# Group Project: ML based Modelling, and Performance Evaluation of Field Dataset

## 1 Introduction

Before any civil engineering work, computer-based structural analysis should be performed to design the appropriate loading to the material properties and structure geometry. The common approach of Structural analysis (e.g., in the construction and foundation works) is to build a geometrical model and assign the material properties such as mechanical, physical, and Elastic. Apply all possible loading scenarios, one can determine the maximum allowable loading that does not cause structure failure. The higher material mechanical strength carries a higher load, and the lower mechanical properties carry a lower load. Therefore, when designing a structure, the maximum applied load is designed based on the strength of the structure, such as the elastic, tensile, and Uniaxial compressive strength.

In this project, we will deal with the **strength of the Uniaxial Compressive Strength (UCS) of drilling formation,** which is one of the basic input parameters for **well collapse** stability analysis. Moreover, the UCS of the drilling formation is also the key parameter **to design drilling optimization**.

## 1.1 Wellbore Stability Design

In petroleum well, wellbore stability design is the first step before drilling a well. The wellbore stability window allows designing the appropriate applied well pressure so that pressure above or below the allowable pressure results in well collapse and well fracturing. **Figure 1** illustrates this.

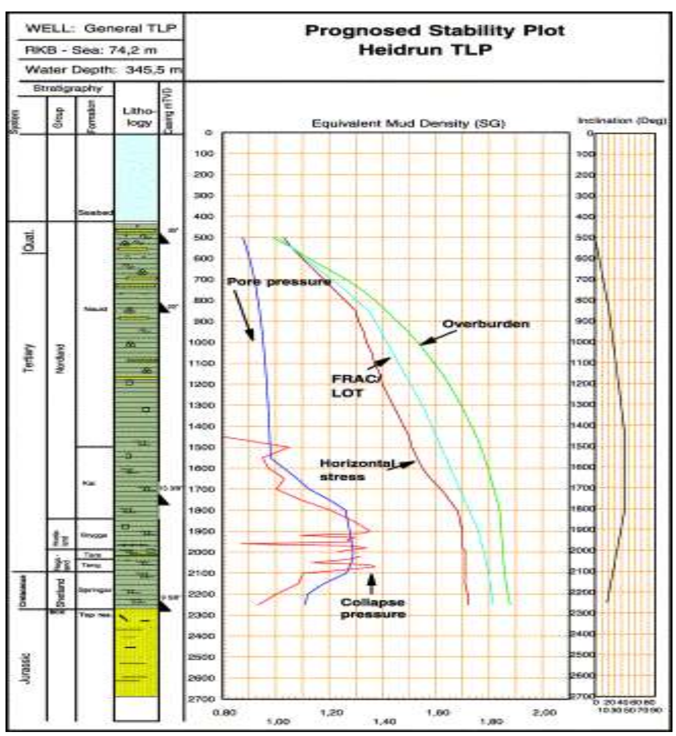



Figure 1: Prognosis stability plot for a typical Heidrun TLP well (Stjern et al. 2003) [1]

The **well collapse** pressure is determined from the model among others (Fjær et al. 2008) [2]:

$$P_{wel\ collapse} \leq \frac{3\sigma_y - \sigma_x - C_0 - [\alpha * P_f(1 - \tan^2\beta)]}{1 + \tan^2\beta} \qquad \mathbf{1}$$

Where, σx, and σy are the horizontal stresses. $P_f$ is the pore pressure and β is the rock failure angle. Co is the UCS of the drilling formation.

## 1.2 What is the problem with collapse model calculation?

As shown in the collapse model (Eq.1), Co is the UCS of the drilling formation and is an input parameter to generate the collapse gradient shown in Figure 1 as a profile. The Uniaxial Compressive strength (UCS) of the structural element determines the load-carrying capacity of the structure.

***The UCS of the rock is the desire of this project work.***

The commonly used approach to measure the UCS of a structure (e.g., rock, concrete) is by taking a cylindrical sample and placing it in the Uniaxial compressive strength test. During testing, the applied load on the core specimen increases until it reaches the maximum load and then fails, from the load and deformation the maximum load before failure is used to compute the UCS as

$$\textbf{UCS} = \mathbf{F_{max}/Area} \qquad \mathbf{2}$$

Figure 2a: Uniaxial Compressive Test machine

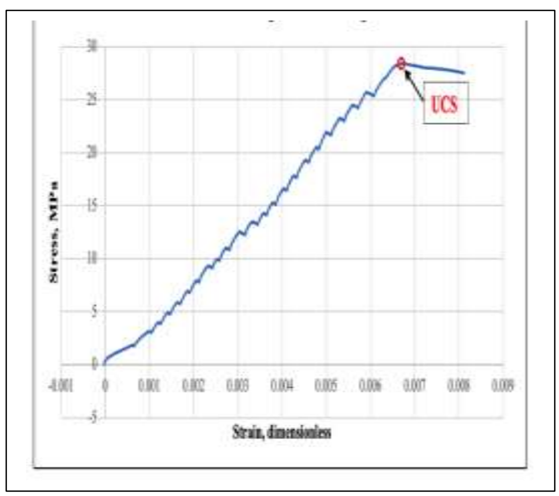



Figure 2b: Uniaxial compressive stress test result

However, **<u>the problem is that it is practically impossible to take rock samples continuously</u>** from the drilling formation and perform a UCS test in the laboratory.

So, how can we estimate the UCS of a drilling formation then?

## 1.3 What is the Solution for UCS estimation?

To solve the issue of estimation of UCS continuously in the drilling depth, it is a common practice to estimate rock strength based on wireline logs that measured the formation responses continuously. Several investigators have shown the relationship between different logs. **It means that they develop machine learning-based empirical** models that estimate one parameter based on the other measured parameter. The following presents two examples **along with a solution for UCS**.

**Example 1:** From a rock sample obtained from the Gulf of Mexico, Gardner et al. (1976) [3] have observed density and compressional wave velocity data trends as a power law as shown in Figure 3. They applied Machine Learning curve fitting and generated a model that estimate density (g/cm$^3$) from the compressional wave velocity (Vp (km/s)). The model is very popular among geophysicists. The model reads:

$$\boldsymbol{\rho} = \alpha * \boldsymbol{v}_{\boldsymbol{p}}^{\beta} \qquad \mathbf{3}$$

They found the optimized curve fitting constants as $\alpha = 0{,}23$ and $\beta = 0{,}25$

**Example 2**: From the compressional wave velocity (P_wave) and the Shear wave data (S-wave), Castagna et al. (1984) [4] have shown linear types of data variation trends as shown in **Figure 4**. Therefore, using the linear regression Mapping function, he generates a machine learning model that estimates the compressional wave (Vp, km/s) from the measured shear wave velocity, (Vs, km/s). The model is very popular among geophysicists. The model reads:

$$\boldsymbol{v}_{\boldsymbol{p}} = 1{,}16 * \boldsymbol{v}_{\boldsymbol{s}} + 1{,}36 \qquad \mathbf{4}$$

**Example 3**: Similarly, from a rock extracted from the North Sea field, Horsrud (2001) [5] has performed laboratory tests to investigate if there is a correlation between the destructive test. (i.e., UCS) and Non-Destructive test (Compressional wave, Vp). He made a cylinder core specimen and then he first measured the compressional wave velocity, $V_P$ and then he put the sample under destructive test as shown in Figures 2a and 2b to determine the UCS. Different sample have their own VP and UCS.

He then plotted the dataset UCS vs Vp. As shown in **Figure 5**, the dataset trend variations are like the Power law. Appling Machine Learning to train the data with the selected Mapping function, the ML optimizer computes the best constants that provided that best-fit curve. The UCS (Co [MPa]) estimates from the compressional wave velocity (km/s) given (Horsrud 2001) [5]:

$$C_0 = 0{,}77 * v_p^{2{,}93} \qquad \mathbf{5}$$

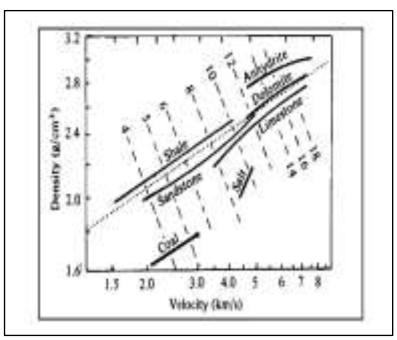



Fig.3: r vs. Vp (Power, Eq. 3)

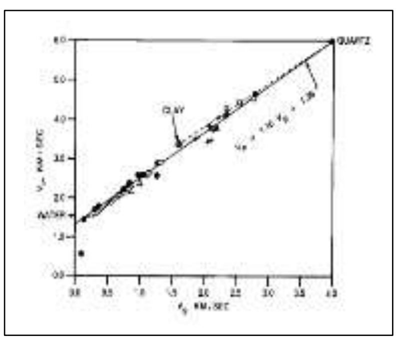



Fig.4: Vp vs. Vs (Linear, Eq.4)

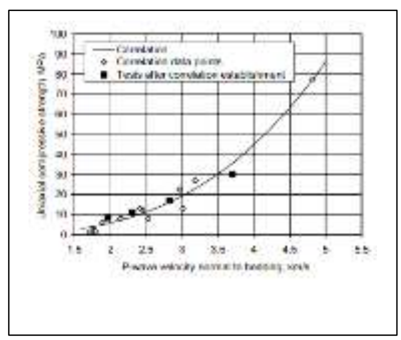


Fig.5: UCS vs Vp(Power, Eq.5)

**<u>What can we learn from Chapter 1? What should be remembered from ML modeling?</u>**

From the examples presented, the application of data-driven-based modeling allows us to estimate desired parameters from other measured parameters provided that the input and output parameters have good correlation so that the ML model predicts the output with a quite reasonable estimate. It means that it is always important to evaluate the model accuracy performance of the ML models.

# 2 Your Task

In Chapter 1, the concept of structural analysis and specifically, wellbore stability design associated with the well collapse are presented. Moreover, the issue of UCS estimation from Vp based on the **<u>Horsrud Data-Driven model as a solution is discussed</u>**. In the absence of the Vp measurement, we can estimate for example Vp from Vs (Eq. 4) and Vp from density (Eq. 3).

However, in this group project briefly, you will develop **a new ML model** based on the three ML training algorithms that estimate Vp from other log datasets (DEN, NEU, Vs) and also you will compare your model estimated with the literature models (Eq. 3 and 4) as well.

During your work, you will apply the workflow shown in **Figure 6**. More information on the project activities is presented in sections §2.1-2.4.

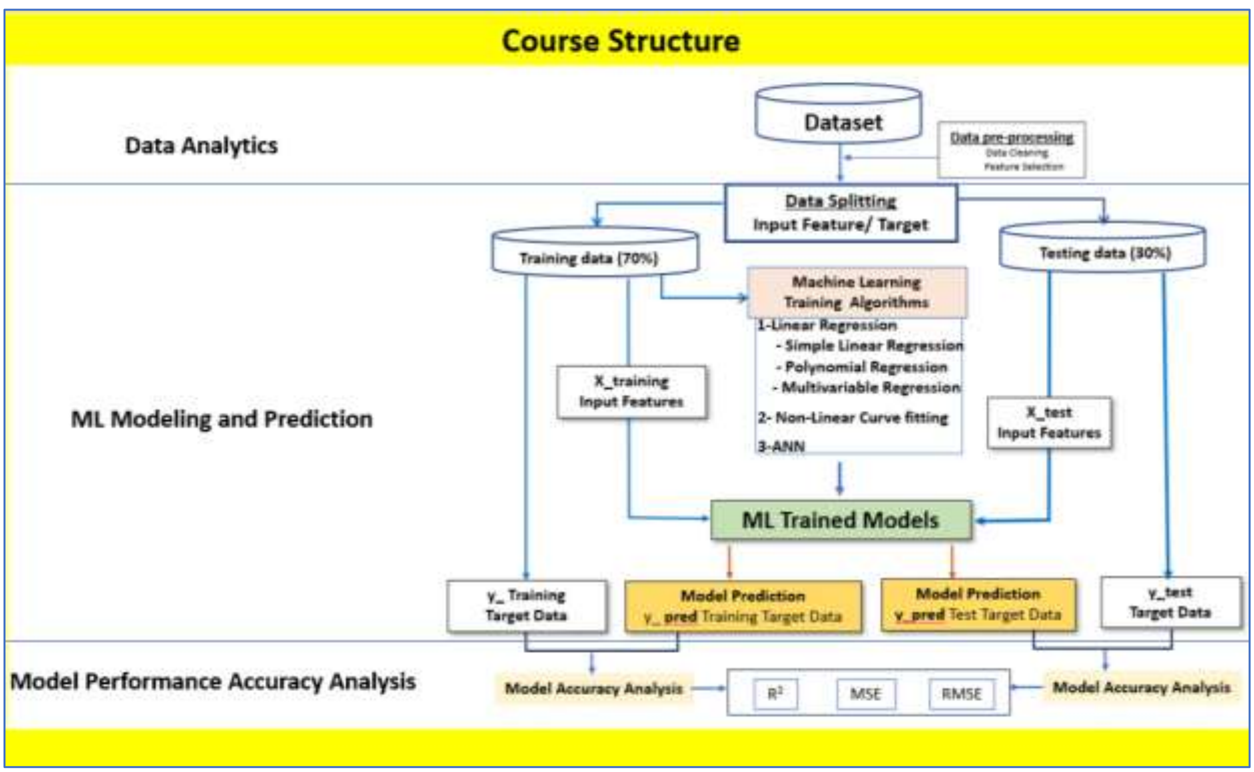



Figure 6: ML workflow to be implemented in your project

## 2.1 The Project

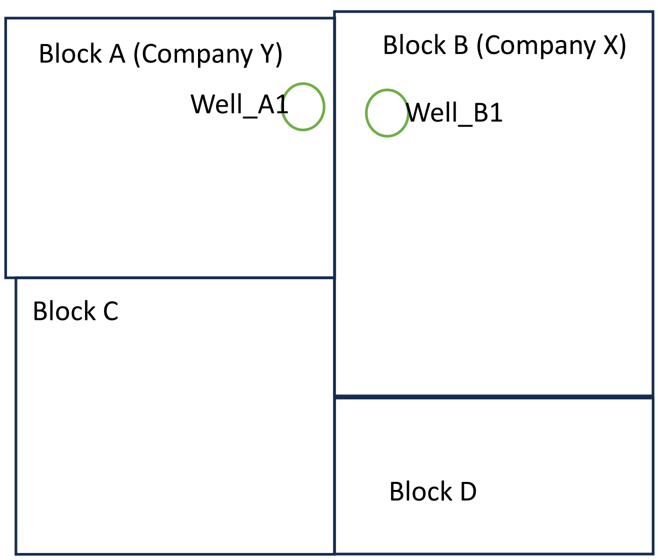
Your company X is planning to drill a new well in **Block B** and the well will be called Well B1.

Your boss asked you to design a wellbore stability design. Since the in-situ stresses are available, it is easy to estimate the well fracturing profile.

But, **for the well collapse**, the **Uniaxial compressive Strength** of the formation to be drilling data is not available. Since well B1 is the first well in block B, there was no measured log data available.

However, as shown in Block A, Well_A1 has been drilled by Company Y. Since the Well_A1 and Well_B1 are very close, **it is assumed** that the lateral geologies of the formations are similar.

**Therefore, Company X** managed to get the log data of **Well_ A1 as provided in the table below.**




**Well Log Data Well-A1**

| Vs | DEN | NEU | Vp |
|---|---|---|---|
| 1.68 | 2.38 | 0.28 | 3.05 |
| 1.68 | 2.21 | 0.25 | 2.97 |
| 1.68 | 2.14 | 0.26 | 2.88 |
| 1.68 | 2.17 | 0.26 | 2.93 |
| 1.68 | 2.12 | 0.26 | 2.91 |
| 1.69 | 2.15 | 0.27 | 2.91 |
| 1.68 | 2.18 | 0.28 | 2.96 |
| 1.67 | 2.14 | 0.29 | 2.92 |
| - | - | - | - |
| - | - | - | - |

## 2.2 Project Questions?

**Task 1: Scenario 1**: Use Vp as the true data and compute UCS (Co) from Vp.

- The result is considered as true UCS so that the result will be compared with Vp models that will be estimated from other logs trained by different ML algorithms.

**Task 2: Scenario 2**: What if we don't have measured Vp, can we estimate Vp from other logs?

1) Which **logs (DEN, NEU, Vs)** are related to Vp to develop a good model?

2) Which **ML regression algorithm**s generate a good model to estimate Vp?

3) Does **your model Vp prediction** show better than the **literature models (Eq. 3 and Eq. 4)**?

## 2.3 Result

To answer the research question, you need to apply the workflow shown in F**igure 6**.

a) **Apply the three ML algorithm to create ML-based models such as:**
   1) **. Linear regression**
      - Simple linear regression: Vp = a* (vs, or Den, or NEU) + b
      - Polynomial regression: Vp = a+ b* (vs, or Den, or NEU) + c* (vs, or Den, or NEU)$^2$
      - Multivariable regression: Vp = a+ b* vs+ c*Den+ d*NEU  or a combination of two logs.
   2) **Non-Linear curve fitting** ( Power, Exponential, Log (ln),  Vp = a*Vs**b + c ……)
   3) **ANN ML modeling** Vp is the target and Input Features are vs, or Den, or NEU, or their combinations.

b) **Model performance accuracy Analysis**

- Select one best model from each algorithm.
- Compute UCS-based Vp, and Model predicted Vp
- Generate R2 for each model.
- Finally, select the best
- Plot USC (Vp) with UCS (Vp model)
- List down in the order of best model…from each model….
  ++ other important information you obtained from the work!

## 2.4 Report

- Your report should be written formally as outlined in the report format file uploaded in Canvas.

## References


[1] G. Stjern, A. A., P Horsrud (2003). "**Local rock mechanical knowledge proves drilling performance in fractured formations at the Heidrun field**." Journal of Petroleum Science and Engineering 38(3-4): 83-96.

[2] E. Fjær, R. M. H., P. Horsrud, A.M. Raaen & R.Risnes (2008). **Petroleum Related Rock Mechanics**. Hungary, Elsevier publication

[3] *Gardner, G.H.F.; Gardner L.W.; Gregory A.R. (1974). "**Formation velocity and density -- the diagnostic basics for stratigraphic traps**" (PDF). Geophysics. 39: 770–780. 1974*

[4] Castagna, J.P., Batzle, M.L., and Eastwood, R.L., 1985, **Relationships between compressional-wave and shear-wave velocities in clastic silicate rocks:** Geophysics, 50, 571-581

[5] Per Horsrud //Est**imating Mechanical Properties of Shale From Empirical Correlations**//June 2001 SPE Drilling & Completion