A.	Integer
Section#	N.A.	Nominal
Tool#	N.A.	Integer

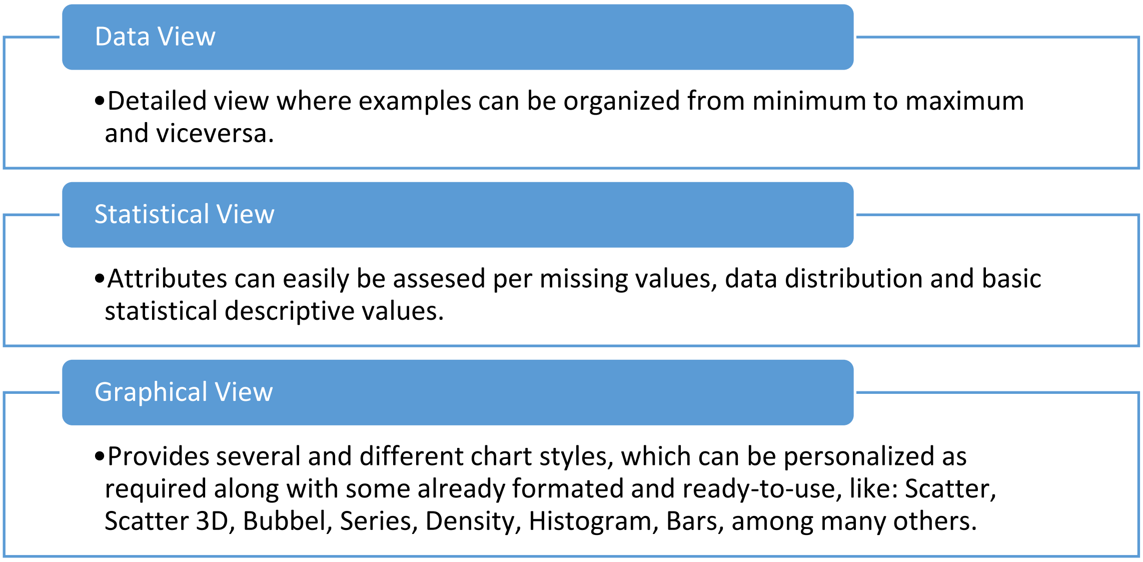
Table 6 Summarize of Attributes including unit of measurement and data type

The last three attributes were added to improve the work and visualization of the data. Regarding the section, it was necessary to change it to Nominal, because in its original state as real, it creates confusion to the model by considering it as a numerical value. The attribute "Comment" refers to the Geological Formation name.

4.2.5 Data Cleaning

As mentioned earlier, it corresponds to the more time consuming step, where data needs to be carefully examined to filter out those examples that potentially could deteriorate the analysis and prediction. It involves reducing the data size by removing examples or attributes with missing data or redundancy. Furthermore, it is a step where Data Visualization plays an essential role, to improve the identification of unbeneficial data.

Therefore, one of the characteristics of data mining software is its visualizations tools, and RM is not the exception, offering several ways to visualize the data:



Data View

- Detailed view where examples can be organized from minimum to maximum and viceversa.

Statistical View

- Attributes can easily be assesed per missing values, data distribution and basic statistical descriptive values.

Graphical View

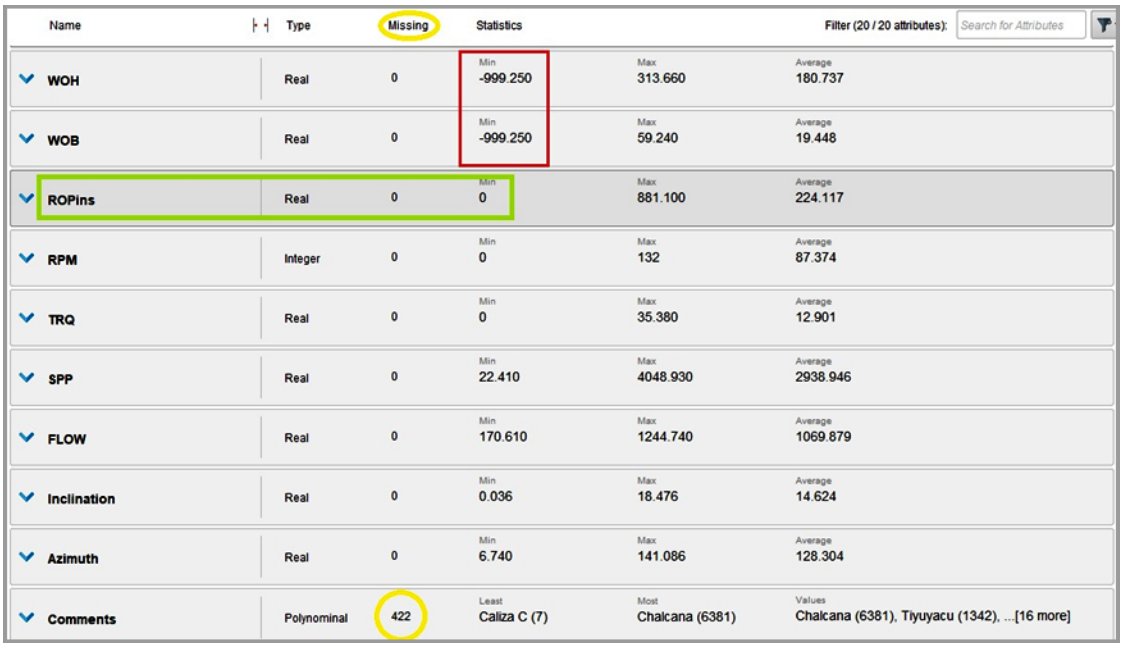
- Provides several and different chart styles, which can be personalized as required along with some already formated and ready-to-use, like: Scatter, Scatter 3D, Bubbel, Series, Density, Histogram, Bars, among many others.

Figure 26 RM Data visualization options

The visualization options are interchangeable between each other, which increase the effectiveness of the process.

4.2.5.1 Data Cleaning and Filling

Using the statistical view, it was possible to identify in a first glimpse missing values (marked in yellow), null values (in red) and some data inconsistency (in green) that needed to be cleaned.



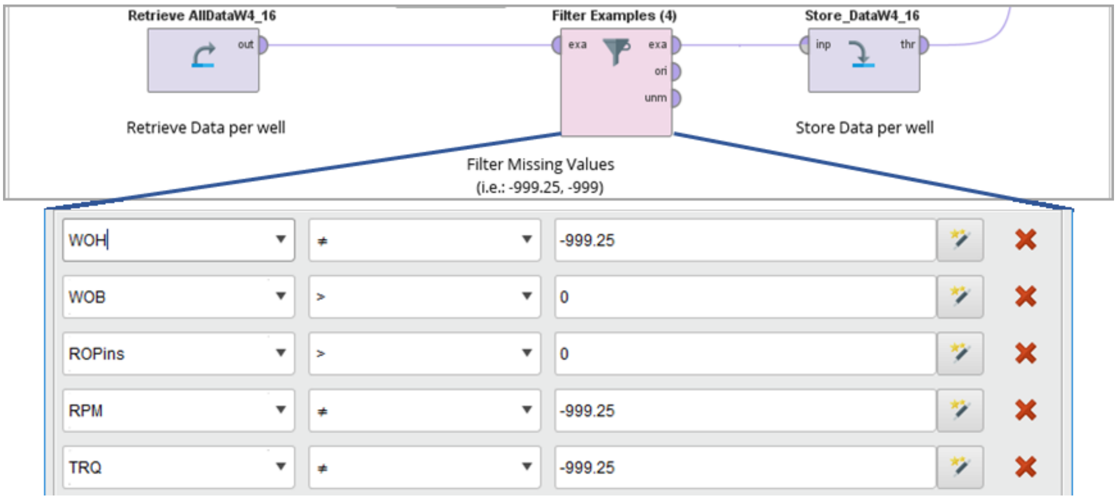
Filter (20 / 20 attributes): Search for Attributes

Name	Type	Missing	Statistics		
WOH	Real	0	Min -999.250	Max 313.660	Average 180.737
WOB	Real	0	Min -999.250	Max 59.240	Average 19.448
ROPins	Real	0	Min 0	Max 881.100	Average 224.117
RPM	Integer	0	Min 0	Max 132	Average 87.374
TRQ	Real	0	Min 0	Max 35.380	Average 12.901
SPP	Real	0	Min 22.410	Max 4048.930	Average 2938.946
FLOW	Real	0	Min 170.610	Max 1244.740	Average 1069.879
Inclination	Real	0	Min 0.036	Max 18.476	Average 14.624
Azimuth	Real	0	Min 6.740	Max 141.086	Average 128.304
Comments	Polynominal	422	Least Caliza C (7)	Most Chalcana (6381)	Values Chalcana (6381), Tiyuyacu (1342), ...[16 more]

Figure 27 Statistical Visualization of the data

One key part of the cleaning process includes removing the missing values (Process: 003RemovingMissingValues). This is possible by retrieving the data per well (AllDataW#) and using the Filter Examples operator.

In this case, the software can detect only "real" missing values, i.e., when no data is available for a particular attribute. However, the O&G industry uses its own standard value for "null data", known as -999.25, which can also be straightforwardly removed per attribute once identified. Then the results can be properly stored (DataW#).



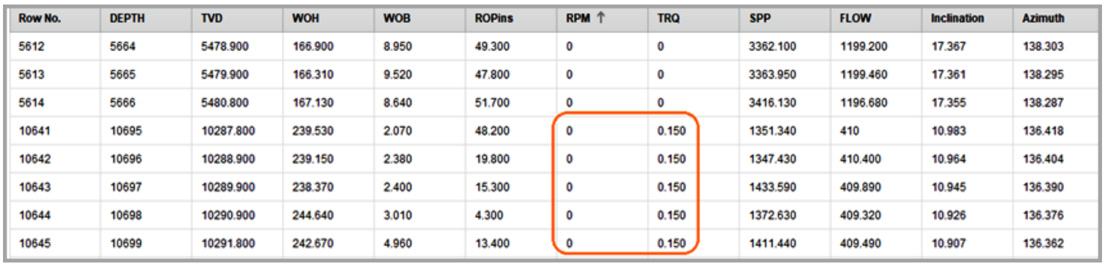
WOH	≠	-999.25
WOB	>	0
ROPins	>	0
RPM	≠	-999.25
TRQ	≠	-999.25

Figure 28 Part of the process to remove the null values -999.25. Description of the content inside the Filter Example operator, where conditions can be set as required and per attribute

In this particular case, Figure 28, shows how WOB and ROP attributes were restricted to filter only > 0 values, to remove some inconsistent values like negative WOB or 0 values for ROP.

Moving forward with the cleaning process (Process: 004CleaningData), additional steps can be taken to treat other inconsistencies found related to the values for RPM and TRQ. During this step two approaches were followed:

1. Examples were directly excluded from the data based on depth and using the Filter Example operator.
2. Examples were adjusted to be usable through a sub-process.



Row No.	DEPTH	TVD	WOH	WOB	ROPins	RPM ↑	TRQ	SPP	FLOW	Inclination	Azimuth
5612	5664	5478.900	166.900	8.950	49.300	0	0	3362.100	1199.200	17.367	138.303
5613	5665	5479.900	166.310	9.520	47.800	0	0	3363.950	1199.460	17.361	138.295
5614	5666	5480.800	167.130	8.640	51.700	0	0	3416.130	1196.680	17.355	138.287
10641	10695	10287.800	239.530	2.070	48.200	0	0.150	1351.340	410	10.983	136.418
10642	10696	10288.900	239.150	2.380	19.800	0	0.150	1347.430	410.400	10.964	136.404
10643	10697	10289.900	238.370	2.400	15.300	0	0.150	1433.590	409.890	10.945	136.390
10644	10698	10290.900	244.640	3.010	4.300	0	0.150	1372.630	409.320	10.926	136.376
10645	10699	10291.800	242.670	4.960	13.400	0	0.150	1411.440	409.490	10.907	136.362

Figure 29 Inconsistency in TRQ values in relation to RPM values

The Scatter chart was used to identify erratic negative values for RPM while sliding (orange highlighted). For example, in case of Well #4, those values if removed would lead to the wrong perception that the well was drilled only rotating. Unfortunately, slidings sheets where not available, however drilling parameters and survey data is sufficient to determine the sliding times.

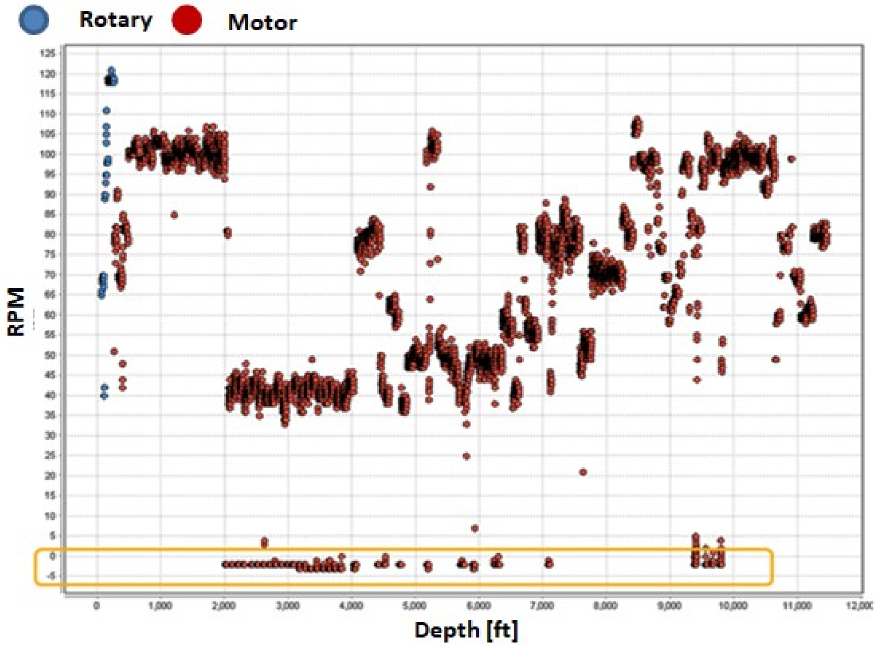


Figure 30 Depth vs. RPM based on the tool used.

Considering that the drill-string rotation produce a corresponding torque value. The TRQ attribute is added to the graph to help identifying inconsistencies.

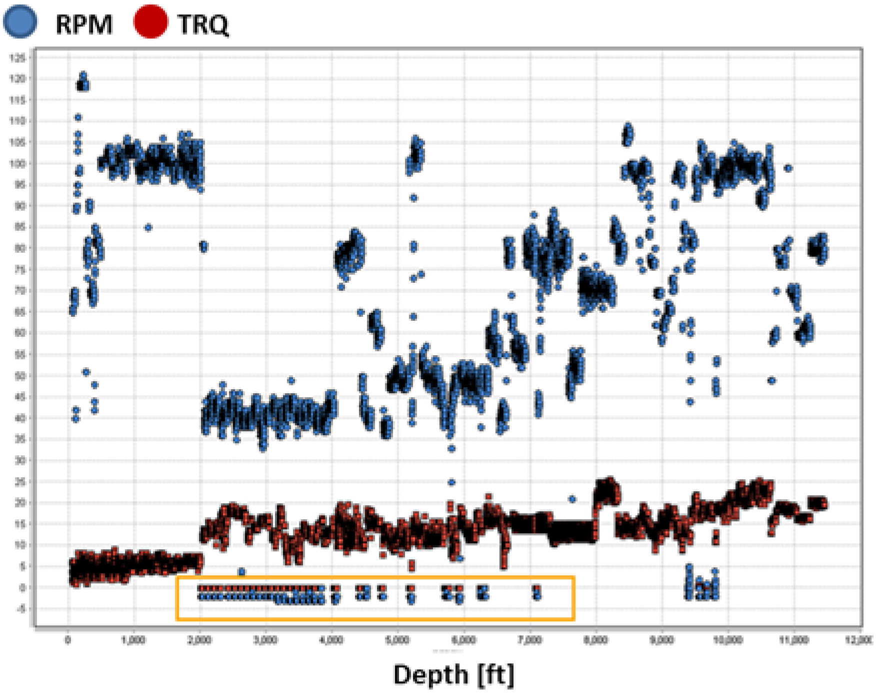


Figure 31 Depth vs. RPM & TRQ

Because a Motor was used as tool to deviate the well, which is only possible while sliding, the Inclination is another attribute useful to interpret the mismatch values.

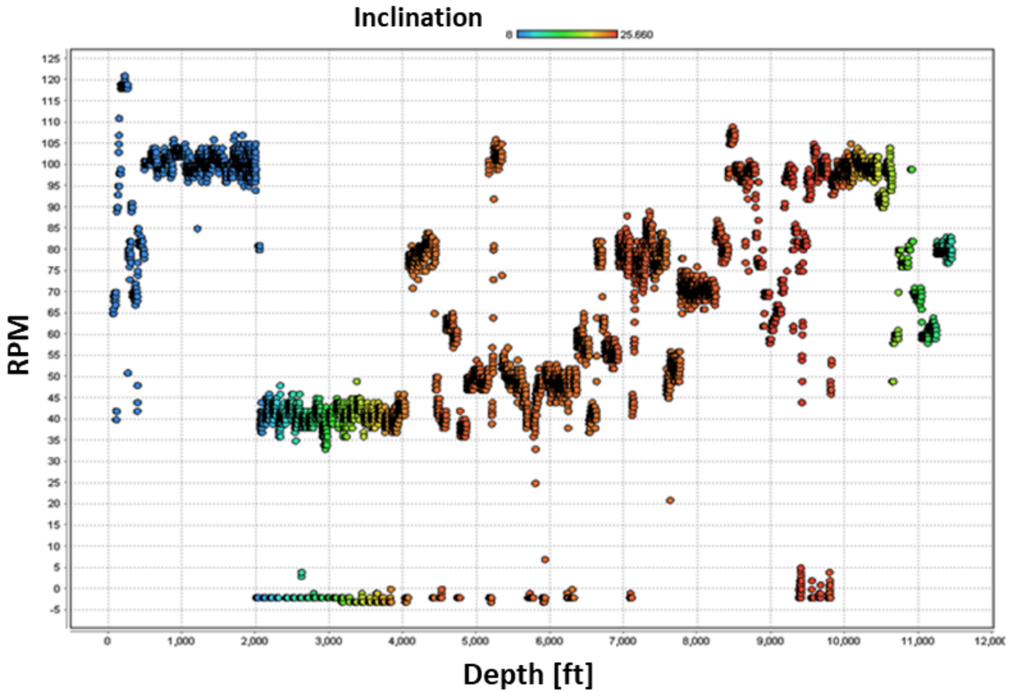


Figure 32 Depth vs. RPM in contrast with the Inclination in colos scale

Parallel analysis were performed for each well, to implement the cleanse process for erratic RPM and TRQ. In brief, the corrections were done in independent sub-processes specific per situation:

- Well #1: TRQ values were adjusted to correspond with RPM values equal to 0.
- Well #2: did not need corrections, as it was drilled mainly using Rotary Steerable System (RSS).
- Wells #3 & #4: negative RPM values were adjusted to match with sliding events.

4.2.5.2 Data Quality Control (QC)

With the data stored as DataCleanW#, a process for a technical review was implemented (Process: 004CleaningData_QC) to remove data of poor or questionable quality.

The first step was to expand the information earlier presented in Table 3, showing the similarities and differences between wells, including the deflection tool used per run.

	W1			W2			W3			W4		
	MD [ft]	BHA #	Tool	MD [ft]	BHA #	Tool	MD [ft]	BHA #	Tool	MD [ft]	BHA #	Tool
16"	6490	2	Motor	3354	2	RSS	6502	2	RSS	6520	2	Motor
				6280	3	RSS						
12.25"	9513	3	RSS	9355	4	RSS	10820	3	Motor	6606	3	Motor
	10387	4	Motor	10493	7	RSS				9417	4	Motor
										10627	5	Motor
8.5"	11250	5	Motor	10629	8	RSS	11660	4	Motor	11455	6	Motor
				11950	9	RSS						
6.125"				11955	10	Motor						
				12330	11	RSS						
Inc/VSA [°]:	18.476 / 136.087			88.794 / 98.375			30.993 / 35.682			25.66 / 158.608		

Table 7 Well data set including deflection tool per run

It was then clear that only the data gathered in Wells #1 and #3 would serve the purpose to train a model to predict the ROP of Well #4. Well #2 was left out due to its profile differences, reaching horizontal and aggregating an additional section to the design.

Thus, the data from both wells was combined to create and store the final training set after the proper QC sub-process, specific per section, as the hole diameter differs and the drilling conditions change and based on the following main criteria:

1. WOB Operational Limits.
2. WOH Expected Behaviour.
3. RPM Outliers.

The sub-process for the 16" sample is presented in Figure 33. The first filter applied is based on WOB operational limits (green square), considering that the technical specifications for the bit type used in this section cannot overcome 50 Klbm, and that any value below 2.5 Klbm would not be representative.

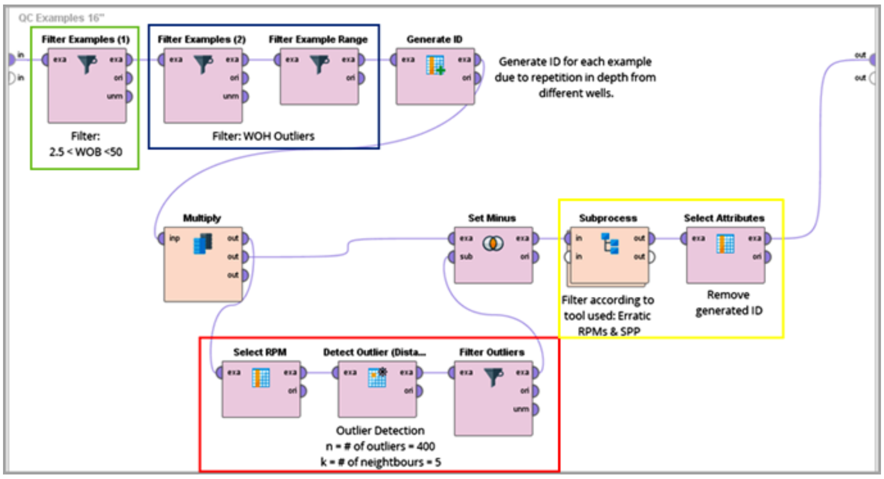


Figure 33 QC sub-process to prepare the 16" training set

The next filter was based on WOH behaviour (blue square), which theoretically should increase gradually with the increase of depth and in relation with the inclination as well.

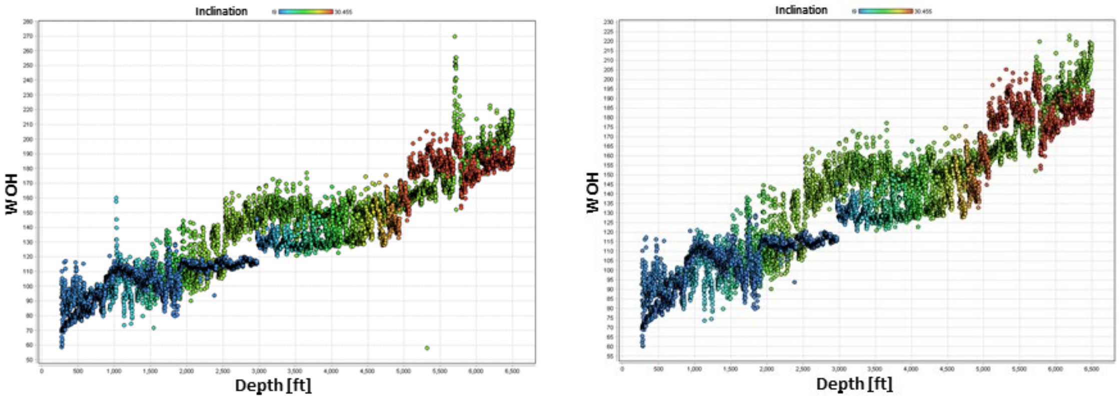


Figure 34 The left chart shows data for WOH before the QC process. The right chart show the data once removing the unreliable values (59 Examples were removed)

To continue with this process, one data mining technique was considered to clean the data in a more automatic way. The Outlier Detection operator (inside the red square) based on distance between data points is a functional algorithm that combined with the proper inputs can facilitate the QC process.

Figure 35, shows the applied RPM in relation to the directional tool used, with several clear spots of erratic RPM values. After applying the Outlier Detection and understanding the results, it is possible to filter away all TRUE outliers, keeping in mind that still some values need to be carefully evaluated, and manually removed in the following step with the support of a sub-process for this purpose only (yellow square).

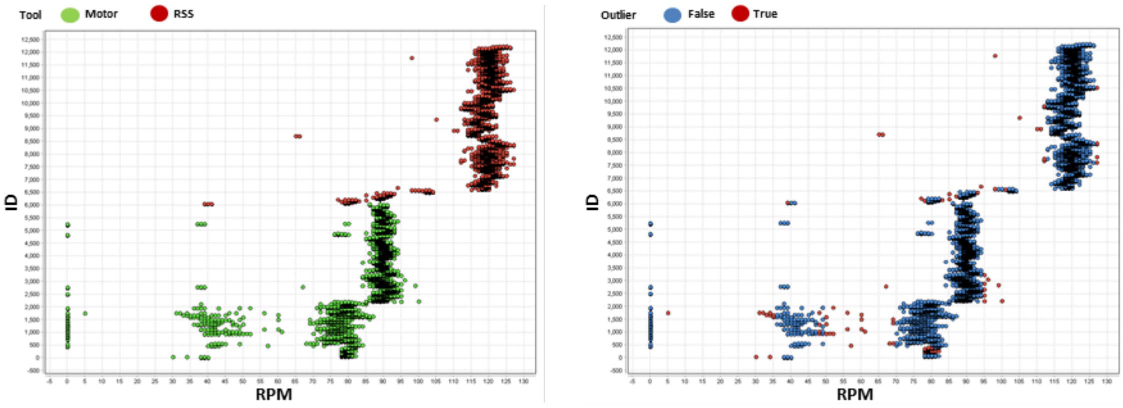


Figure 35 The first chart shows the RPM values in relation to the tool used. The second chart shows in red the values calculated as outliers

The result is the required training data set including Well #1 & #3, ready to be used and stored as QCDataW13_16in. Similar procedure was followed for sections 12.25” and

8.5", to obtain the inputs for the models for each section. Table 8 summed up the results:

Data_set	Examples	Attributes
QCDataW13_16in	11583	20
QCDataW13_12.25in	8025	20
QCDataW13_8.5in	1639	20

Table 8 Training sets per section after QC

4.3 Data Processing

Once the Pre-processing of the data was completed, the training data sets are finally ready to be processed to create the model. To recapitulate, this phase looks for the implementation of a model to predict the ROP response based on the 20 attributes preselected and prepared for the task.

The most important step during this phase is to identify in which main task group the problem lays. Data mining functionalities were discussed in Chapter 2 (2.1), however, to facilitate the task selection, Table 9 provides a simple rather basic guideline established with some simple questions to answer.

Question:	Task:
Is this A or B? Will this be A or B?	Classification
How much or how many?	Regression
How is this organized? What belongs to each other?	Clustering
What happens together? What changes together?	Associations and Correlations
Is this weird?	Anomaly Detection

Table 9 Basic guideline to select the task.

To fulfil the goal of the thesis, the question should be "How much would be the ROP value?" Therefore, it is a Regression task. Then the next step consists in selecting the algorithm to use, which might be challenging depending on the task and the data.

In this regard, it is important to mention the "No Free Lunch Theorems for Optimization" (Wolpert and Macready 1997), which have proved that there is nothing like a perfect model to fit all data sets and that consequently, the effort should be on understanding which model perform better for a specific problem. Considering the theorem statement that when an algorithm performs well for a particular task. As a result, it will degrade its performance on all remaining tasks.

Then, the focal point should be in aligning the algorithm as precise as possible with the features of the actual goal, and then construct it knowing that the same algorithm cannot serve under different conditions. For that reason, each section should have its own model for ROP prediction, and based on the specific inputs discussed during the Pre-processing phases.

RM offers two main alternatives to process the data. The conventional one, where users build the processes block-by-block, analysing the data and testing the results, and a more automatic one with the Auto Model extension available with RM version 9.0. It is an option intended to accelerate the process of building and validating models. It includes well defined steps to optimize parameters with software assistance recommendations based on the data, the task and the variable to predict.

4.3.1 Manual Model Implementation

For the first alternative (Process: 007Model), the QC training set per section is retrieved to create the model. Attributes like Well# and Section# were removed as unnecessary. The ROP attribute role was set as label and a Cross Validation operator was used to train and test the model.

The error was calculated and generated per example as an additional attribute. The model selected for the task was k-Nearest Neighbours (k-NN) due to its working principals and popularity for classification and regression tasks. Neural Networks was also considered and tested (block disable in grey); however, the results presented higher performance errors than k-NN results.

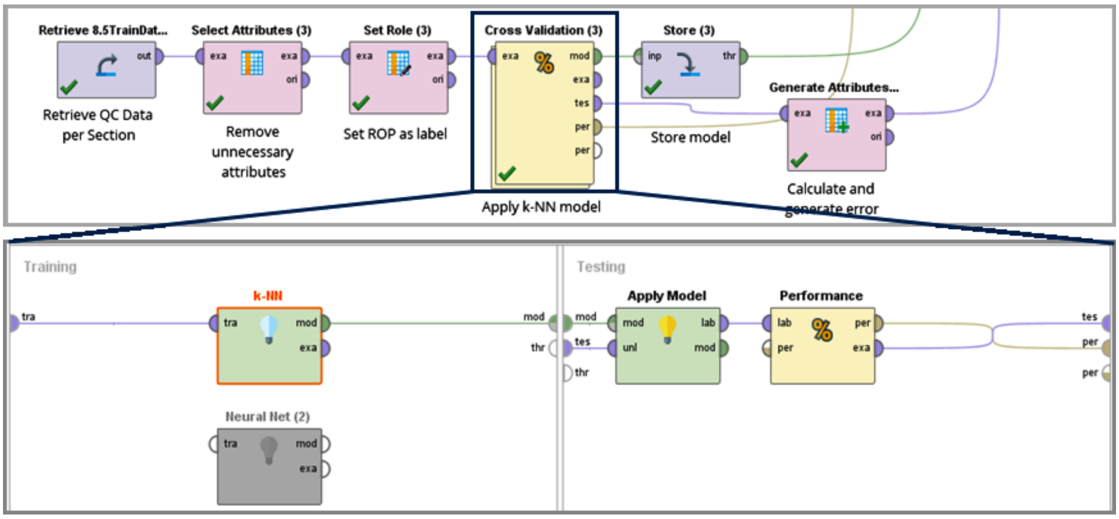


Figure 36 k-NN model using a Cross Validation operator for optimization. Sub-process inside the Cross Validation operator: the left side is the training part for the model, and the right side is the testing part and performance evaluation

The Cross Validation (blue square) is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set. A number of validations must be entered, *n*, which will indicate the time of iterations. The number would define in how many parts a data set will be break into, and there are three types of sampling to build the subsets. Then, *n-1* subsets of data will serve to train the model, to later test it in the excluded subset.

The process repeats for *n*-iterations and the final accuracy is calculated based on the average of the results of the *n*-iterations. For this project, the number of folds, *n*, was determined as 50, and the shuffled sampling was selected to build random subsets of the training data set.

k-NN can be used for regression predictive problems, and as previously described in chapter 2, it works based on similarities, which aligns with the fundamental criteria for data selection and preparation for the training sets.

The "k" is the nearest neighbours considered to take votes from, and it is as crucial parameter for the functionality of this algorithm. Based on trial and error method, the selected value for k was 8, which means that the algorithm creates a circle with the new sample as centre just as big as to enclosure only 8 data points on the plane. Then predictions are calculated by the majority votes of its neighbours, by assigning the average value of the values of its k-NN. In conclusion, the model stores the entire training data set as part of the model and uses it for its prediction.

4.3.1.1 Model Evaluation

To discuss the model results, there are different methods to analyse how well the model performs using some of the tools available for its conception:

- Performance Error
- Graphical View
- Statistical Description

Performance Error:

Based on the Performance operator, which provides different criteria to calculate the error by measuring the difference between the predicted values and the actual values (Li 2017), including, among others:

- Root mean squared error:

$$RMSQErr = \sqrt{\sum_{1}^{n} \frac{(y_i - \bar{y}_i)^2}{n}} \tag{4}$$

- Absolute error:

$$AErr = \sum_{1}^{n} \frac{|y_i - \bar{y}_i|}{n} \tag{5}$$

Where:

n is the number of examples in the data set
y_i is the observed value for i-example
$\bar{y}_i$ is the prediction for i-example

In both cases, errors are given in the unit of measurement of the ROP attribute, i.e., ft/hr.

The same procedure for model implementation and evaluation was followed for the other two sections, with the corresponding QC training sets, and using k-NN algorithm. The calculated performance errors in each case were:

		TRAINING ERROR	
		Using Wells 1 & 3 for training and testing	
Section		*RMSQErr*	*AErr*
2	16"	53.224 +/- 6.632	33.901 +/- 3.008
3	12.25"	32.441 +/- 3.388	23.205 +/- 1.791
4	8.5"	20.321 +/- 3.446	15.612 +/- 2.427

Table 10 *RMSQErr* and *AErr* for all sections using k-NN

Graphical View:

In the graphical view, there are different ways to visualize the errors. For example, when comparing the measured values for ROP with the predicted ones (Figure 37). Ideally, the result would be a straight line in the form of *prediction(ROP) = ROP.*

This graph can be accompanied by indicating a colour scale for the generated Error attribute (ERR = |ROP - *prediction(ROP)*|) to show how the prediction error spreads.

Another example is obtained by plotting the Depth vs. the generated Error, which shows higher differences in shallow depths (Figure 38).

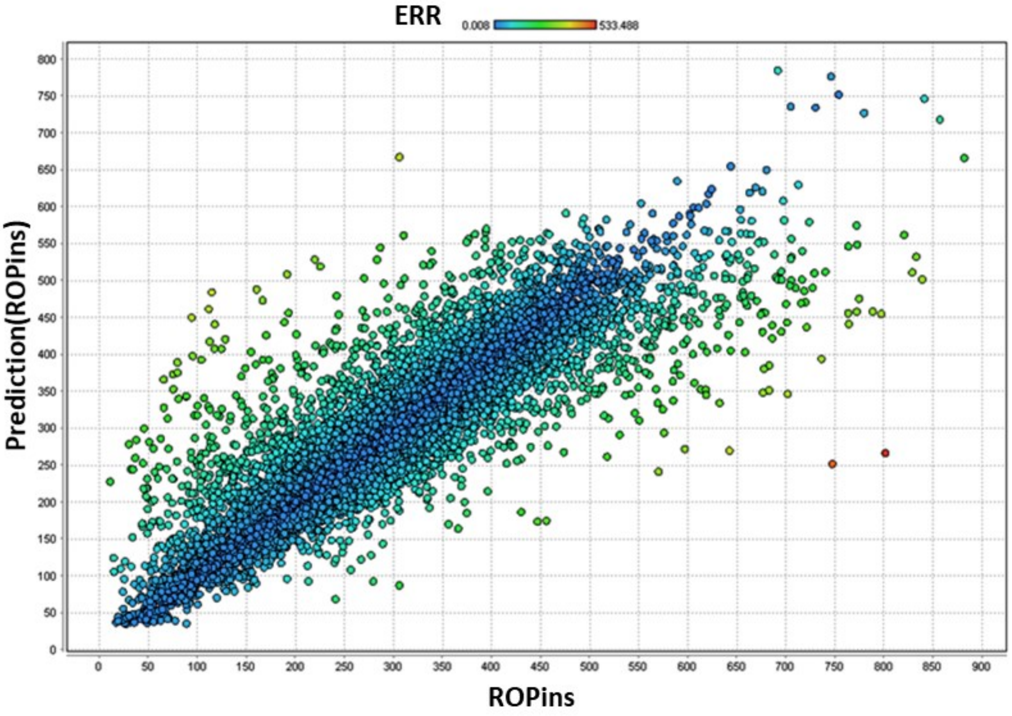


Figure 37 ROP vs. prediction(ROP) using k-NN for 16” Section training set. In colour scale is the generated difference between both values, suggesting the tendency for a straight line as wanted

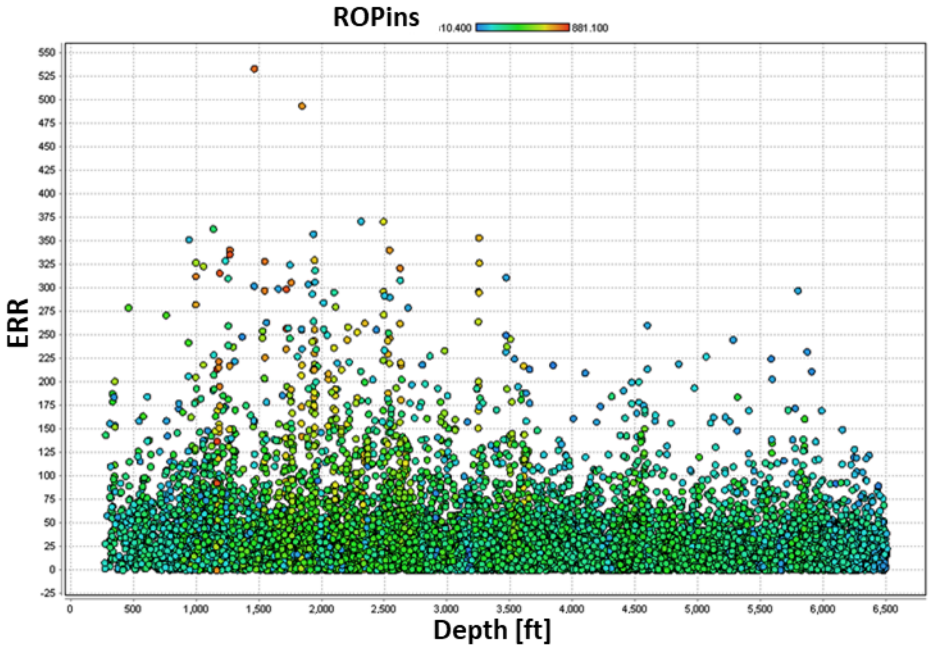
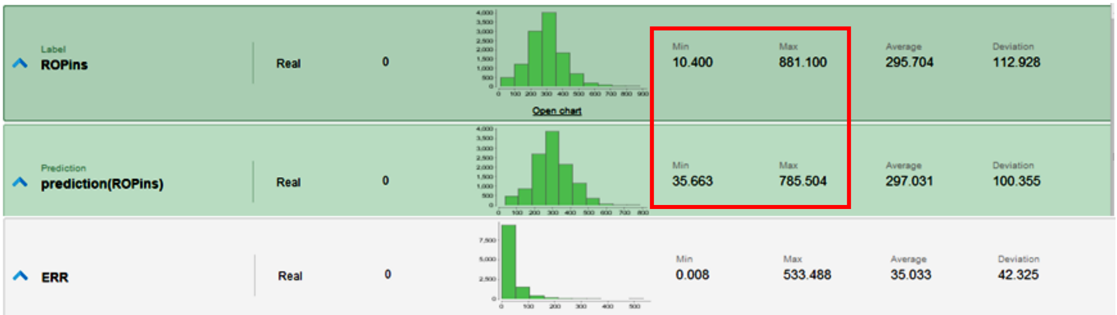


Figure 38 Depth vs. Error using k-NN in 16" Section

Statistical Description:

To complement the graphical and performance error methods, the statistical view, as well offers valuable information to understand the range in which the values of ROP are measured (Minimum and Maximum), and in which range the prediction is obtained (red square):



Label ROPins	Real	0	Open chart	Min 10.400	Max 881.100	Average 295.704	Deviation 112.928
Prediction prediction(ROPins)	Real	0		Min 35.663	Max 785.504	Average 297.031	Deviation 100.355
ERR	Real	0		Min 0.008	Max 533.488	Average 35.033	Deviation 42.325

Figure 39 Statistical summarize of results using k-NN in 16" Section

4.3.2 Auto Model Extension

Auto Model provides a sequential steps workflow to go through the process of creating a regression model.

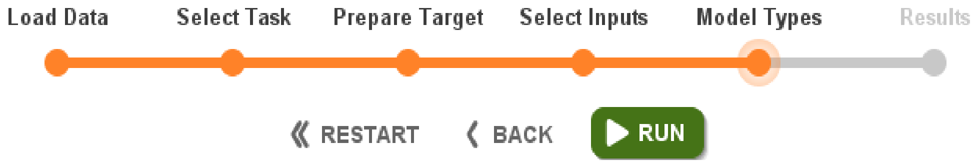
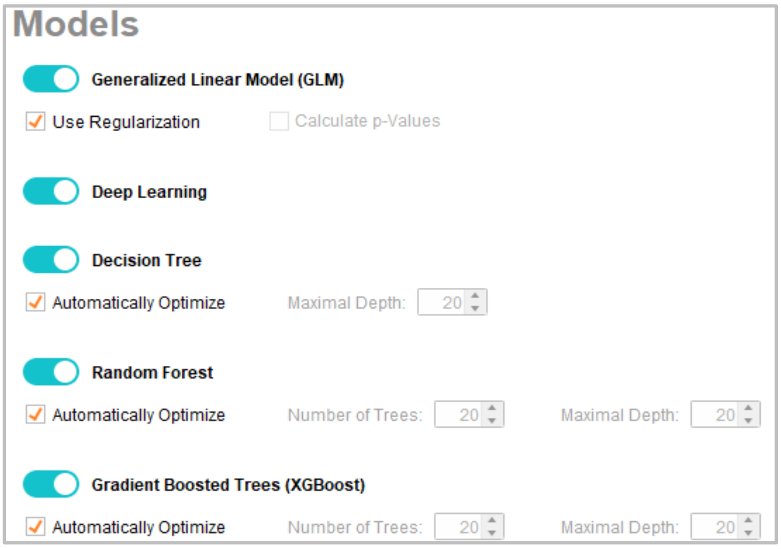


Figure 40 Auto Model sequential workflow

4.3.2.1 Model Selection

Once the data is loaded, it is defined as a prediction problem and the target is addressed as a regression task. Then the inputs are selected from the 20 attributes available, where one is the label attribute (ROP), and some others are left out, based on redundancy, correlation, and relevance, ending with 12 attributes to train the model.

Based on the choices then some relevant machine learning model types are suggested by RM, and displayed in Figure 41 to solve the task.



Models

Generalized Linear Model (GLM)

☑ Use Regularization □ Calculate p-Values

Deep Learning

Decision Tree

☑ Automatically Optimize Maximal Depth: 20

Random Forest

☑ Automatically Optimize Number of Trees: 20 Maximal Depth: 20

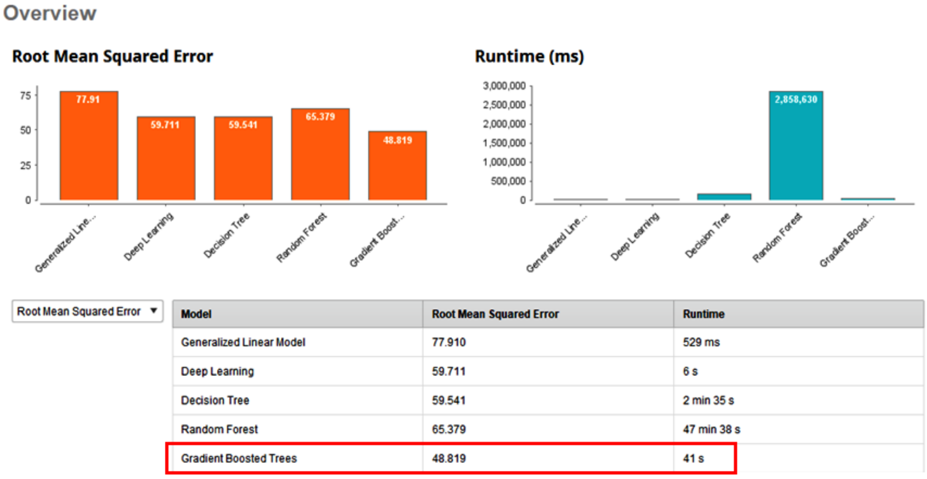
Gradient Boosted Trees (XGBoost)

☑ Automatically Optimize Number of Trees: 20 Maximal Depth: 20

Figure 41 Model Types step

Selection between models is possible, but when all are applied, then it generates generate a comparison between models. In addition, based on the model type, an option for automatic optimization can be selected too.

Figure 42 shows the results for all selected models in two main graphs, one for the error (RMSQErr in this case) and one for the runtime in miliseconds (*ms*). In both cases, results are presented per model and summarized in its numerical form in a table where the type of error to displayed can be changed as well.



Model	Root Mean Squared Error	Runtime
Generalized Linear Model	77.910	529 ms
Deep Learning	59.711	6 s
Decision Tree	59.541	2 min 35 s
Random Forest	65.379	47 min 38 s
Gradient Boosted Trees	48.819	41 s

Figure 42 Auto Model results comparisson

According to the results, Gradient Boosted Trees offers (GBT) the smaller Error (red square). GBT is considered one of the most powerful techniques to build predictive models and was derived from the idea that a weak learner can be modified to become better (Brownlee 2016).

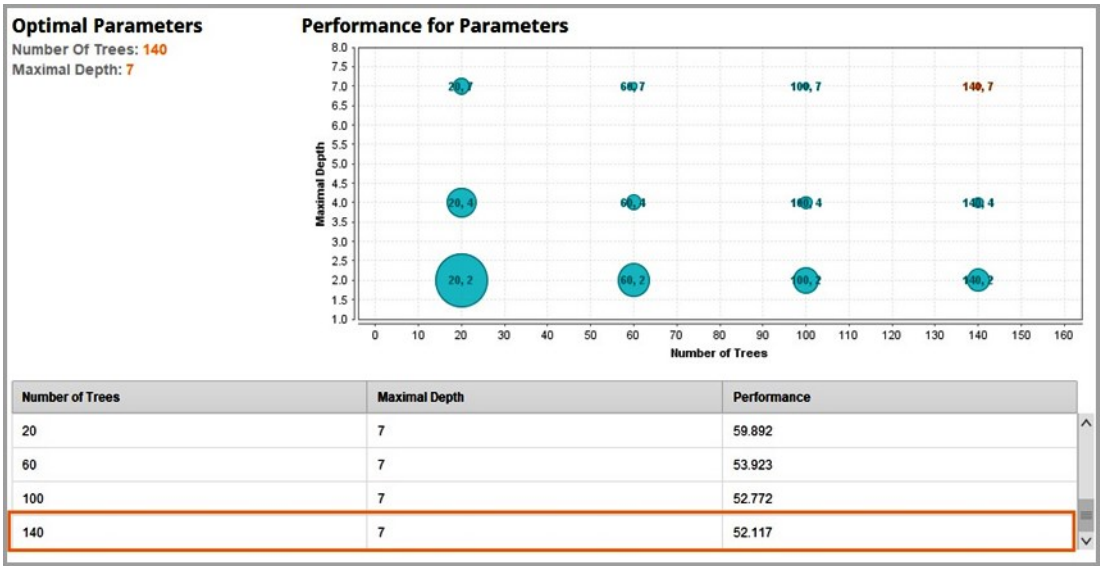
The fundamental idea was to filter observations based on difficulty, leaving the easy ones and focusing on the difficult ones by developing new weak learners to handle them. At the end, the weak learning method is used repetitively, with a succession of refocused observations that the previous learners could not solve properly. Then predictions are made by majority vote of the weak learners' predictions, in accordance to their individual accuracy, i.e., difficult observations receive larger weights until the algorithm identifies the model that better suit them (Kuhn and Johnson 2013).

The model was further developed as a numerical optimization problem with the objective of minimizing its losses. To sum it up, it involves three main components (Brownlee 2016):

1. The loss function to be optimized, which could be the squared error in the case of a regression problem.
2. A weak learner to make predictions. As the name suggested, "Decision Tress" are used as the weak learner, with real values outputs to choose the best split points to later be added together. Generally, larger trees can be used with 4 to 8 levels.
3. An additive model to add weak learners to optimize the loss function. In this case, trees are added one at a time, while existing trees are left unchanged. Furthermore, a gradient descent procedure is applied, where the loss is calculated, then a tree is added to the model to follow the gradient and reduce the loss. Finally, the output of the new tree is added to the output of the existing sequence of trees to improve the final output until an acceptable level or when no longer improve is achieved.

4.3.2.2 Model Implementation and Evaluation

GBT model reaches its optimal results with 140 Trees and a Maximal Depth of seven levels (Figure 43). In addition, a chart plotting the Number of Tress vs. the Maximal Depth is presented to compare the results regarding the model inputs, which allows the evaluation of the Performance for Parameters resulting in the optimal selection.



Number of Trees	Maximal Depth	Performance
20	7	59.892
60	7	53.923
100	7	52.772
140	7	52.117

Figure 43 Graphical visualization of the Performance for Parameters and table of Performance

Due to the size of the model, its visualization in only one image is hardly legible. However, a GBT model can be calculated with restriction of parameters in order to offer a visualization of the model that can be discussed to understand the concept.

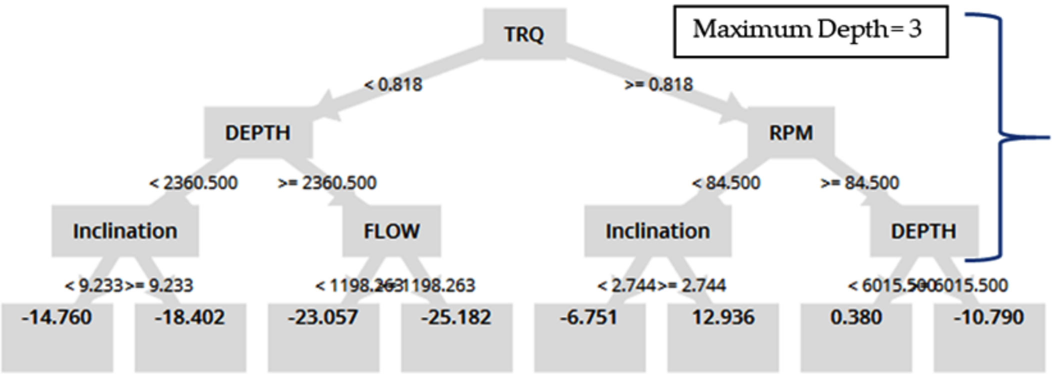


Figure 44 Gradient Boosted Trees model with restricted parameters. First tree

Figure 44 shows a GBT model for the same training set but with a Maximum Depth of 3 levels and a limited Number of Trees to 3. The Maximal Depth is highlighted by the right brace in blue. The given Number of Trees, for this case, restricts the possible combinations to 2 another similar decision trees (Figure 45) that complement the one presented below, to finally form the model.

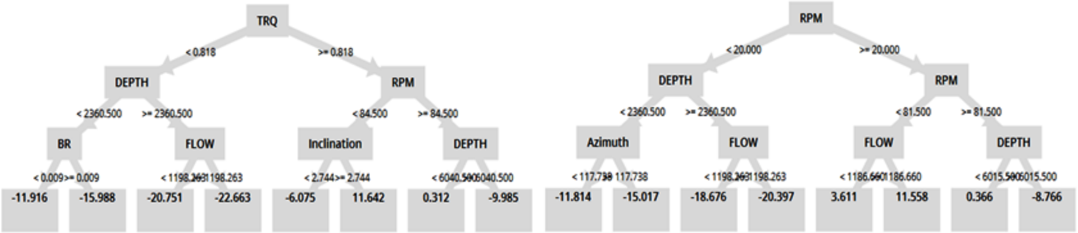


Figure 45 The two remaining trees that complete the model for the limited case

As expected, a restricted model results in a poorer performance with higher errors. For this example: RMSQErr = 102.55 and AErr = 77.413 +/- 67.259.

The following evaluation mainly corresponds to the GBM optimized model created for the 16" Section data set (Process: 007ModelGradientBoostedTrees), with 140 Number of Trees and a Maximum Depth of 7.

The structure presented for the model evaluation and Error methods will be the same as the one used with k-NN model.

Performance Error:

Using the QC training sets for each section, each GBT model was trained and tested. The performance results are as follow:

		TRAINING ERROR	
		Using Wells 1 & 3 for training and testing	
Section		***RMSQErr***	***AErr***
2	16"	48.819 +/- 0	32.010 +/- 36.859
3	12.25"	29.905 +/- 0	21.164 +/- 21.128
4	8.5"	19.776 +/- 0	14.886 +/- 13.019

Table 11 *RMSQErr* and *AErr* for all sections using optimized GBT.

Graphical View:

During the model implementation, the same process was followed to generate a calculated error as an additional attribute, by comparing the measured ROP with the predicted value.

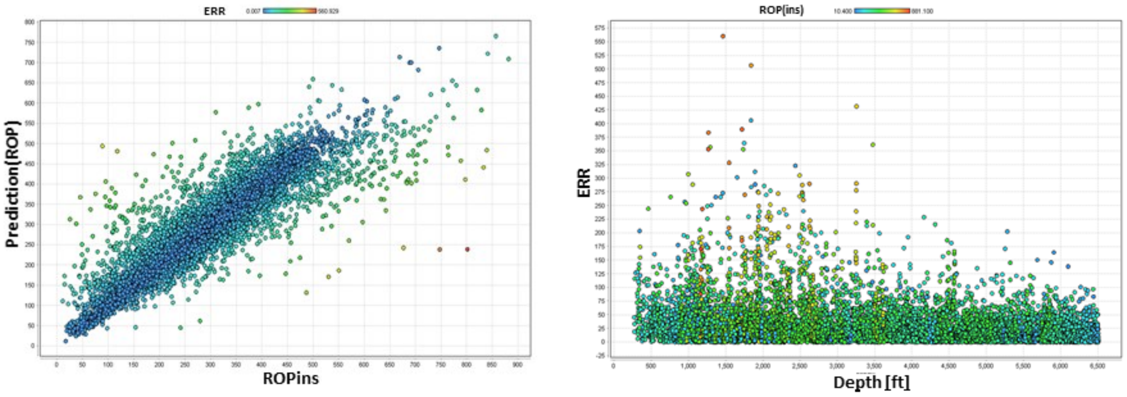


Figure 46 Left: ROP vs. prediction(ROP). Generated Error in colour scale. Right: Depth vs. Error

Statistical Description:

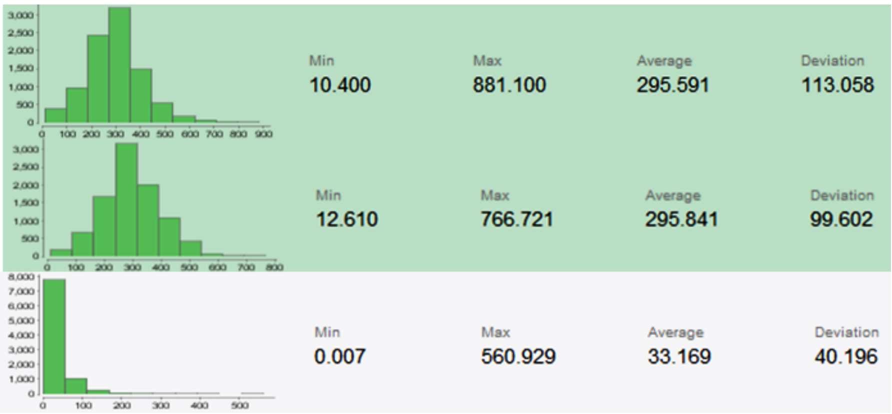


Figure 47 Statistical data for a) The measured ROP, b) The predicted ROP, and c) The Error

The proper discussion for the results of both models is prepared and presented in the Data Analysis and Discussion chapter.

Chapter 5 Data Analysis and Results Discussion

With the data processed and prior to discuss the results, data needs to be further analyzed using the visualization tools, considering the types of errors and using descriptive statistics to improve the understanding of the variables on research.

5.1 Training Error and Prediction Error

During the previous stage, models were implemented and tested, providing a comparison between the measured values for ROP and the predicted ones. That difference was called "Error". However, in prediction modelling, there are two well-defined types of errors, and quite different in importance (Nivre 2007):

1. Training error: Assess the model about the answer in comparison to the training sample. The error is the mean error over the same data used for its creation.
2. Prediction error: Also known as "Test error", the model is tested with unseen data sets. It refers on how well would do a model with an independent test sample.

To this point, only the Training errors have been calculated and presented for the two algorithms used, k-NN and GBT.

5.2 Model Evaluation

In order to calculate the Prediction error, both models need to be tested in a "new" Well. In this case, the initial data set included four Wells drilled in the same field and in consequently order. Well #2 was excluded for the modelling due to its particularity in the profile and design. Wells #1 and #3 were used to create the models, which can now be tested in Well #4.

This stage is called deployment process (Process: 008Deployment), and its structure is basically the same for both models. It starts by retrieving the corresponding created model to apply it into the new Well. Data from new set must be filtered per section as each section has its corresponding model. Finally, the Prediction errors are calculated and consequently , the performance per model and per section can be generated.

5.3 Models Comparison

With both models fully deployed and tested on a new data set, it was necessary to compare its performance per section. Comparison was done following the same criteria earlier defined using the Performance Error, the Graphical View and the Statistical Description methods.

5.3.1 Performance Error

Table 12 shows the results for the prediction error after testing both algorithms using the data set from Well #4. Results are presented per section, as each section has its own model.

	PREDICTION ERROR			
Model:	**k-NN**		**Gradient Boost Trees**	
Section	**RMSQErr**	**AErr**	**RMSWErr**	**AErr**
16"	143.775 +/- 0	115.031 +/- 86.250	106.588 +/- 0	82.672 +/- 67.278
12.25"	63.729 +/- 0	47.259 +/- 42.755	62.424 +/- 0	48.830 +/- 38.890
8.5"	29.163 +/- 0	22.922 +/- 18.030	26.952 +/- 0	21.361 +/- 16.436

Table 12 Prediction error per model and per section

5.3.2 Graphical View and Statistical Description

The graphical view along with the statistical description are displayed together to allow the comparison for testing results per model and for each section.

Under ideal conditions, where the measurement and the prediction would be equal, results should be concentrated in a 45° diagonal, with no dispersion around it. Therefore, what is expected in the charts is that the majority of the data points follow the diagonal with a minimum of dispersion.

In addition, the statistical values could be reflected in the charts too. For example, in cases where the prediction values are lower than the real measurements, this would change the data concentration slope.

16” Section:

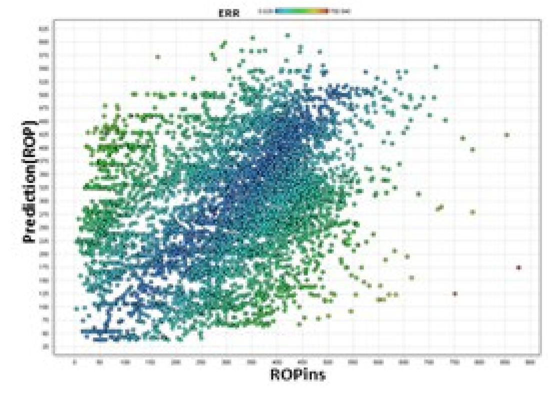
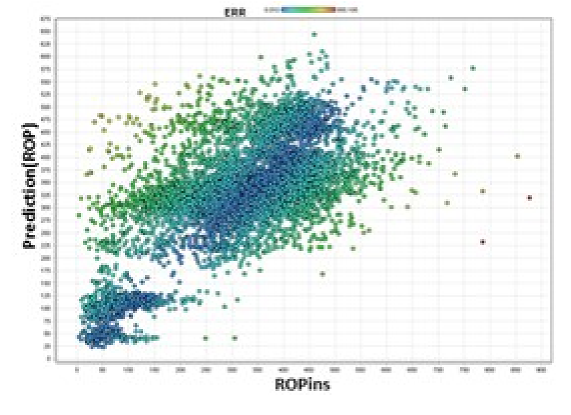
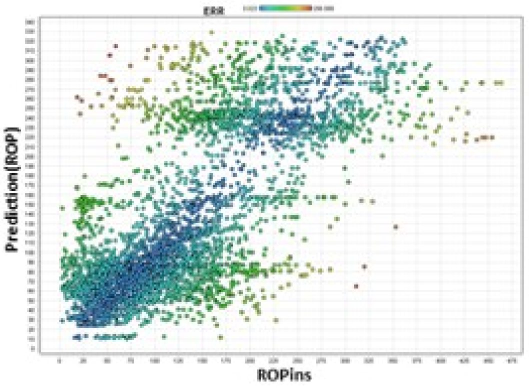
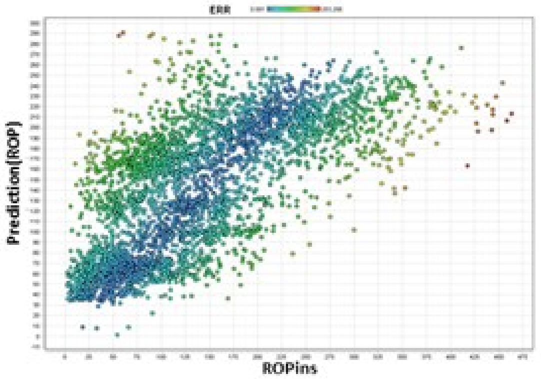
k-NN			**GBT**	
				
Attribute	**Min**	**Max**	**Min**	**Max**
ROP	2.800	875.700	2.800	875.700
Prediction	38.852	613.700	24.846	644.588
Err	0.029	700.540	0.010	555.105

Table 13 16” Section results for both models

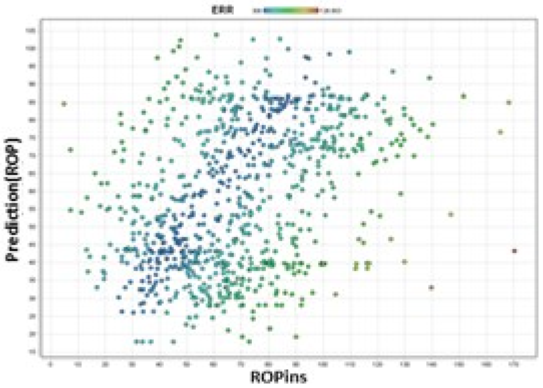
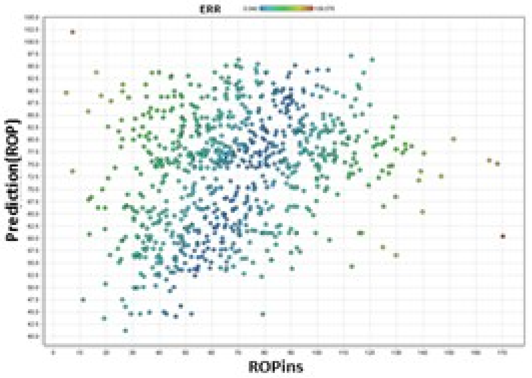
12.25″ Section:

k-NN	GBT
	

Attribute	Min	Max	Min	Max
ROP	2.400	462.500	2.400	462.500
Prediction	11.189	329.498	1.961	291.037
Err	0.023	256.589	0.001	253.256

Table 14 12.25″ Section results for both models

8.5″ Section:

k-NN	GBT
	

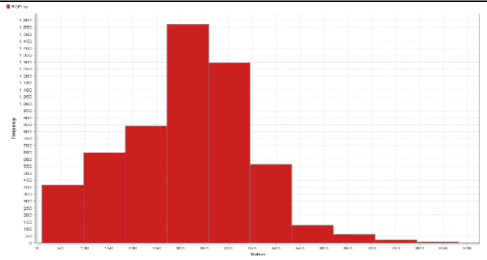
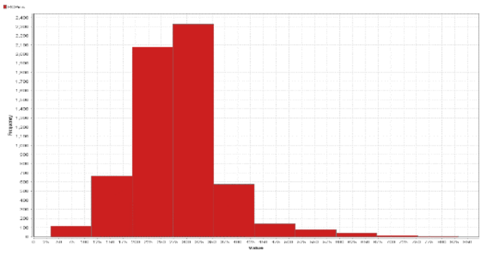
Attribute	Min	Max	Min	Max
ROP	4.700	170.100	4.700	170.100
Prediction	17.944	103.942	41.281	102.039
Err	0.008	126.803	0.040	109.576

Table 15 8.5″ Section results for both models

5.4 ROP Statistical Summaries

Prior to discuss the results, descriptive statistic shall be used to summarize the ROP behavior from the training samples, i.e., Wells #1 and #3. A process was created (Process: 005Statistics), where the training data sets are retrieved and combined, to later be filtered per well and per section. The Aggregate operator was used to add the calculation of the median and mode to the statistical results.

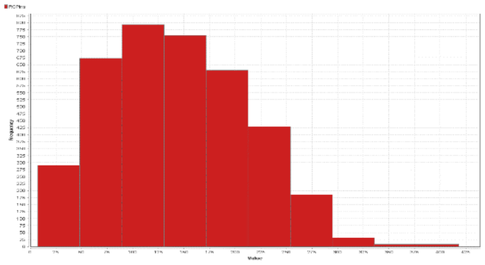
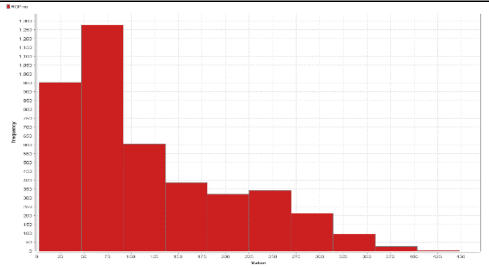
16″ Section

Well #1	Well #3
	

Well	Min	Max	Mean	Median	Mode	Standard Deviation
#1	10.400	881.100	312.888	324.300	305.200	133.382
#3	33.100	832.200	279.885	277.600	278.700	87.149

Table 16 ROP Histogram and basic summary statistics for 16″ Section.

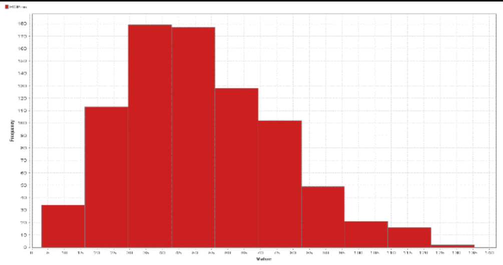
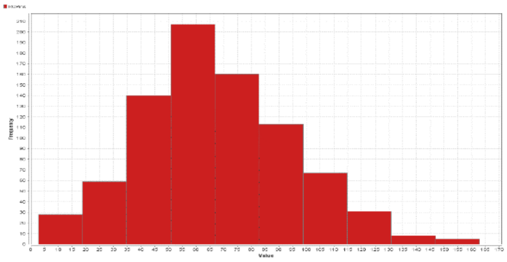
12.25″ Section

Well #1	Well #3
	

Well	Min	Max	Mean	Median	Mode	Standard Deviation
#1	7.300	418.100	143.258	138.200	99.200	68.863
#3	2.400	447.900	117.693	85.500	48.400	88.092

Table 17 ROP Histogram and basic summary statistics for 12.25″ Section

8.5″ Section

Well #1	Well #3
	

Well	Min	Max	Mean	Median	Mode	Standard Deviation

#1	3.000	135.400	51.638	49.000	48.400	23.789
#3	2.800	162.800	67.183	65.000	43.700	27.613

Table 18 ROP Histogram and basic summary statistics for 8.5″ Section

The histograms for all cases show data concentration is in the lower side of the ROP measurements values. At the same time, the high values of the standard deviation reveal a large amount of variation in the sample. This could be a reflection of reality, but it could also mean noise in the measurements, or simply due to the presence of remaining outliers (extremely high or extremely low values).

In this case, another property can be considered using the Pearson mode skewness formula, which provides a reference of the data skewness.

$$Pearson's\ first\ coefficient\ of\ skewness = \frac{mean - mode}{standard\ deviation} \tag{6}$$

The following table summarize the results:

Section	Mean	Mode	Standard Deviation	Skewness
16″	312.88	305.2	133.382	0.057579
	279.885	278.7	87.149	0.013597
12.25″	143.258	99.2	68.863	0.639792
	117.693	48.4	88.092	0.786598
8.5″	51.638	48.4	23.789	0.136113
	67.183	43.7	27.613	0.850433

Table 19 Pearson’s first coefficient of skewness calculation

Zero value would mean no skewness, and positive values, mean Positive skewness, in other words, the ROP distribution is skewed to the right.

5.5 Evaluation of Results

For the evaluation of this work and its results, three outcomes are considered:

1. Visualization Tools Functionalities
2. Predictive Modelling Evaluation
3. Resource Constraints

5.5.1 Visualization Tools Functionalities

Visualization tools have proved to be essential while working with data. Thus, through the methodology phases, data mining software visualization tools were used in five of the six steps followed during this project, in other words during the Pre-processing, Processing, Analysis, Evaluation, and Results.

The different options delivered:

- Relationships between attributes using scatter plots or correlation matrix.

- Relation between examples using histograms.
- Support to identify outliers.
- Simplification and promptness for data processing.
- Pre-defined descriptive statistics options to improve analysis.

5.5.2 Predictive Modelling Evaluation

It is necessary to clarify that the evaluation is not regarding the algorithm used, but the developed model for the proposed problem and its implementation process.

The algorithms selected to model the ROP prediction for a new well in the same field were k-NN and Gradient Boosted Trees. The model evaluation should consider three important aspects:

Aspects	k-NN	GBT
1. Ease to interpret the output:	Use the database in which data points are separated to make predictions just-in-time by calculating the similarity between an input sample and each training instance.	Works on the principal of reconstruction of the residual, considering that the best possible next model in combination with previous weaker ones will improve the result.
2. Calculation time:	Low	Low
3. Predictive power:	Low	Low

Table 20 Model Evaluation aspects

Regarding the first aspect, k-NN is considered easier in terms of model description; however, the calculations behind it are not quite clear. On the other hand, GBT seems simple, but potentially extensive and therefore, harder to follow. Nevertheless, calculations behind its results are transparent.

In term of Performance results, it is important to consider, that the MSQErr along with the AErr serve well as a general purpose error metric, but both only indicate the magnitude of the average error, where GBT seems slightly better than k-NN (Table 12). This aligns with the corresponding charts for ROP vs. prediction(ROP) presented in the model comparison section, where results appear less spread for GBT compared to k-NN.

Moreover, the concepts of the Training and Testing error are the ones that need to be taken into account. In a good prediction model, both should be close. When the Testing error is higher means that the model performance for prediction is low; therefore the prediction power in both cases was found to be low.

An interesting point to consider is the prediction range (Table 13 – Table 15). Only in the 16” Section, GBT prediction reaches a ROP maximum value higher than one obtained using k-NN model. In the other two sections, k-NN prediction reaches higher values. Still, in both cases, the prediction maximum values are rather below the maximum measured values, which could be due to the positive skewness of the data used to train both models.

Other important conclusion which related to the modelling evaluation and worth to be mentioned here is: results show that prediction under specific conditions is possible, but highly depending on the data availability for the model input, in two fronts: quantity and quality.

For this project, the label attribute information was obtained in the form of a Depth based LAS file with a granularity per foot. This could be improved when Time based LAS files are available and for a fair amount of candidate wells.

It would also require an extensive quality control and higher processing power as earlier exemplified in chapter 4.

5.5.3 Resource Constraints

Finally, yet importantly, the resource constraints need to be mentioned and assessed, starting with the data availability. Data mining reaches its potential based on its capacity to handle huge amounts of data and extract useful information from it.

Unfortunately, for this study data was restricted in several ways:

- Samples, i.e., the number of well candidates was limited. The amount of examples for 16" Section was much higher compared to the other two sections (Table 8).
- Quality of the data. During the pre-processing stage, the data cleaning process demanded extra QC work due to inconsistencies in the data. The outlier detection was used for this aim through manual inspection and using an automated detection operator (LOF distance).
- The geological attribute was the one including more missing values. It was not complemented with a formation description to better feed the model.
- No metadata was available in the form of Daily Drilling Reports, Mud Reports, Slide Sheets, Geological Reports, etc.

As equal in importance as data availability, is data understanding. Once the data is obtained, understanding its format and the fields within it represents a challenge for any outsider trying to analyse it. Particularly when not familiar with the data acquisition process, which could result in unrepresentative data that would lead to unpredictable results.

Chapter 6 Conclusions & Recommendations

6.1 Conclusions

The main conclusions of the thesis can be summarized in the following points:

- Referring to the overall process, extracting value from data should be considered an iterative process that consists of specific phases, following clear objectives with the corresponding acceptance criteria.
- When working with real data, quality issues will always come across, where the proper counter actions need to be put in place.
- There are several software including different types of visualizations tools that can be used in combination with descriptive statistics to increase efficiency while performing data mining. However, in terms of processing, sufficient computational power must be considered.
- Data availability and its understanding are the main constraints for modelling and prediction, along with the time frame needed to perform a good research of the variable of concern and the data processing.
- Training sets were summarized per section and using only the attributes that could affect the outcome.
- While performing algorithms selection, concepts need to be clear, considering the "No Free Lunch Theorems for optimization".
- Model performance will vary depending on the amount of examples and attributes, but typically requiring large volumes of training data to be effective. In this context, data Pre-processing is essential to prepare a data set capable of being mined in a reasonable amount of time without sacrificing accuracy.
- k-NN model has two main parameters to be set: the distance measure method used and the number of neighbours to choose. The number of neighbours is, in fact, the most important parameter for this algorithm to perform properly, and it is usually selected by training and evaluating the model.
- GBT can slow the training process when lot of trees are used. In this regard, optimization of parameters is needed to define a sweet spot involving the maximum depth, because the deeper the tree, the more information it captures about the data.
- Performance optimization shows improvement in the prediction values for both algorithms tested. However optimization was handled in different forms, for:
    - k-NN: a Cross Validation operator was used to optimize the model based on random combinations of the training and testing sets from the original sample.
    - GBT: the performance optimization parameters functionality was used, allowing evaluation of different model parameters, i.e., Maximum Depth and Number of Trees, until the lower error were achieved.

6.2 Recommendations

Based on the findings of this thesis the following recommendations can be drawn:

- Data mining demands data quality. It is highly recommended that during the data acquisition process, sensors' operators get a clear understanding of their role in constantly checking the sources of the data for accuracy. Most surface sensors in the O&G industry still require often recalibration to avoid recording null values or issuing readings with values physically not possible. Furthermore, the implementation of Quality Control measurements for data during acquisition and prior to delivery must become a standard procedure.
- When possible, redundancy in the measurements should be considered, to provide means for data validation, and to improve data quality.
- It is suggested to assess the use of the Directional Difficulty Index (Oag W. and Williams 2000), instead of some of the Directional Drilling attributes. This is due to the differences in the ranges of values between attributes, which for directional drilling attributes are considerable low compared to the other ones. By reducing the difference between features values, attribute's weighting could be prevented.
- Consider a scalable infrastructure for high-density data, due to data acquisition in two domains: depth and time. Additionally, balance of the data must be taken into account to prevent effects on the validation of the performance.
- Especial attention handling missing values is required, with focus in understanding its type, possible effects and categorising how to do its processing.

6.3 Further Work

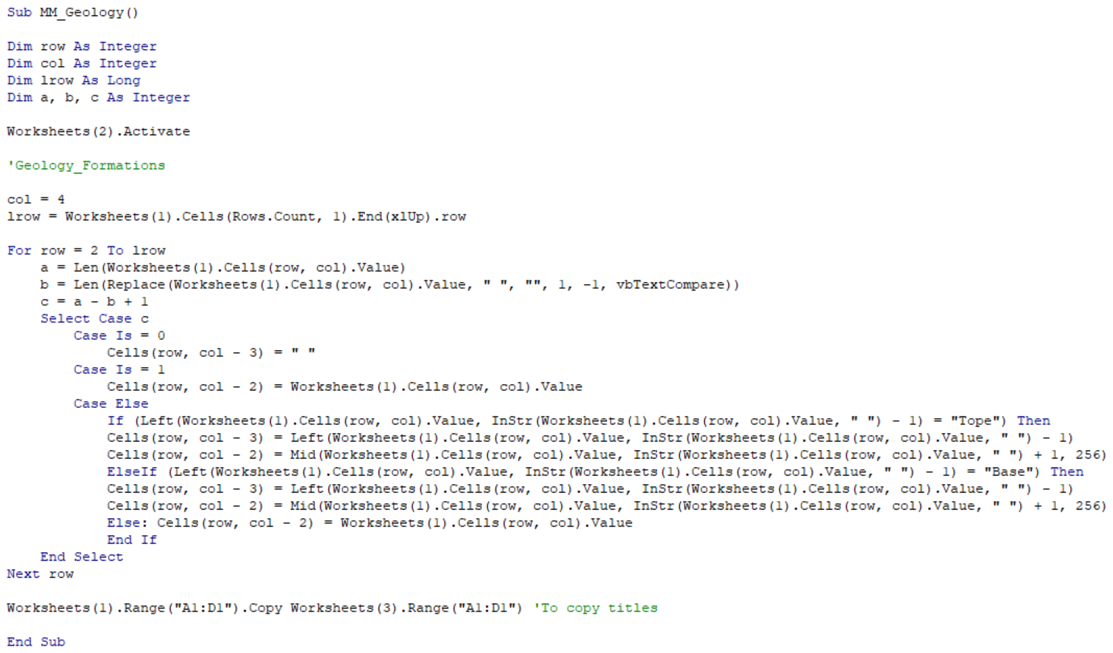
The main goal was to apply data mining to assess ROP response. Although this objective was partially reached, mainly due to the resources constraints and the resulted low prediction capability covered during the discussion of results, the processes presented using drilling data endorse the application of data mining for ROP analysis and prediction, where the further work should focus on:

- Improving the prediction capability of the model, by overcoming its uncertainty. A concept should be developed to generate uncertainty windows for each predicted value.
- Working through the cases where the actual ROP is below the predicted value.
- Assessing the error per case, and as a group looking for common patterns.
- Analyzing the factors contributing to the deviation from the reference.

Appendix

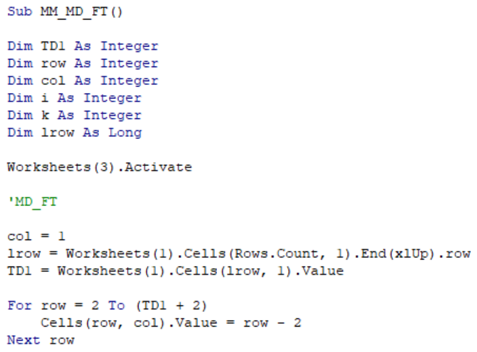
A.1 VBS

A.1.1 Assigning of geological information to all the survey stations.

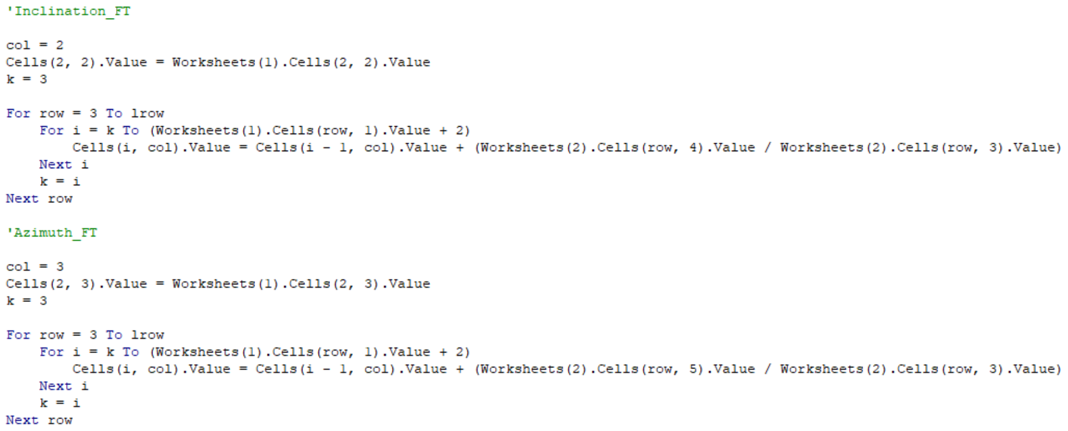


```
Sub MM_Geology()

Dim row As Integer
Dim col As Integer
Dim lrow As Long
Dim a, b, c As Integer

Worksheets(2).Activate

'Geology_Formations

col = 4
lrow = Worksheets(1).Cells(Rows.Count, 1).End(xlUp).row

For row = 2 To lrow
    a = Len(Worksheets(1).Cells(row, col).Value)
    b = Len(Replace(Worksheets(1).Cells(row, col).Value, " ", "", 1, -1, vbTextCompare))
    c = a - b + 1
    Select Case c
        Case Is = 0
            Cells(row, col - 3) = " "
        Case Is = 1
            Cells(row, col - 2) = Worksheets(1).Cells(row, col).Value
        Case Else
            If (Left(Worksheets(1).Cells(row, col).Value, InStr(Worksheets(1).Cells(row, col).Value, " ") - 1) = "Tope") Then
            Cells(row, col - 3) = Left(Worksheets(1).Cells(row, col).Value, InStr(Worksheets(1).Cells(row, col).Value, " ") - 1)
            Cells(row, col - 2) = Mid(Worksheets(1).Cells(row, col).Value, InStr(Worksheets(1).Cells(row, col).Value, " ") + 1, 256)
            ElseIf (Left(Worksheets(1).Cells(row, col).Value, InStr(Worksheets(1).Cells(row, col).Value, " ") - 1) = "Base") Then
            Cells(row, col - 3) = Left(Worksheets(1).Cells(row, col).Value, InStr(Worksheets(1).Cells(row, col).Value, " ") - 1)
            Cells(row, col - 2) = Mid(Worksheets(1).Cells(row, col).Value, InStr(Worksheets(1).Cells(row, col).Value, " ") + 1, 256)
            Else: Cells(row, col - 2) = Worksheets(1).Cells(row, col).Value
            End If
    End Select
Next row

Worksheets(1).Range("A1:D1").Copy Worksheets(3).Range("A1:D1") 'To copy titles

End Sub
```

A.1.2 Survey data per foot.

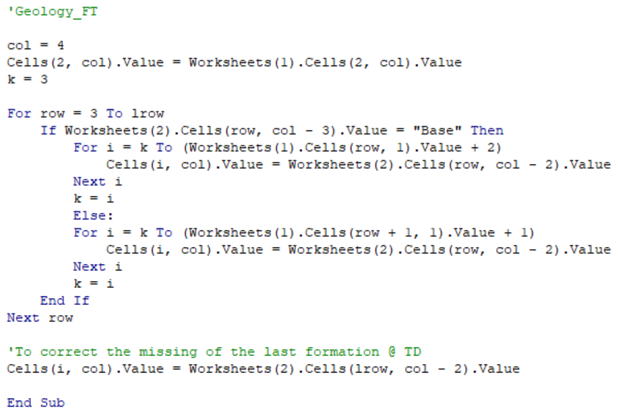


```
Sub MM_MD_FT()

Dim TD1 As Integer
Dim row As Integer
Dim col As Integer
Dim i As Integer
Dim k As Integer
Dim lrow As Long

Worksheets(3).Activate

'MD_FT

col = 1
lrow = Worksheets(1).Cells(Rows.Count, 1).End(xlUp).row
TD1 = Worksheets(1).Cells(lrow, 1).Value

For row = 2 To (TD1 + 2)
    Cells(row, col).Value = row - 2
Next row
```



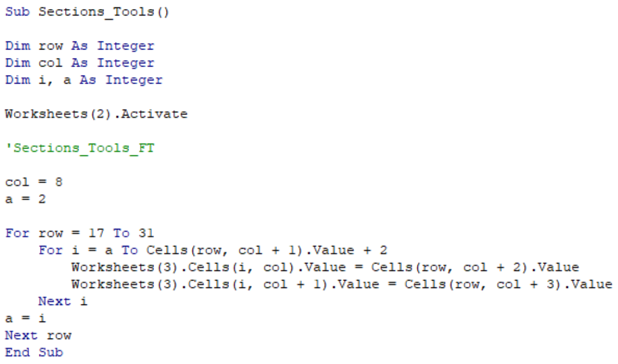
```
'Inclination_FT

col = 2
Cells(2, 2).Value = Worksheets(1).Cells(2, 2).Value
k = 3

For row = 3 To lrow
    For i = k To (Worksheets(1).Cells(row, 1).Value + 2)
        Cells(i, col).Value = Cells(i - 1, col).Value + (Worksheets(2).Cells(row, 4).Value / Worksheets(2).Cells(row, 3).Value)
    Next i
    k = i
Next row

'Azimuth_FT

col = 3
Cells(2, 3).Value = Worksheets(1).Cells(2, 3).Value
k = 3

For row = 3 To lrow
    For i = k To (Worksheets(1).Cells(row, 1).Value + 2)
        Cells(i, col).Value = Cells(i - 1, col).Value + (Worksheets(2).Cells(row, 5).Value / Worksheets(2).Cells(row, 3).Value)
    Next i
    k = i
Next row
```

A.1.3 Geological data per foot.



```
'Geology_FT

col = 4
Cells(2, col).Value = Worksheets(1).Cells(2, col).Value
k = 3

For row = 3 To lrow
    If Worksheets(2).Cells(row, col - 3).Value = "Base" Then
        For i = k To (Worksheets(1).Cells(row, 1).Value + 2)
            Cells(i, col).Value = Worksheets(2).Cells(row, col - 2).Value
        Next i
        k = i
        Else:
        For i = k To (Worksheets(1).Cells(row + 1, 1).Value + 1)
            Cells(i, col).Value = Worksheets(2).Cells(row, col - 2).Value
        Next i
        k = i
    End If
Next row

'To correct the missing of the last formation @ TD
Cells(i, col).Value = Worksheets(2).Cells(lrow, col - 2).Value

End Sub
```

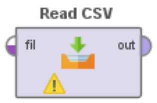
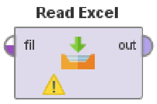
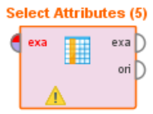
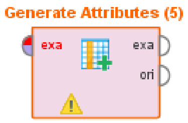
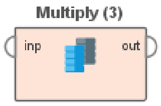
A.1.4 Sections and tools used per foot



```
Sub Sections_Tools()

Dim row As Integer
Dim col As Integer
Dim i, a As Integer

Worksheets(2).Activate

'Sections_Tools_FT

col = 8
a = 2

For row = 17 To 31
    For i = a To Cells(row, col + 1).Value + 2
        Worksheets(3).Cells(i, col).Value = Cells(row, col + 2).Value
        Worksheets(3).Cells(i, col + 1).Value = Cells(row, col + 3).Value
    Next i
a = i
Next row
End Sub
```

A.2 Main RM Operators used

List of the main operators used to create the processes along with a brief description based on RM Studio Help:

Operators	Description
	Reads a data file from the CSV format.
	Reads a data file from the xls format.
	Pick a subset of specific Attributes of a data-set selected by the user and removes the ones unselected ones. Provides an option to invert the selection.
	Selects which Examples are kept and which ones are removed based on different conditions manually defined including missing values, comparative options, etc.
	Stores an IO Object in the data repository folder selected by the user.
	Access data sets from the repository to be used in the process.
	Join two data sets using one or more attributes of the input data as key attribute for the joining.
	Creates new attributes using mathematical expressions and according to the user specifications.
	Makes copies of the selected data set to be used it as different inputs of other processes.

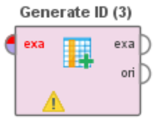
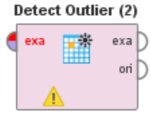
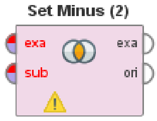
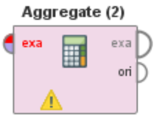
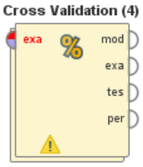
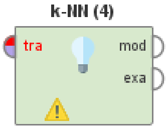
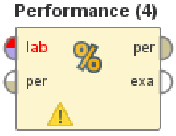
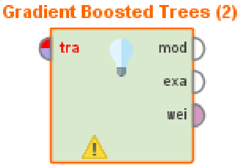
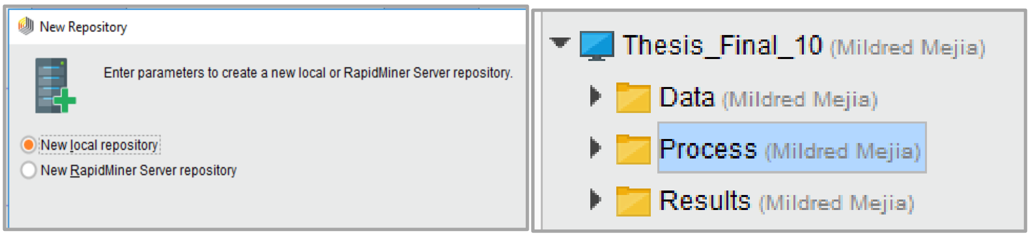
 	Adds a new attribute with an ID role selected by the user.
 	Identifies n outliers in a data set based on the distance to their k nearest neighbors, where n and k are user defined parameters.
 	Returns the examples of the data whose IDs are not part of the other data set.
 	Merges two or more compatible data sets into one combined set.
 	Aggregation different functions, among others, statistical measurements.
 	Described in detail in Section 4.3.1. It performs a cross validation to estimate the statistical performance of a model.
 	Generates a k-NN model.
 	Delivers a list of performance criteria values for statistical performance evaluation.
 	Executes Gradient Boosted Trees algorithm as defined by user.

Table 21 List of main operators used for the model implementation and testing.

A.3 RM Project stages

Project creation and structure:



New Repository

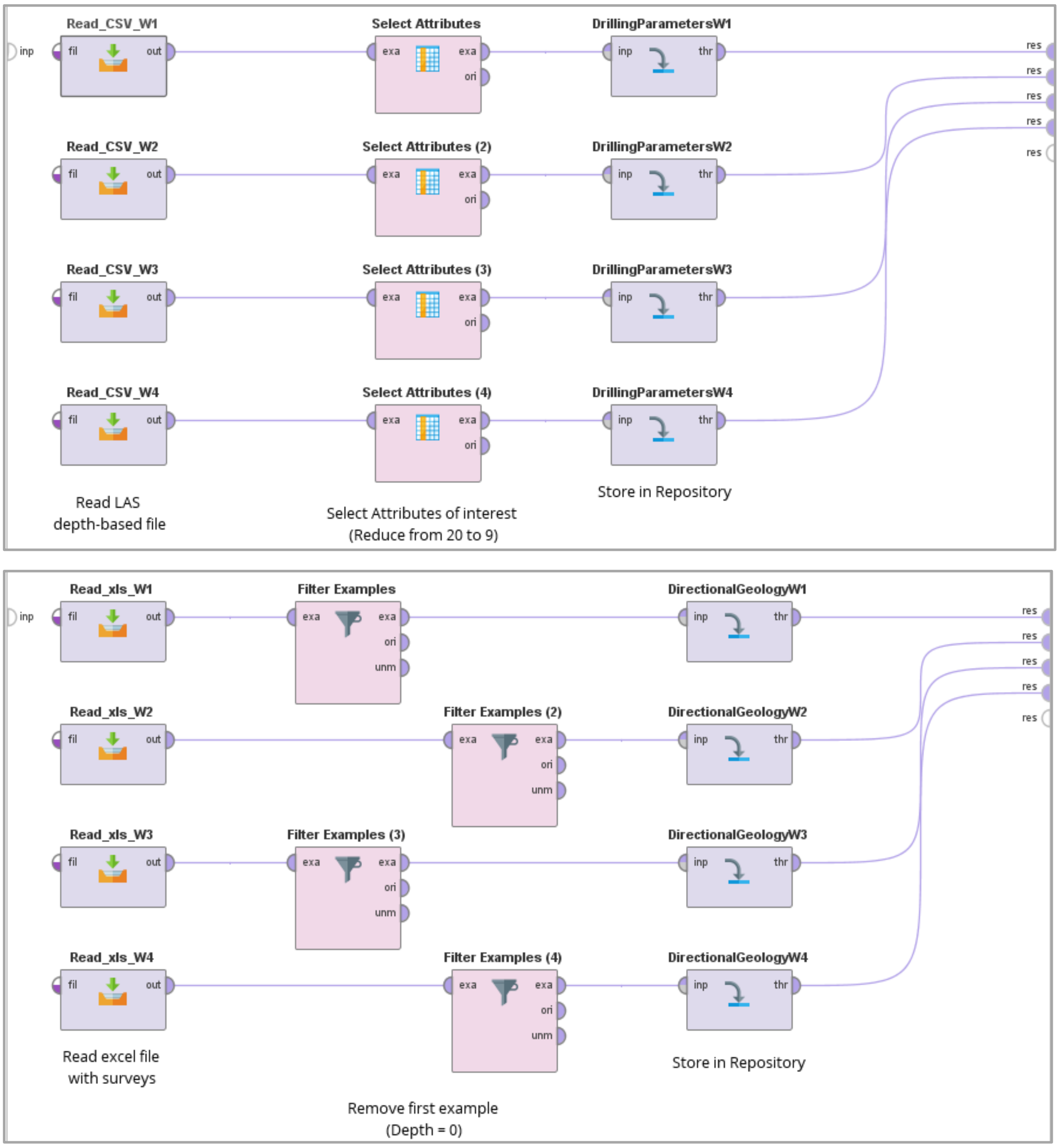
Enter parameters to create a new local or RapidMiner Server repository.

● New local repository

○ New RapidMiner Server repository

Figure 48 Creation of a local Repository and folders to store data and processes.

Process: 001DataLoadDP & 001DataLoadDG respectively



Read LAS depth-based file

Select Attributes of interest (Reduce from 20 to 9)

Store in Repository

Read excel file with surveys

Remove first example (Depth = 0)

Store in Repository

Figure 49 Data load of LAS File and Survey listing.

Process: 002DataPerWell

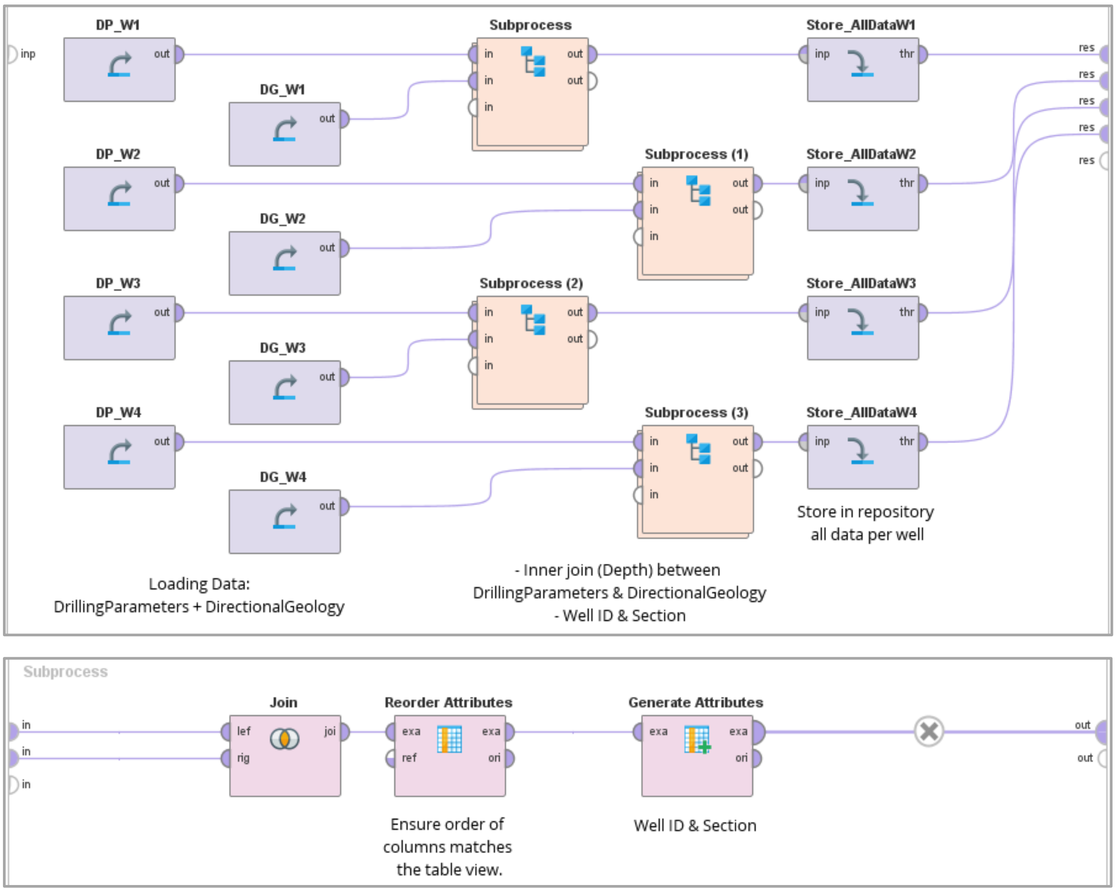


Figure 50 Data Integration. The block called sub process corresponds to a super operator, which purpose is to join the data and generate a WellID Attribute.

Process: 003RemovingMissingValues

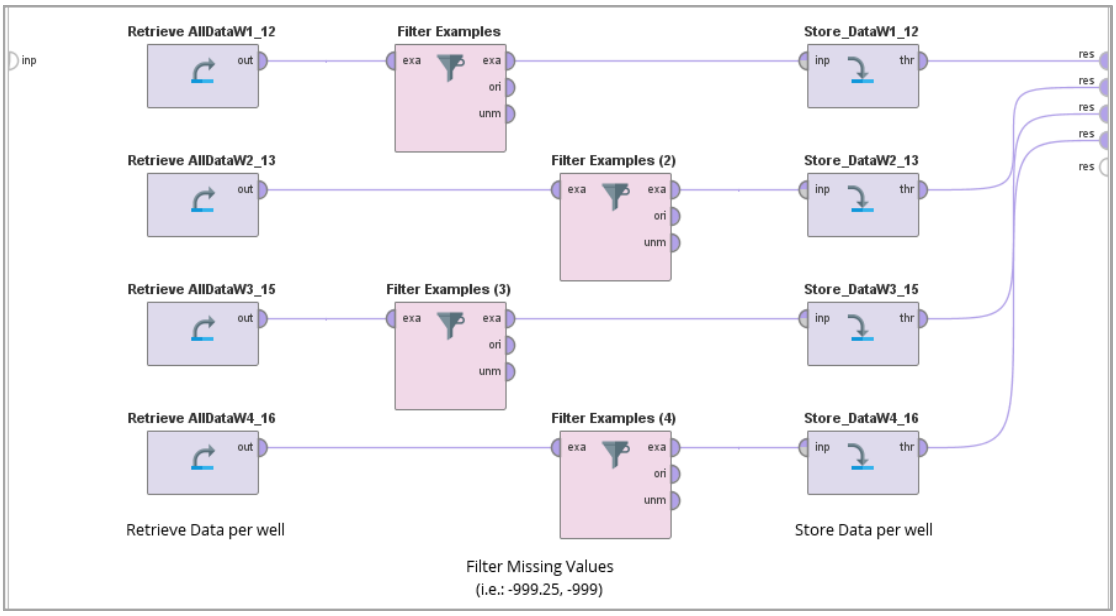
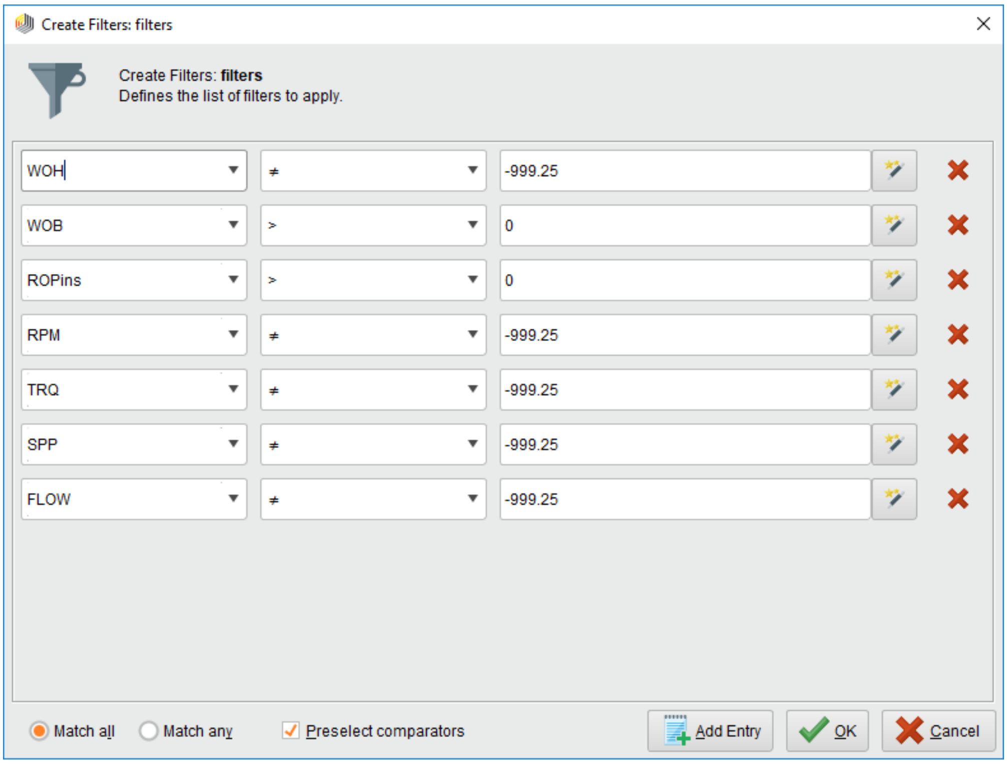


Figure 51 Filter examples to remove null values.



Create Filters: filters

Create Filters: **filters**
Defines the list of filters to apply.

WOH	≠	-999.25
WOB	>	0
ROPins	>	0
RPM	≠	-999.25
TRQ	≠	-999.25
SPP	≠	-999.25
FLOW	≠	-999.25

● Match all ○ Match any ☑ Preselect comparators

Figure 52 Removing null values per attribute.

Process: 004CleaningData

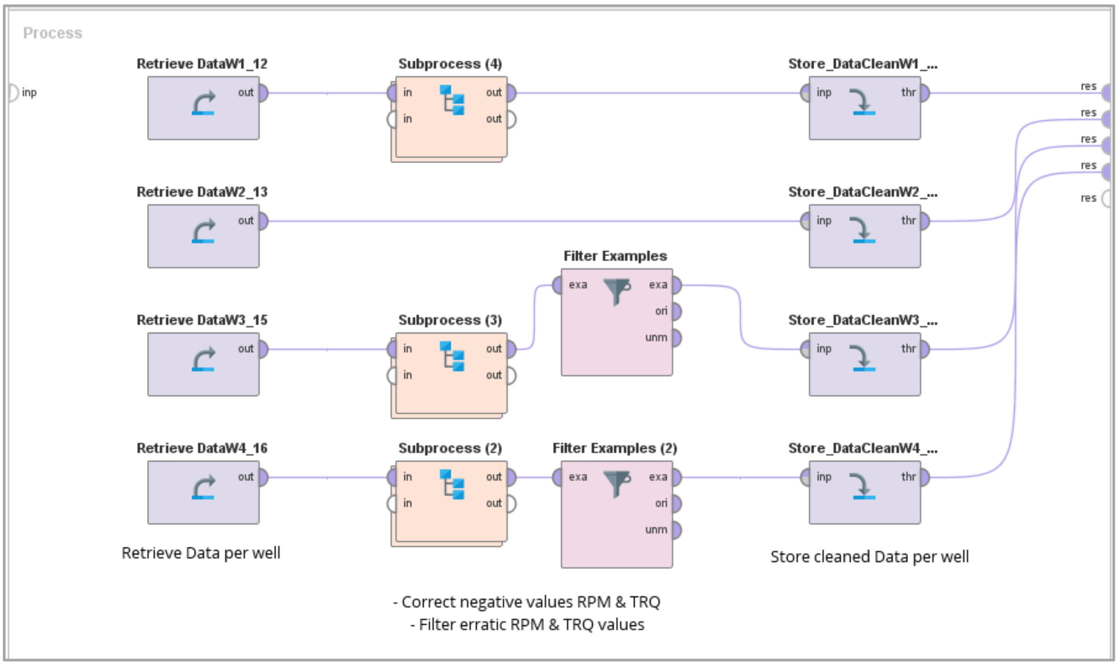


Figure 53 Process to correct erratic values in RPM and TRQ. Sub-processes were used per case. In addition, the Filter Example operator was used to remove those wrong examples that could not be further corrected.

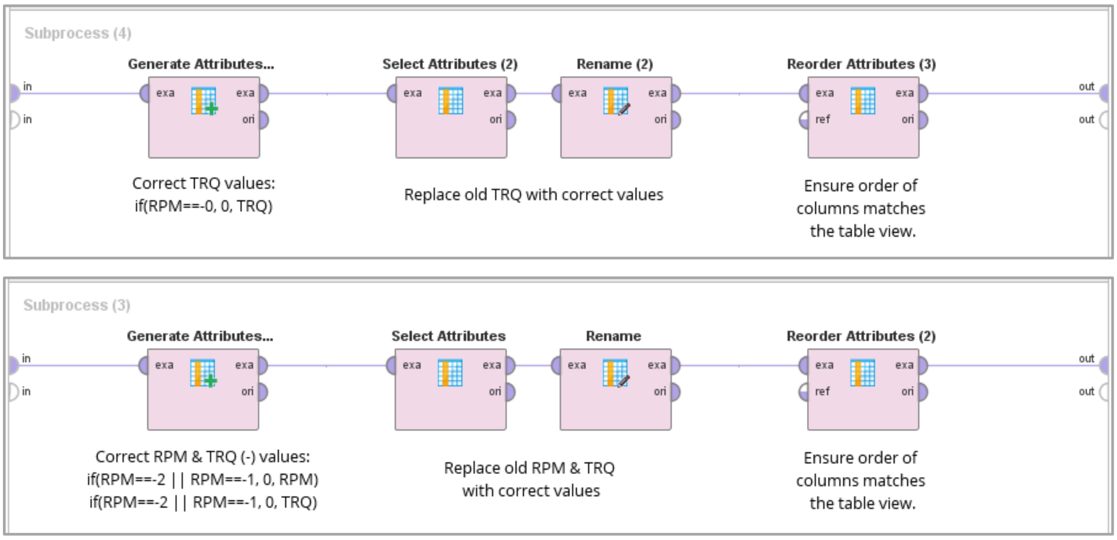


Figure 54 Internal description of the subprocesses where erratic values were adjusted per well.

Process: 004CleaningData_QC

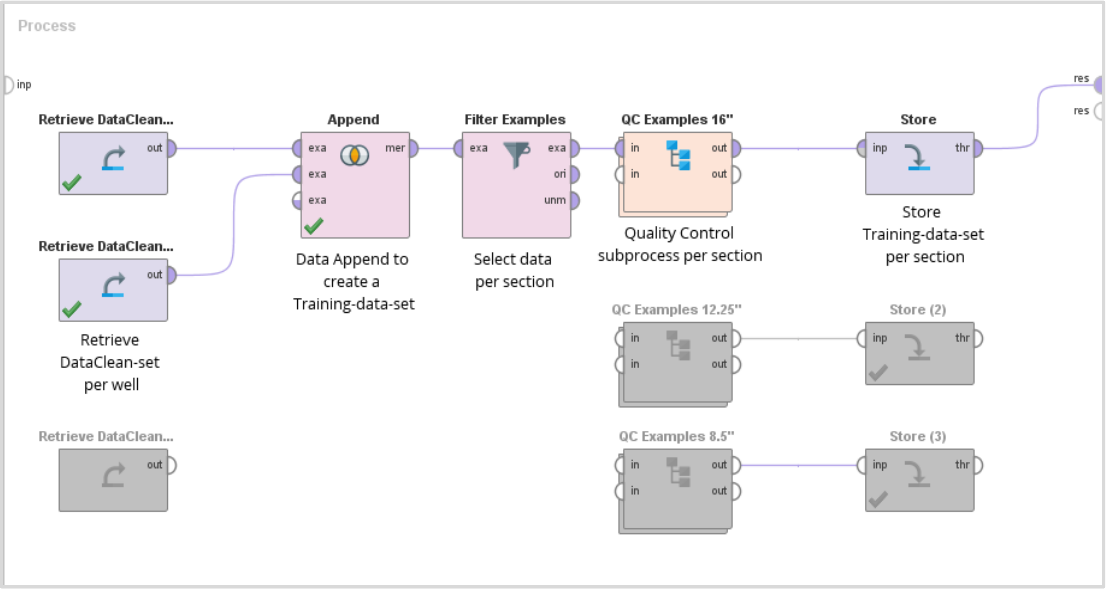


Figure 55 Creation of the training data set using Wells #1 and #3, after final QC per section.

A sub-process operator was used for the final QC, to then store the training data that will serve as input for the model. Sub-processes per section were created with similar analysis, but distinguish QC processes.

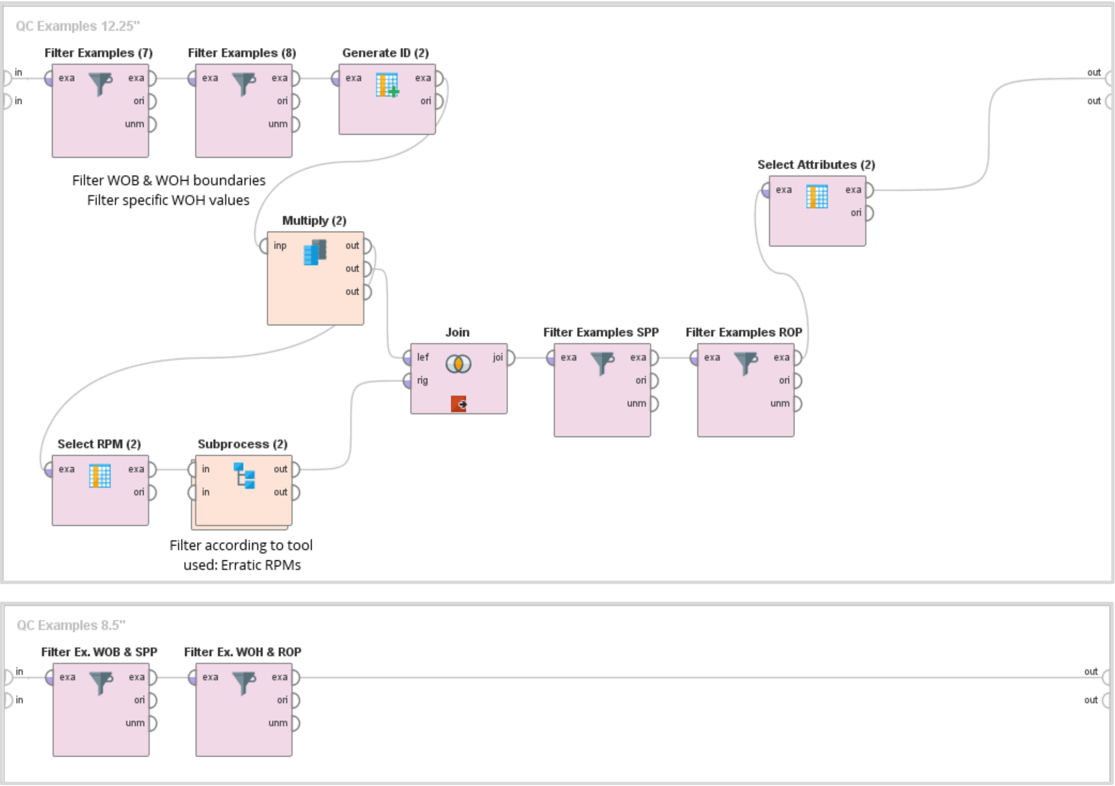


Figure 56 QC Sub-processes for the other two sections.

Process: 005Statistics

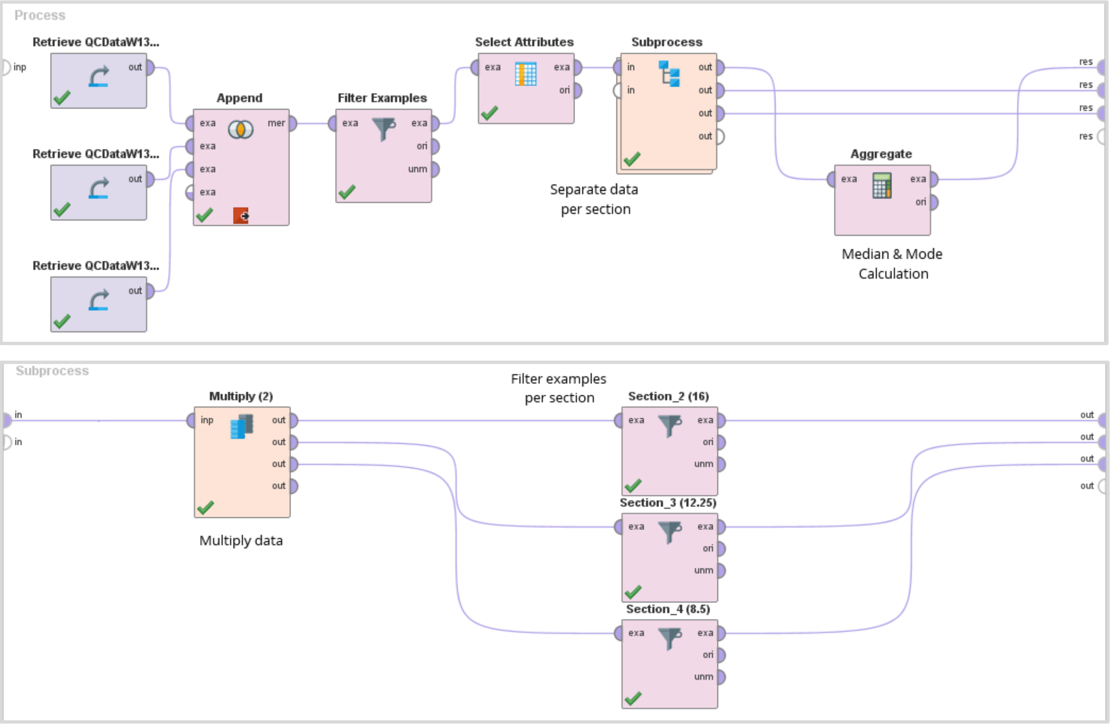


Figure 57 Process to obtain descriptive statistic data for the ROP for training wells.

Process: 007Model

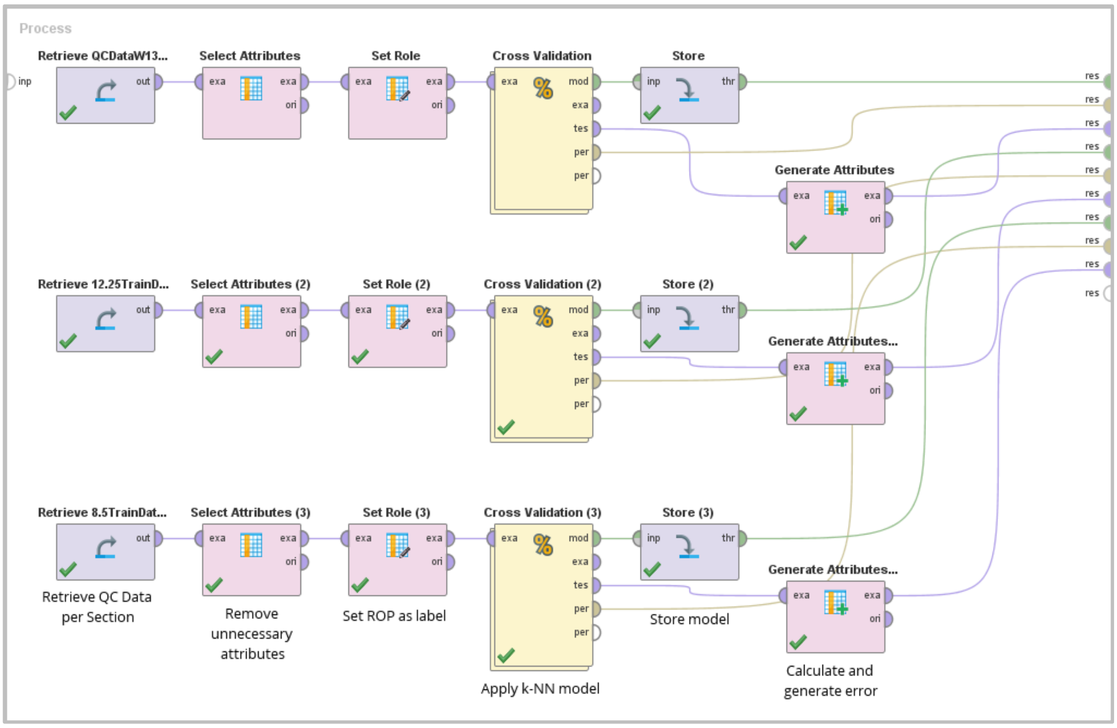


Figure 58 Model Implementation using k-NN algorithm inside a Cross Validation operator for optimization. Implementation is done per section.

Process: 007ModelGradientBoostedTrees

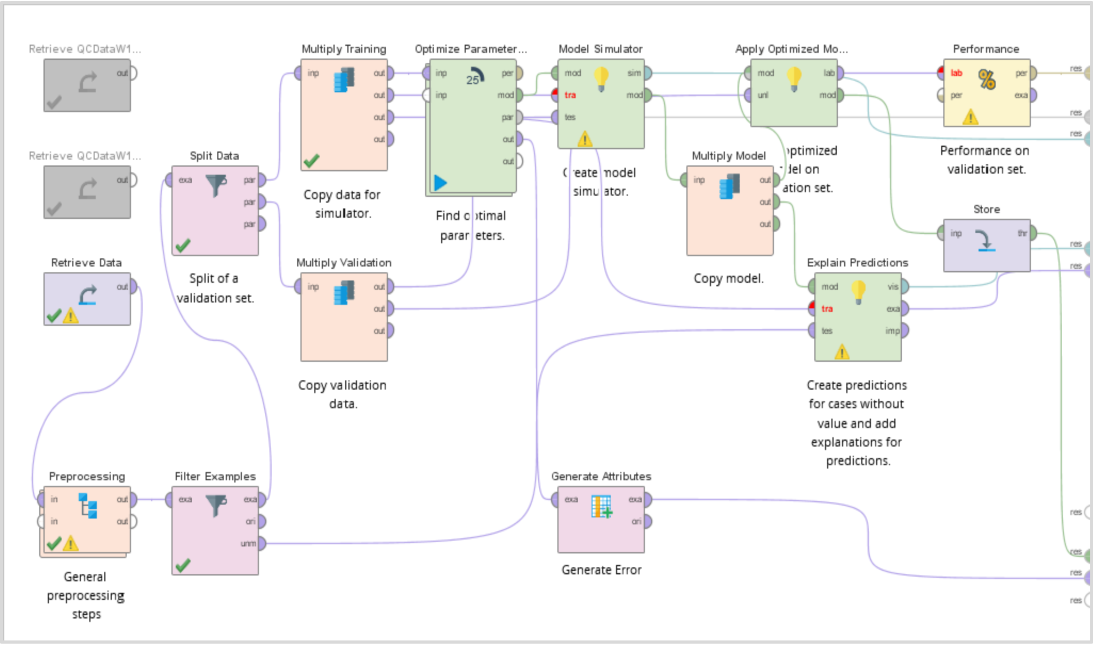


Figure 59 GBT implemantion and performance evaluation.

Process: 008Deployment

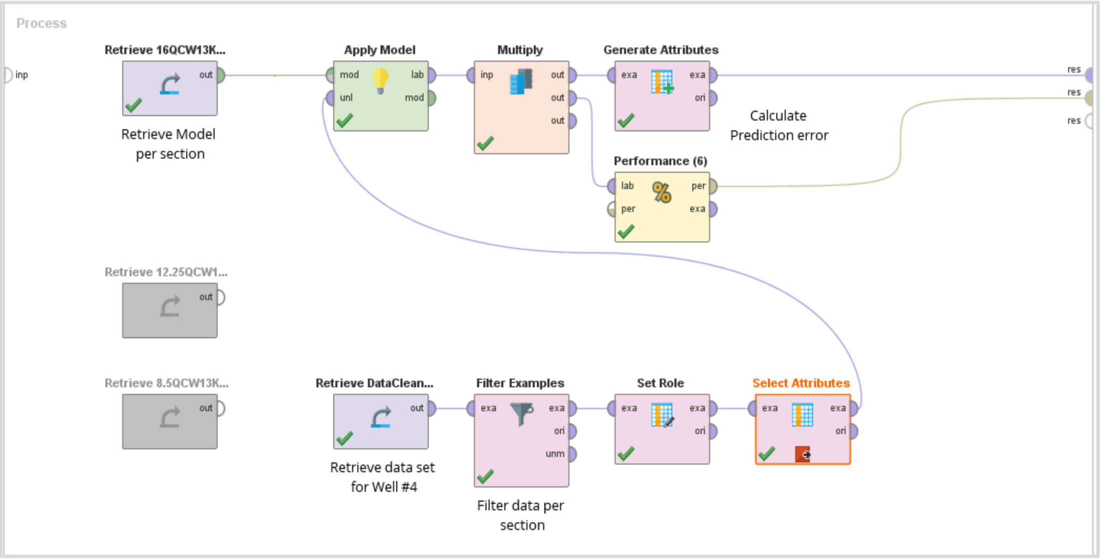


Figure 60 Deployment process used to test both models in Well #4 sample. Well #4 set was filtered per section to test each model.

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Acronyms

ROP	Rate of Penetration
O&G	Oil and Gas
VBS	Visual Basic Script
WOB	Weight on Bit
WOH	Weight on Hook
SPP	Standpipe pressure
TVD	True Vertical Depth
DLS	Dogleg Severity
BR	Build-Rate
TR	Turn-Rate
RM	RapidMiner Studio
RSS	Rotary Steerable System
k-NN	k-Nearest Neighbours
RMSQErr	Root Mean Square Error
AErr	Absolute Error
GBT	Gradient Boost Trees
KDD	Knowledge Discovery from Data
NGL	Natural Gas Liquid
QC	Quality Control

Symbols

I	Inclination	[degrees]
A	Azimuth	[degrees]
ds	Course length	[ft. or m]
n	number of examples in a data set	[-]
y_i	observed value for *i*-example	[depends on example]
$\bar{y}_i$	prediction for *i*-example	[depends on example]

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