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Assessment of the relationship between Measurement While Drilling parameters and resulting data from pre-excavation grouting

A case study on the Fv. 659 Nordøyvegen project

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Tittel: Assessment on the relationship between Measurement While Drilling parameters and resulting data from pre-excitation grouting.
A case study on the Fv. 659 Nordøyvegen project

Faglærer: Prof. II Eivind Grøv

Samarbeidspartner, bedrift el.l: Bever Control AS, Skanska Norge AS og Statens vegvesen.

Utfyllende tekst for oppgaven: Det er et uttrykt ønske fra tunnelbransjen om å ta mer aktivt i bruk MWD-data under tunneldriving. Det fulle potensialet ved bruk av disse data er enda ikke fullt utnyttet i alle ledd av drivefasen samtidig som Bever Control utvikler nye og supplerende tjenester. Dette gjelder særlig for oppfølgingen av selve injeksjonsutførelsen.

Denne oppgaven ønsker å ta for seg muligheten til å bruke MWD-data mer aktivt i injeksjonsforløpet. Mer spesifikt er målsettingen å undersøke om det finnes signifikant korrelasjon mellom de ulike tolkede MWD data som innhentes fra borrhøen, og injeksjonsparametere som finnes for injeksjonsarbeidet som utføres i de sammen hullene. Disse resultatene vil først brukes til å forstå injeksjonsarbeidene bedre og dernest bidra til å kunne bestemme hvilke parametere som bør inngå i et mer automatisert injeksjonssystem basert på MWD.

For denne oppgaven skal det benyttes data fra prosjektet Nordøyvegen som består av flere seriekoblede undersjøiske vegtunneler og som bygges av Skanska AS med SVV som byggherre. Oppgaven gjennomføres i nært samarbeide med Bever Control som utvikler oppfølgingsverktøyet. Det skal også benyttes PF-indeksen som ble utviklet av PhD Helene Strømsvik gjennom hennes PhD-arbeid i forskningsprosjektet TIGHT.

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Abstract

Uncontrolled drainage of groundwater into the tunnel space represents one of the most serious threats to any tunnel project. Water-ingress into tunnel spaces is associated with multiple negative consequences, such as: settlement damage on surrounding structure, disturbance of surrounding ecosystems, stability issues during and after construction, including unfavorable working conditions inside the tunnel. A common mitigation method to control the water-ingress is called *pre-excavation grouting*, where cement is grouted ahead of the advancing tunnel face, forming a protective curtain surrounding the advancing tunnel. *Measurement while drilling* (MWD), is a drilling technology that allows for continuously monitoring and logging of drilling parameters from the drilling jumbos. The tunneling industry has expressed a desire to use this MWD data more actively during the construction phase, and that includes using MWD data more actively during the grouting process.

The main objective of this master thesis is to gain a deeper understanding of the presumed relationship between these interpreted MWD parameters (MWD DPI), and the different grouting parameters. This is done through various statistical methods. For this purpose, data from a large ongoing infrastructure project (2020) located in western Norway, Fv.659 Nordøyvegen, is used. MWD DPI- and grouting data are gathered from 13 different chainages across 2 different tunnels, comprising over 350 boreholes. The grouting data is also analyzed for hydraulic jacking events (HJ), relying on the newly developed PF index.

The main conclusions from this research, indicate that *no* apparent relationship exists between the MWD DPI- and grouting variables. Suggesting that alternative approaches to the research question are needed, to further verify or dismiss this relationship. Furthermore, it is advised that further developments in today's MWD technology are likely needed before it can be relied on as an effective tool in the grouting process. It is found that MWD DPI's are successful in detecting larger scale weakness zones ahead of the tunnel face. The ability to use the PF index as a visual tool in detecting potential hydraulic jacking events (HJ) has been tested. It is found that 23% of all grouted holes were possibly exposed to HJ events. Indications for higher grouted volumes and time consumption for HJ holes were also found. This thesis highlights some possibilities and limitations of today's industry-standard MWD technology, including the relationship between the MWD- and grouting-data, which is not yet fully understood.

Sammendrag

Ukontrollert drenering av grunnvann inn i en tunnel, representerer en av de vanskeligste utfordringene for et hvert tunnelprosjekt. Vannlekkasjer inn i tunnelen er assosiert med flere negative konsekvenser, som f.eks. setningsskader på omkringliggende bygninger og infrastruktur, forstyrrelser av økosystemer, stabilitetsproblemer i tunnel både under og etter bygging, og ugunstige forhold for arbeid på tunnelstuff. Den vanligste metoden for å motvirke innlekkasje er gjennom *forinjeksjon*, hvor sement injiseres med høyt trykk foran tunnelstuffen. Slik at det formes en beskyttende skjerm rundt tunnelkonturen. *Measurement while drilling* (MWD), er en boreteknologi som muliggjør fortløpende logging og monitorering av bergmassen fra boreriggen. Det er uttrykt et klart ønske fra tunnelindustrien om å bruke denne MWD dataen mer aktivt i selve injeksjonsprosessen, i et forsøk på å forbedre og effektivisere metoden.

Hovedformålet med denne masteroppgaven, er å etablere en dypere forståelse for sammenhengen mellom disse MWD- og injeksjonsparameterne. Dette er gjort gjennom forskjellige statistiske metoder. For dette formålet er data innhentet fra et stort pågående infrastrukturprosjekt (2020) lokalisert i Vest-Norge, Fv.659 Nordøyvegen. Både MWD- og injeksjonsdata er hentet inn fra 13 forskjellige stuffer og 2 tunneler, med et totalt datagrunnlag på over 350 borehull. Injeksjonsdataen er også analysert for tilfeller av hydraulisk jekking (HJ), ved hjelp av den nylig utviklede PF indeksen.

Denne masteroppgaven konkluderer med at *ingen* signifikante korrelasjoner ble funnet mellom MWD DPI- og injeksjonsparameterne. Hvilket innebærer at det trengs alternative tilnæringer til denne problemstillingen, for å videre kunne verifisere eller avkaste påstanden om sammenheng mellom disse to datagrupperne. Videre er det foreslått et behov for nyutviklinger i dagens MWD teknologi, for å forbedre kvaliteten til MWD og muliggjøre bruken av denne dataen i en injeksjons-sammenheng. Muligheten til å bruke PF indeksen visuelt for å bestemme tilfeller av HJ i injeksjonsdata er blitt testet. Potensielle tilfeller av HJ, ble funnet i 23% av alle injiserte borehull. Det ble også funnet en viss sammenheng mellom økt tidsforbruk og volum for hull med HJ. Denne avhandlingen belyser noen muligheter og begrensninger til dagen MWD-teknologi, samt sammenhengen mellom MWD- og injeksjon, som enda ikke er helt forstått.

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List of Abbreviations

AUC	Area under curve.
BTO	Bever Team Online.
D&B	Drill and blast.
d₉₅	Measure on cement particle size.
DPI	Drill Parameter Interpretation.
FI	Fracturing Index.
FMI	Fullbore Formation Microimager.
GIN	Grout Intensity Number.
HI	Hardness Index.
HJ	Hydraulic jacking.
IDE	Integrated Development Environment.
KMO	Kaiser-Meyer-Olkin test for sampling adequacy.
LRIR	Limit of Residual Inflow Rate.
MFC	Microfine cement.
ML	Machine learning.
MWD	Measurement While Drilling.
NPRA	Norwegian Public Road Administration (Statens vegvesen).
OPC	Ordinary Portland Cement (industry standard cement).
OTV	Optical Televiewer.
PC	Principal Component.
PCA	Principal Component Analysis.
PF index	Pressure Flow index.
PR	Penetration Rate.
ROC	Receiver Operating Characteristic curve.
RTGC	Real Time Grouting Control method.

SP	Superplasticizer, dispersive additive for cements.
SVM	Support Vector Machine.
UCS	Uniaxial Compressive Strength.
UFC	Ultrafine cement.
W/C	Water to Cement ratio.
WI	Water Index.

Introduction

1.1 Background

The exposure of pressurized water represents one of the most challenging conditions faced during underground excavations. The ability to efficiently reduce and control the water-inflow when utilizing underground space, is of great importance for the performance as well as the time/cost aspect of an underground excavation project.

It has been estimated that 20-30% of construction-costs associated with modern tunneling, is directly contributed by rock mass grouting (Holmøy et al., 2015). Holmøy and Nilsen (2014), defines five challenges caused by groundwater inflow:

- Risk of groundwater lowering - potentially causing settlements and damages to surface buildings.
- Drainage of surface areas and lakes - potentially damaging vegetation and recreational areas, interrupting natural discharge system and local eco-systems.
- Difficulties with cost estimates of tunneling projects due to the high degree of uncertainty connected to location and quantity of groundwater inflow.
- Problems related to rock mass stability during and after excavation.
- Expensive and time-consuming grouting (pre- and post-excavation).

A better understanding of the method, as well as optimization and best-practice studies, is of great concern to the tunneling industry as a whole. The standard Norwegian practice for rock

mass grouting in tunneling projects, is pre-excavation grouting, using high pressures and grouting recipes largely based on experience gained from previous projects, as well as the experience of the grouting technicians. *Measurement while drilling*, or simply MWD, allows for continuous monitoring and logging of drilling parameters, this allows for real-time rock mass characterization during excavation. It is believed that this technology could be used more actively for grouting purposes in future applications. However, more research is still needed on the classification accuracy of MWD, including its relation to the different grouting variables.

1.2 Thesis purpose and structure

The main purpose of this thesis is to gain better insight into how the different MWD parameters relate to the grouting parameters, this is mainly done through statistical analyses. The data used is gathered from a large infrastructure project located in western Norway, Fv.659 Nordøyvegen, comprising of multiple subsea tunnel, land reclamation, and new roads.

A large amount of time was used for the initial literature study, to gain a fundamental understanding of all relevant aspects of both grouting theory and MWD data. Investigation on potential projects for data gathering was done early, including then establishing contacts within the relevant contractors and companies to get access to as-built project data on both grouting and MWD. A great deal of time was used in establishing strategies for data gathering, including evaluating different methods on how to conduct the data analyses.

The overall disposition of the thesis is as follows:

- A brief literature review on the presence and influence of water in the rock mass is presented chapter 2.
- Literature review on existing theories and methods for rock mass grouting including the phenomenon of hydraulic jacking, with a focus on Norwegian conditions, is presented in chapter 3
- Literature review on the current state of art and possibilities of MWD technology is presented in chapter 4.
- A review of some multivariate statistical methods is presented in chapter 5.
- Project description and methods for data gathering is presented in chapter 6.

- Results from the data analysis are presented in chapter 7.
- Discussions and critical review of the research results, including a review on important limitations and suggestions for further work, are presented in chapter 8.
- Concluding remarks are presented in chapter 9.

1.3 Extent and limitations

All data used are gathered from two different tunnels from the same project area. Considering the grouting data, differences in grouting recipes such as w/c ratio, cement type, and additives are *not* taken into account in the data analysis. As the emphasis is put on analyzing the physical variables of the grouting procedure, e.g. pressure, volume, flow, and time.

The grouting procedure used for this project in conjunction with Norwegian grouting practice. That means high pressure, systematic pre-excavation grouting. Data used in this research is therefore not necessarily comparable to that of other grouting practices in other countries. Information and measurements of rock mass stresses are not a part of the gathered data, and its influence on the grouting procedure will not be considered in the data analysis.

The time-consuming nature of retrieving and accessing the data, as well as matching the MWD- and grouting data sets, was a limiting factor for the amount of data available for analysis. Problems concerning data gathering are discussed in greater detail in section 6.4 and 8.7. It was also desired to investigate more than one weakness zone and their related MWD DPI responses, as presented in section 7.1. However, due to limited advance on the tunnels at the time of this research, only one of the interpreted weakness zones had been intersected by the tunneling advance.

Hydrogeology

2.1 Groundwater in fractured rock

The groundwater's ability to flow through a rock medium is mainly governed by its fractures and fracture systems (Gunnar Gustafson, 2012). The flow of water through a fractured medium can be simplified and explained through mathematical treatment. Central to the theoretical treatment of water flow in fractured and porous media is *Darcy's Law*:

$$q = \frac{Q}{A} = -\frac{dh}{dl} \cdot K \quad (2.1)$$

The law states that the flow, q , is proportional to the gradient $\frac{dh}{dl}$, with proportionality constant K , which is referred to as the *hydraulic conductivity* [$m^3/s(m^2)$]. This describes ideal flow in a pipe-section of length l with a difference in groundwater level Δh .

As a simplification, fractures can be described as 2D-structures, with a finite extent, l , and a slot aperture b (see figure 2.1). We now need a proportionality constant in the expression (2.1), that can take into account how the flow of water passes through a unit width (l) of the water-bearing fracture. We refer to this constant as the fracture *transmissivity*, T_f , defined as:

$$T_f = \frac{\rho_w g}{\mu} \cdot \frac{b^3}{12} = K_f \cdot b \quad (2.2)$$

Where ρ_w , g , and μ represents the density, acceleration due to gravity, and viscosity of the water, respectively. Equation 2.2, also states that the transitivity is proportional to the cube of the slot aperture, often referred to as the *cubic law*. This implies that a small change in slot aperture will

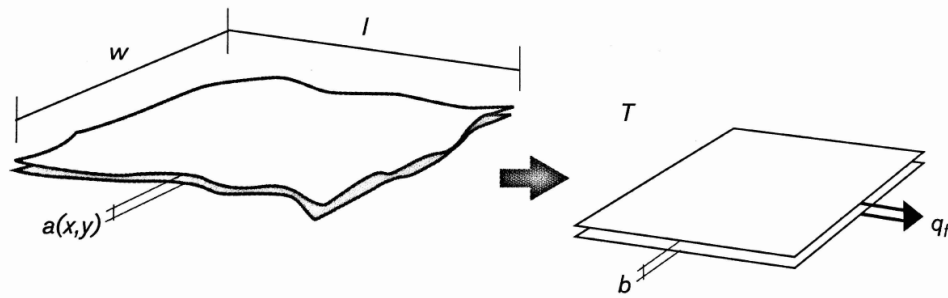


Figure 2.1: Conceptual figure, showing how an uneven fracture plane on the left, can be regarded as an equivalent disc structure (on the right), with aperture (b) and flow (q_f). Figure taken from Gunnar Gustafson (2012).

result in a large increase in transmissivity. This illustrates the importance of fracture aperture width, in the general conductivity of the rock mass. Taking the fracture transmissivity into account, we can then write the Darcy-relationship (eq. 2.1), as:

$$q_f = \frac{Q}{w} = -\frac{dh}{dl} \cdot T_f \quad (2.3)$$

Where w is the fracture width and l the fracture length. The groundwater can then be thought of as flowing through a 2D "fracture disc", with transmissivity (T) (see figure 2.1).

2.2 Influence of rock type

Even though the most significant contribution to the rock mass in terms of increasing the hydraulic conductivity, comes from the degree of fracturing and fracture properties, there is evidence that certain rock types are generally more permeable than others (Gunnar Gustafson, 2012). This can be explained by the mechanical properties dependency on the mineralogical composition of the rock types. It is generally found that dark, mafic rock types (rocks with very low silica content, typically basalt and gabbro), are less permeable than their lighter felsic counterpart (rocks with higher silica content, typically granite). The more mafic rock types tend to have a higher tensile strength but lower modulus of elasticity, than the felsic rock types. This means a generally increased stress concentration in the felsic rock types because of the high elasticity modulus, and in turn, this will cause more brittle fracturing. The dark rock types tend to decompose more easily, resulting in more abundant filling of fractures and a further reduction in permeability (Gunnar Gustafson, 2012).

2.3 Influence of fracture anisotropy and depth

The hydraulic properties of a water-conducting fracture system are *anisotropic*, this is because the fracture system is anisotropic. I.e. it is expected that the measured transmissivities of a fracture system, will fluctuate depending on the direction of measuring. Another factor that influences the permeability of the rock mass is the *depth* to the fracture system. Naturally, the increase of stress with depth will also decrease the width of the fracture apertures, reducing the overall conductivity of the fractures. The depth trend can be described as reducing the conductivity by *one* order of magnitude each 380 m (Gunnar Gustafson, 2012). The depth trend will often not have profound implications on the overall hydro-geological conditions for a typical underground construction, but should be considered especially when dealing with very deep-lying projects.

2.4 Fracture and crush zones

Hydrogeological properties can change dramatically when the rock mass is affected by fracture zones. A fracture zone is a localized concentration of fractures caused by brittle deformation, often with an obvious structural orientation that can be expressed with strike and dip, usually associated with an active or inactive deformation zone (i.e. fault zone) (Gunnar Gustafson, 2012). These zones (often referred to as *weakness zones*), in many cases, represent the most challenging conditions for underground excavations. Not only in terms of high water inflow due to the high permeability of these zones but also because these zones represent structurally unstable parts to the tunnel excavation, permitting uncontrolled collapse during or even a long time after the completion of the project (Bjørn Nilsen and Arild Palmström, 2000). Fracture zones represent anomalous weak structures in the surrounding, stronger rock mass. The large number of fractures that occur throughout a fracture zone means there is often a high probability of representing a high permeable zone (Gunnar Gustafson, 2012). However, the permeability of such zones will vary greatly depending on the structural formation mechanism, mineralogical composition, and dimensions of the fracture/crush zones. The actual permeability of a fracture zone can be classified based on its *permeability structures*.

Caine et al. (1996), discuss and classifies these systems in great detail, and describes how the permeability structures of fracture zones (fault zones) can be influenced by highly localized

conduits and/or distributed conduits, but also as barriers or combined conduit-barrier systems for fluid flow. The central zones of a fault which has undergone considerable displacement, know as the *fault core*, is often associated with lower permeability due to the presence of clay-materials and other slip materials (Bjørn Nilsen and Arild Palmström, 2000). Meaning, it is often the area surrounding the fault core, know as the *damage zone* (which comprises the are just outside the fault core and the *transition zone*), that is often consistent with high permeability structures (see figure 2.2).

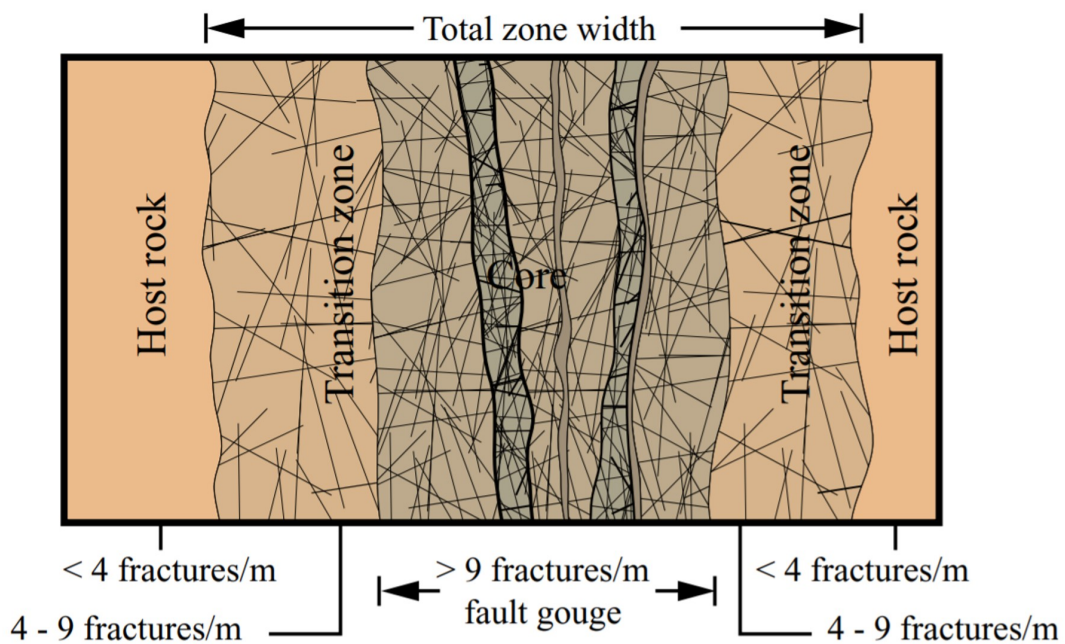


Figure 2.2: Conceptual model of a typical fracture zone. Figure taken from Munier et al. (2003).

Rock mass grouting

The most common method for achieving sufficient sealing against undesired water ingress in underground excavations is *rock mass grouting*. What is defined as "sufficient sealing" of the tunnel is determined by the predetermined requirements for *allowable inflow*. The maximum allowable water inflow is commonly quantified as liter per minute per 100m tunnel-section, often referred to as *Limit of Residual Inflow Rate* or simply LRIR [l/min/100m] (Arnulf Hansen and Grøv, 2017). The practiced LRIR will vary from project to project, often governed by practical, project-specific limitations. The Norwegian Public Road Administration (NPRA), suggests the following LRIR-requirements for Norwegian tunneling.

Extremely strict	Strict	Intermediate	Moderate
< 1–3 LRIR	3–7 LRIR	7–15 LRIR	> 15 LRIR
Urban tunnels, high sensitivity to settlements.	Urban tunnels, sensitivity to disruption of fauna.	Rural transport tunnels and rock caverns.	Rural tunnels.

Table 3.1: Maximum allowable inflow (LRIR) classification and examples of typical excavation types, as suggested by Klüver and Kveen (2004) and Arnulf Hansen and Grøv (2017).

3.1 Properties of grouts

The use of cement-based grout mixtures is by far the most preferred throughout the industry as it is both cost-efficient and poses little direct threat to environmental concerns (Stille, 2015). Alternately, chemical-based grout mixtures can be used, which comprises as all grout masses which have no particles in suspension i.e. they are chemical solutions (Arnstein Aarset and Frogner, 2010). These chemical solutions have very strict usage terms due to the environmental

Cement type	Blaine [m ² /kg]	Specific surface [m ² /kg]	d₉₅ [μm]
OPC			
Industri (Norcem)	550	-	40
Injisering (Cementa) 30	-	1300	30
MFC			
Microfine (Norcem) 20	750	2550	20
Microfin (Mapei) 20	-	-	20
MasterRoc MP 650 (BASF) 20	650	-	20
Ultrafin 16 (Norcem)	-	1600	16
MasterRoc MP 800 (BASF)	800	-	15
Ultrafin 12 (Norcem)	-	2200	12

Table 3.2: Typical grout cements available on the Norwegian market 2019 (table modified from Strømsvik (2019); Arnstein Aarset and Frogner (2010)).

risk they represent, they are also much more costly than their cement-based counterpart (Kjell I. Davik and Heimli, 2002). Chemical grout mixes are usually only used during post-grouting in Norwegian practice (Arnstein Aarset and Frogner, 2010). Since chemical-based grout's are used predominantly in post-grouting, and not pre-grouting, chemical grouting substances will not be discussed further.

Mainly two different cement grout types are used in conventional grouting, industrial cement (OPS) and microfine-cement (MFC), with multiple subcategories mainly based on the particle size of the cement. Arnstein Aarset and Frogner (2010), provides a list of the main grouting cements used in Norwegian tunneling (see table 3.2). Important properties of the grout include:

- *W/C - ratio*, which is the grout cements water to cement ratio. High values will often yield low viscosity liquid with flow characteristic similar to water, while low values tend to be associated with more viscose flow.
- *Blaine fineness*, is a measure on the fineness of a OPS cement, which is measured in specific area (square meter per kg cement).
- *d₉₅*, measure on the overall particle size of the cement, 95% of particle sizes in cement < given value.
- *Bleeding*, refers to the phenomenon in which water and cement disperse in a grout mix, where free water flows to the top of the mixture, this is generally unwanted.

The rheological properties will be governed mainly by the w/c, specific surface and grain size (Blaine) of the grout mix (Scwarz and Krizek, 2000; Stille, 2015). Another important prerequisite for ensuring good performance of the cement-based grout mixes, is the use of fresh cements which is stored properly (Arnstein Aarset and Frogner, 2010; Stille, 2015).

3.2 Grouting methods and principles

There are two different methodology's in rock mass grouting in tunnels; *pre-excavation grouting* or *post-excavation grouting*. In pre-excavation grouting or simply *pre-grouting*, the grout is injected in front of the tunnel face in what is called a *grouting curtain*. Each grouting curtain is made up of 20-70, 18-24m long boreholes (see figure 3.1). The pre-grouting is normally executed after each third or fourth blast round in conventional drill and blast (D&B) tunneling, with each blast round usually set at 5m. Achieving a 6-8m overlap between the grouting curtains is important in order to achieve good interaction between the different curtains, as well as preventing grouting mass from entering into the tunnel space (Arnstein Aarset and Frogner, 2010). The grouting is usually done starting with the bottom holes (invert) and continuing upwards towards the roof (crown) (Arnstein Aarset and Frogner, 2010). Probe drilling is done continuously at the tunnel face to evaluate the water ingress ahead of the face (Arnulf Hansen and Grøtv, 2017).

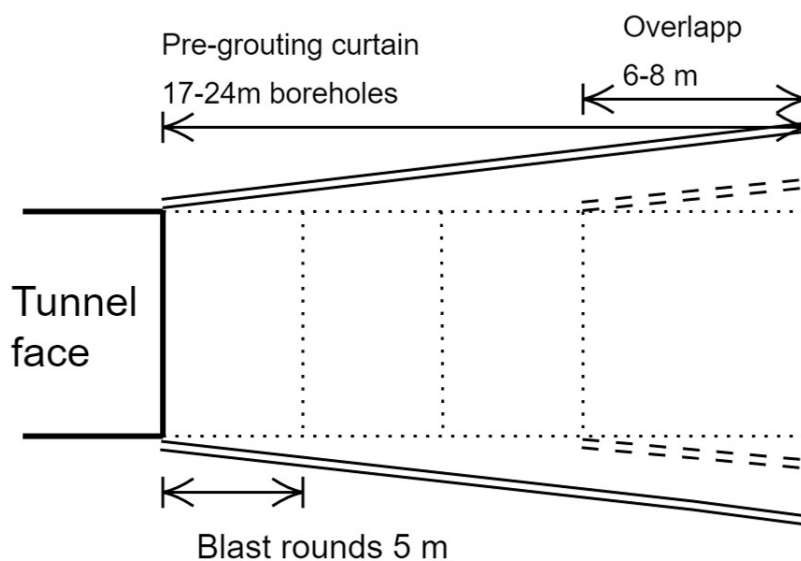


Figure 3.1: Schematic view of the basic concept behind pre-grouting.

The alternative method, is referred to as post-excavation grouting or simply *post-grouting*. Post-grouting is done *behind* (rather than in front of) the advancing tunnel face. This method is rarely done systematically due to the difficulty and time- and cost inefficient nature of the method. However, it can be used as a supplementary grouting campaign to the systematic pre-grouting, when the pre-grouting water inflow allowance is not met (Arnulf Hansen and Grøv, 2017; Arnstein Aarset and Frogner, 2010; Grøv et al., 2014).

Stop criteria for rock mass grouting

The stop criteria is a condition defined prior to grouting, and serves as a threshold criterion for which the grouting is stopped for each hole. In Norwegian practice, this is usually defined based on either maximum grout take (liter grout for each hole) or end-pressure (Arnstein Aarset and Frogner, 2010). The grout end-pressure is achieved through varying the grout flow, pressure, and w/c ratio during grouting. If a end-pressure cannot be achieved, the stop criteria is usually set at a predefined maximum grout take (liters). Another aid in achieving the stop criteria is the ability to control the curing time of the grout, by introducing additives such as *accelerators* into the grout mix.

3.2.1 GIN method

This theoretical grouting method was originally developed for grouting curtains used in dam foundations, as described by Lombardi and Deere (1993). The method relies on the *Grout Intensity Number* (GIN), which is the product of grout take (in liters per borehole meter) and pressure ($v \cdot p$). The idea is to have control over the energy in which is expended into each borehole. This is done practically by monitoring the pressure, flow rate, penetrability, and volume with time until the threshold value for volume, pressure or GIN-number is reached. The limiting GIN threshold value is indicated by the hyperbolic curve on a $p - v$ diagram. From figure 3.2, different grouting paths, all representing different *fracture apertures* can be seen in relation to the GIN threshold. The tightest fracture (path 4) is associated with higher grouting pressure, whilst the open fractures (path 1) will result in higher grout takes at lower pressures to reach the designated GIN threshold value.

As previously stated, this method is developed for use in foundation grouting related to dam constructions. An analysis of the applicability of the theoretical basis for this method for tun-

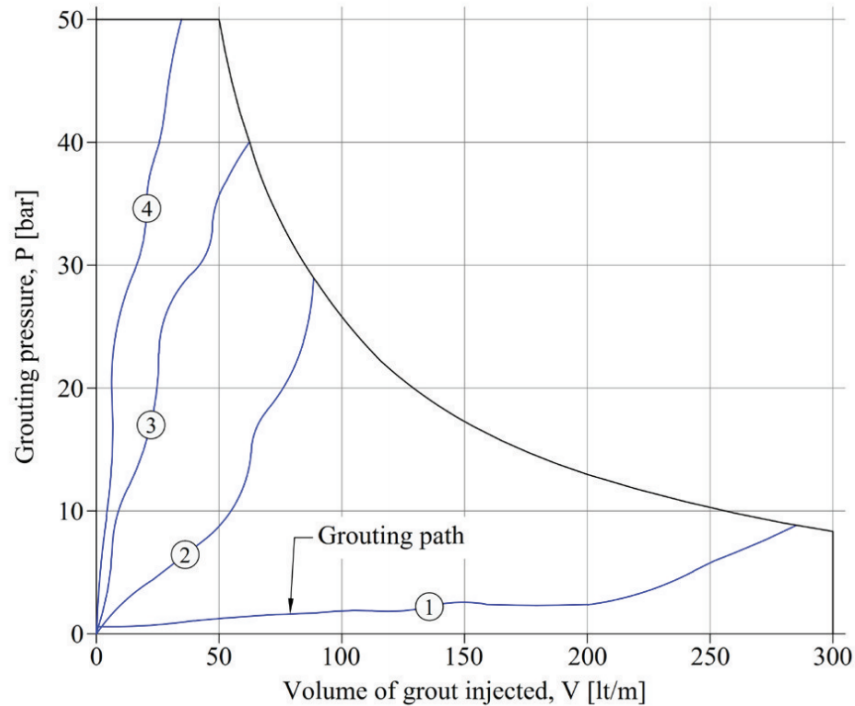


Figure 3.2: Figure shows different grouting paths (path 1-4) for different fissure apertures (narrowing from 1-4) in a pressure vs. grout take diagram. The hyperbole represents the limiting value defined by the GIN. Figure taken from Kettle and Katterbach (2015).

neling use was conducted by Brantberger et al. (2000). The theoretical basis for the method was applied for a tunneling project, with a focus on establishing a theoretical basis for the grout spread and prediction of hydraulic jacking (HJ) of the rock mass in a tunneling context. It was found that the theoretical relation developed by the original GIN-method for preventing hydraulic jacking, was not satisfactory in predicting the risk of hydraulic jacking in a tunneling application.

3.2.2 RTGC method

The *Real Time Grouting Control* (RTGC), is a concept for controlling the grouting in "real-time". The method is based on the theoretical treatment of grout mass rheology, fracture aperture and penetration length. The stop criteria for this method, is defined as when the penetration depth of the finest fractures (b_{min}) has reached a predefined "target value", or when the penetration depth of the largest fractures (b_{crit}) reaches a predefined "limiting value", in which both values is based on preliminary calculations (Kobayashi et al., 2008). Perquisites for this method, is that the rheological properties (viscosity [Pa-s], yield strength [Pas], density [kg/m^3] and bleed [%]), and the penetrability of the grout (min and max penetration length) have been established prior to grout execution (Rolf Christiansson and Carlsson, 2014; Kobayashi et al.,

2008).

The algorithmic structure of the RTGC method, is illustrated in figure 3.3. The method can be conceptualized to the following steps:

- Rheological properties of the grout, yield stress (τ_0) and viscosity (μ), are measured in laboratory methods and assumed constant with time. Penetrability properties of the grout mix, and slot apertures; b_{min} and b_{crit} are established.
- Penetration length of the grout (I_D) is calculated real time based on relative grouting time (t_D) required to obtain sufficient grout penetration.
- The grouting pressure (p_n), is chosen based on desired penetration length in addition to preventing jacking due to high pressure (see section 3.3).
- Real time comparison of recorded- and estimated flow, is used to verify assumptions on grout- and fracture dimensionality.
- This is repeated through time steps - n, until the penetration depth (I) coincides with a predefined stop criteria ("target value" or "limiting value").

Kobayashi et al. (2008), claims that the method is applicable for predicting water leakage into the tunnel and establishing the risk of uplift (hydraulic jacking). The method has been developed over many years of research, predominantly in Sweden, and has been performance-tested and verified in underground excavation projects with satisfactory results (Rolf Christiansson and Carlsson, 2014; M. Holmberg and Stille, 2012). The algorithmic structure also illustrates the possibilities for real-time monitoring and analytical applications using RTGC.

3.2.3 Grout penetrability

An important property of the grout is its ability to penetrate into very fine fractures in a rock mass, is dependent on the fineness of particles which are suspended in a cement-based grout mixture. Grout is a mixture in which various cement particles are held in suspension with a variable w/c-ratio. Cement particles in a suspension, especially grouts of the finer constituents (MFC and UFC), tend to fluctuate and form so called *filter cakes* during the hydration process (Stille, 2015). These filter cakes will prohibit the grouts ability to penetrate finer fractures, and is therefore unwanted. To counteract such behavior of the cement particles in suspension, dis-

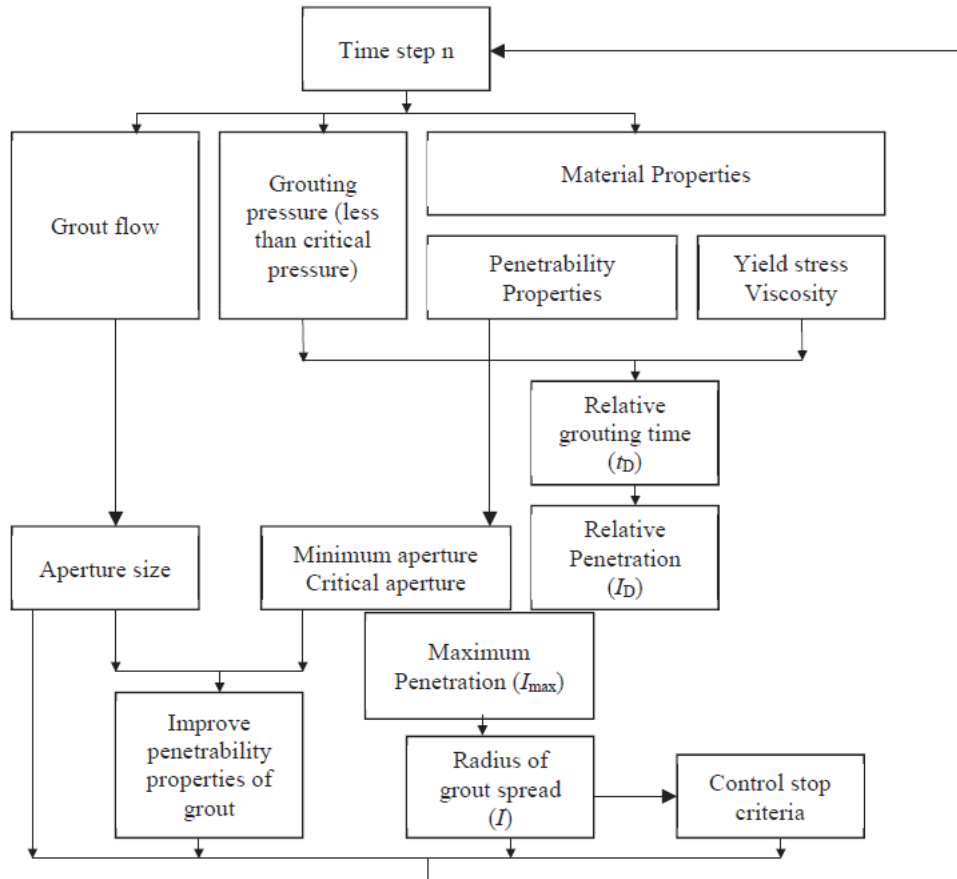


Figure 3.3: Algorithmic structure of RTGC (Jalaleddin Rafi and Johansson, 2017).

persive additives such as *superplasticizers (SP)* are usually added (Arnstein Aarset and Frogner, 2010).

A method for evaluating the grouts ability to penetrate a rock fracture of aperture b , including describing this filtration process, has been conducted by Eriksson and Stille (2003). The study found that the grout's ability to penetrate was largely dependent on the aperture size of the fractures. If the aperture sizes of the fractures is larger than an upper limit (b_{crit}), the grout is allowed to flow freely without filtration and filter-cake formation. Contrarily, if the aperture sizes are too small (b_{min}), no grout will be passed through the fracture. Considering aperture sizes between this upper and lower limit, filtration over time may cause gradual pressure build-up and turbulence or even complete blockage of the slot (Stille, 2015).

These limiting values (b_{min} and b_{crit}) can be established by using the *Penetrability Meter* (see Eriksson and Stille (2003)). The general perception regarding cement grain size and penetra-

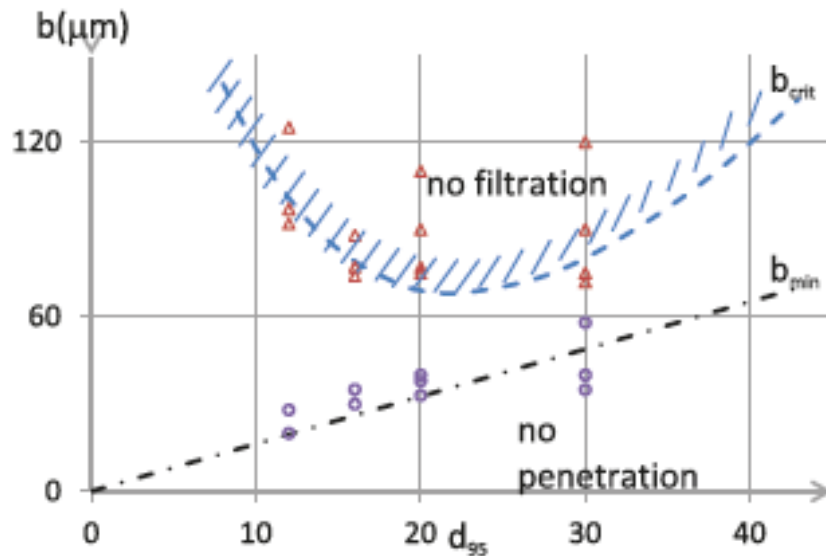


Figure 3.4: b_{crit}/b_{min} as a function of grain size (d_{95}), derived from laboratory testing conducted by Eklund and Stille (2008) (figure taken from Stille (2012))

bility, has been that an decrease in grain size (d_{95}) will allow for penetration into finer fracture apertures (b_{crit}). Laboratory research conducted by Eklund and Stille (2008), indicates that the penetrability in regards of b_{crit} , does not decrease for finer d_{95} , it actually increases, as can be seen in figure 3.4. This is because of the high surface activity and high specific surface of fine cements, which are more prone to cluster formation. According to Stille (2015), the chosen grout mix should be based on its ability to penetrate of the smallest fractures.

There are, however, differences of opinion regarding the relationship between d_{95} and grout penetrability. Barton and Quadros (2019), argues that the Swedish approach of testing the penetrability by using of the *filter pump*, which is developed by the Swedish State Power Board (Stille, 2015); is inadequate in describing flow through at fixed aperture. This because of a supposedly unnatural blockage phenomenon that occurs in the filter when testing the desirable UFC and MFC with low w/c-ratios through this filter pump, which is similar to what occurs when grout flows through a porous media such as sand or a similar porous rock medium due to extensional velocity effects (increase in viscosity during penetration causing a "stiffening" grout front (Khan et al., 2004)), and not necessarily representative of grout flow in typical hard rock conditions with sporadic aperture slots.

3.3 Hydraulic jacking

A grouting pressure above the surrounding ground-water pressure is the basic prerequisite for grout to intrude into the fracture systems around the boreholes. In Norwegian grouting practice, the use of high pressure has become the norm, the use of high pressure has become the norm, sometimes utilizing pressures up 100 bar above actual water head (Grøtv et al., 2014). It is important to distinguish the phenomenons *hydraulic jacking* (also termed hydraulic uplift in some literature) from *hydraulic splitting* (also termed hydraulic fracturing or hydro-fracturing in some literature), which is the formation of new fractures in previous competent rock due to pressure exceeding the tensile strength of the intact rock (Lombardi, 2003; Arnstein Aarset and Frogner, 2010). Hydraulic fracturing have many different appliances in rock- and petroleum engineering; it is used for conducting rock stress measurements in-situ, and is also an important concept in the petroleum industry to increase reservoir capacities.

When the pressure of the grout in the fractures (p_g), exceeds the the normal pressure acting on the fracture (the in-situ effective stresses σ_n'), this could lead to hydraulic jacking (HJ) of the grouted fracture, resulting in an increase of the fracture aperture. Based on this, the following basic criteria describes when HJ can be expected to occur in a grouted bore hole:

$$p_g > \sigma_n - p_w \quad (3.1)$$

Where p_g is the grouting pressure inside the borehole, p_w the water-pressure, and σ_n the in-situ total normal stress. Another analytical method for establishing the risk of HJ, was developed by Brantberger et al. (2000), which is based on the GIN-method (see section 3.2.1). It is based on the relation between normalized pressure exerted by the grout (p_n), and normalized grout spread (I_n), which is a function of fracture density, grout spread and fracture aperture:

$$p_n < 1 + \frac{1}{I_n} + \frac{1}{3 \cdot I_n^2} \quad (3.2)$$

Equation 3.2, defines the condition for which p_n -values represent *no risk* for hydraulic jacking. p_n is described by the following:

$$p_n = \frac{p' \cdot k_2}{3 \cdot \rho \cdot g \cdot h} \quad (3.3)$$

Where:

p' = effective grouting pressure ($p_g - p_w$).

k_2 = factor describing the grout spreading angle.

ρ = density of rock.

g = acceleration due to gravity.

h = height to fracture from ground level.

Equation 3.3, suggests the pressure required to cause hydraulic jacking, is equal to 3 times the overburden weight pressure. Assuming a horizontal fracture, which is deemed to be the most critical fracture orientation (Brantberger et al., 2000).

Stille (2015) suggest three stages of grouting-related hydraulic jacking:

1. Initially the stresses in the borehole have not yet reached the normal stresses acting on the fractures ($p_g < \sigma_n$). This will result in reduction of the contact forces acting between asperities in the fracture. Aperture widening due to the stress change is only marginal, in the scale of 10 μm .
2. When grouting pressure is exceeding the normal stresses ($p_g > \sigma_n$), elastic deformation of the fracture will occur. Depending on the grouting pressure and elastic modulus of the rock mass. This stage is associated with the positive effects of HJ, such as increased grout spread and penetrability rate. Even though the deformation of the rock mass is elastic, it will not be reversible due to the hardened grout present in the fracture. This could also lead to jacking of fractures outside the grouted zone, with an increase of permeability outside the grouted zone.
3. The last stage is referred to as *ultimate jacking*. It relates to when the ultimate bearing capacity of the rock mass has been reached ($p_g \gg \sigma_n$), this is the same condition as illustrated by equation 3.2. The deformations will potentially be uncontrollable and permanent.

3.3.1 Consequences of HJ

It has been conducted a number of researches on the presumed consequences of HJ.

Stille (2015), states that HJ events in a grouting context, poses the risk of:

- Uncontrollable grout *spread and penetration*.
- Considerable *permanent deformation* to the surrounding rock mass, in the case of ultimate

jacking.

- Potentially causing uplift and disturbance of sensitive structures at ground level (above the excavation).
- Decreased *rock mass stability* at the tunnel face, including limited *sealing effect*.
- Strømsvik (2019), concludes in *increased grout and time consumption* for holes where HJ was detected.

3.4 Detection of jacking events

Methods for discovering events of HJ from grouting data has been investigated in multiple studies, including: Strømsvik (2019), Lombardi and Deere (1993) and Stille (2015). These include analyzing the time series plot of pressure and flow versus time, and deriving qualitative and/or quantitative approaches for discovering the presence and onset of potential HJ events.

Pioneering work for discovering HJ events was made by Lombardi and Deere (1993). In this study, it was suggested to use relationship between grouting pressure p and grout flow q , which is defined as the grout *penetrability* - p/v , plotted against time. Possible HJ events can then be defined by qualitative assessment of the plot (see figure 3.5). The pressure build up is described by the increase in total cohesive forces between the grout and rock fissures as the grout spreads and fills voids in the rock mass. The onset of HJ can be observed by sharp spikes or peaks in the penetrability (see figure 3.5).

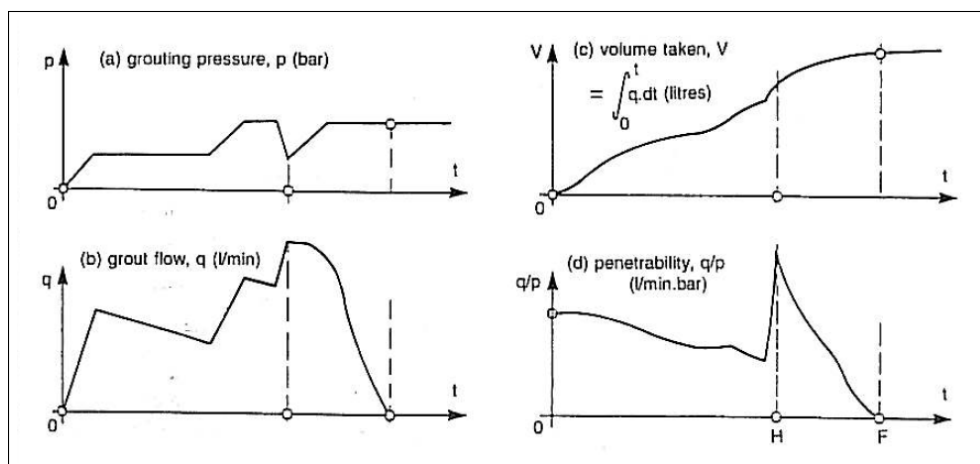


Figure 3.5: Time series plots from the grouting process, (a) - pressure (p), (b) - grout flow (q) and (d) - penetrability (q/p). Plot (d) at lower right, shows interpreted onset of HJ event at point H. Figure from Lombardi and Deere (1993).

Stille (2015, 2012), bases the detection of HJ events on the RTGC method (see section 3.2.2). Where the jacking events are indicated by a deviation of the recorded flow path from the predicted flow path. A basic assumption using the RTGC method, is that the predicted grout flow path will start to drop once constant pressure is achieved. And if the recorded flow remains approximately constant, this is an indication that jacking has occurred (as seen in figure 3.6). Another indication of hydraulic jacking according to RTGC, include constant pressure at increasing flow. These scenarios are both considered to be effects of either hydraulic jacking or due to wrong assumptions on the calculated theoretical apertures or dimensionality (1D or 2D) of the fractures.

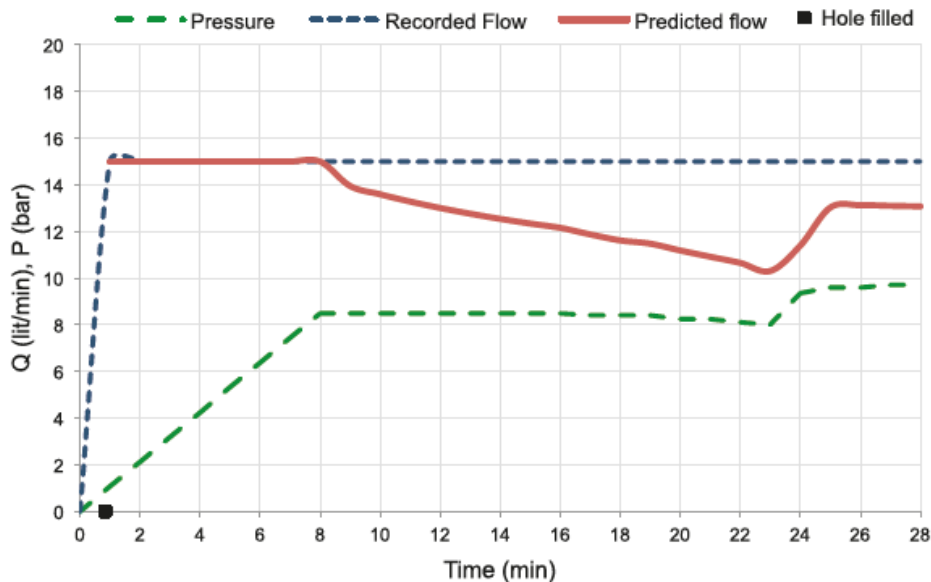


Figure 3.6: Figure depicts an interpreted jacking event, using the RTGC method for predicted flow path. Note the deviation between the predicted and recorded flow paths, (Stille, 2015).

3.4.1 PF index

The approach presented by Lombardi and Deere (1993), was found unrepresentative for Norwegian conditions by Strømsvik (2019), due to the use of significant higher pressures in Norwegian grouting practices. The use of high pressure grouting implies relatively high pressure rates compared to the flow rate, which often causes too small or negligible responses in q/p ratio. To compensate for this effect and providing an applicable method for high pressure grouting in detecting possible HJ events, Strømsvik et al. (2018) introduces the *PF index*. The PF index is

a dimensionless index value which, among other purposes, can be used to detect the onset of possible HJ events. The PF index is defined as:

$$PF\ index = 0.9\ min/l * Q_v - \frac{0.9 * P}{1\ bar} + 81 \quad (3.4)$$

Q_v is the mom. flow in l/min while P is the pressure measure at the grouting rig. Before applying the PF index method, the input pressure (p) and the calculated PF index must be filtered. The pressure filtration involves applying a simple moving median (SMM) with a window of 3 samples, this data smoothing technique removes some unwanted disturbances in the pressure series, such as momentous pressure drops and increases unrelated to HJ events. Filtration of the PF index involves applying a double moving average (DMA) with a window of 5 samples, this smoothing filtration removes unwanted noise caused by pump oscillation (Strømsvik et al., 2018).

The actual onset of a possible HJ event is found by implementing the PF index together with the logged pressure and flow with time in an algorithmic approach. The full algorithm defined by Strømsvik et al. (2018), defines various conditional arguments to be achieved for each sampling interval, in which the boundary condition for possible HJ events are based on literature study, hydraulic fracturing test, numerical modeling and study of grouting logs. Figure 3.7, shows the PF index logged together with the pressure and flow, on two different grouting logs. Looking at figure 3.7 - example (a), the PF index algorithm detects an possible HJ event after approx. 7 minutes, this is because it detects a pressure drop together with a constant flow. In example (b), a possible HJ event is detected just after 35 minutes, starting from at this point there is both decreasing pressure and increasing flow.

The PF index can also be used as a visual tool in detecting possible HJ events. This is done by analyzing graphs of the PF index together with the logged pressure and flow. Strømsvik and Grøv (2017) defines some characteristic features which can be used as tools in visual interpretation of pressure/flow graphs to evaluate the presence of HJ events:

- Momentary decrease in pressure while the flow remains constant.
- Momentary increase in flow while the pressure remains constant.

- Increase in flow and decrease in pressure.
- Stable flow and pressure, after a period of pressure increase.

While these are all indications of jacking events in a borehole, the same behavior will be seen due to other indicators *not* related to HJ events, such as: when fracture infill are cleared out by the penetrating grout, movement of still grout in the fracture system, grout pressure fluctuations due to operator control and grouting rig pump, and low-pressure grouting in a rock mass with an open fracture system. This makes it difficult to determine if the observed indications are actual jacking events or due to other, "false" effects (Strømsvik and Grøv, 2017; Strømsvik et al., 2018). Another limitation to consider when applying the PF index, is that the grouting rig is required to provide a sampling frequency of approximately one sample every 10th second. This implies that PF index as a method for detecting HJ events, can *not* be applied when considering data with a lower sampling frequency.

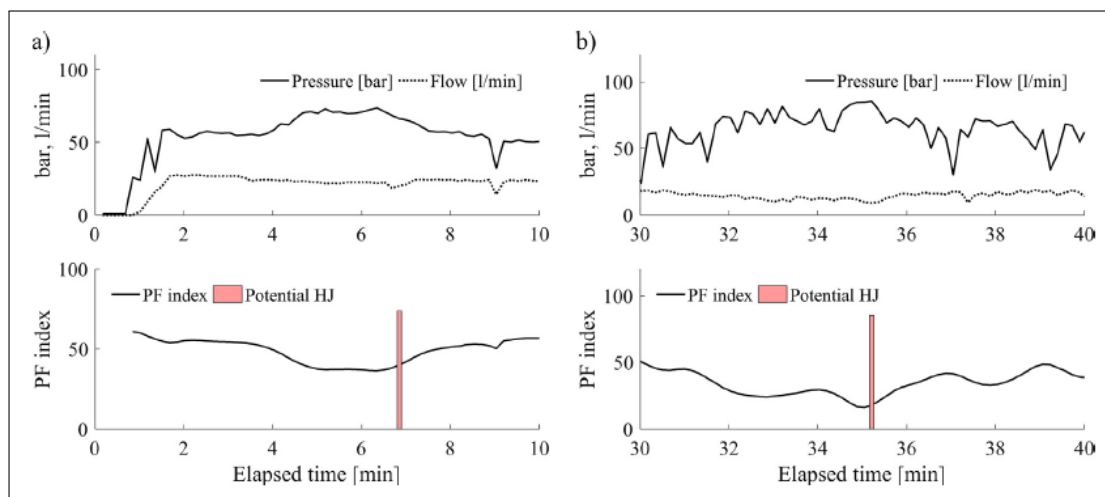


Figure 3.7: Figure shows time series of pressure and flow on top for grouting instances a and b with corresponding PF index beneath. Potential HJ events are indicated in both instances. Figure taken from Strømsvik et al. (2018).

Measurement While Drilling data

Measurement while drilling (MWD), is a drilling technology that allows for continuously logging and monitoring of numerical drilling data collected from instrumented drilling jumbos. The technology has been used in the petroleum industry since the early 1900s, after pioneering work on downhole electrical logging was done by Schlumberger in 1911. But it wasn't until the introduction of the computer that the real applicability of MWD technology was fully realized (Segui and Higgins, 2002). MWD technology has in recent years been developed into an important tool for tunneling and underground excavation, although its application today is mostly limited to ahead geological monitoring through probe drilling, and as an evaluation tool for rock support based on weakness zones and water inflow (Arnulf Hansen and Grøv, 2017). Use of MWD data directly for evaluating grouting methods is not common practice today, and a very limited number of studies have been done on this area (Høien and Nilsen, 2014).

4.1 MWD parameters

There are predominantly 8 different physical *drill parameters* measured (depending on instrumentation specifications of the drilling jumbo), representing the *raw* MWD data from the drill rig:

- Penetration rate (PR) [m/min]
- Percussion/Hammer Pressure (HP) [bar]
- Feeding Pressure (FP) [bar]
- Rotation Speed (RS) [rpm]

- Rotation Pressure (RP) [bar]
- Dampening Pressure (DP) [bar]
- Water Flow [l/min]
- Water Pressure [bar]

During drilling, all these parameters together with the hole depth, time and hammer ID are logged and saved in corresponding files for each borehole. According to van Eldert et al. (2017), these drilling parameters can be categorized into either *dependent* or *independent* parameters, depending on their drill-bit to rock dependency. The independent parameters include hammer pressure, feeding pressure, and rotation speed. These are dependent on the operator, settings and control system of the drilling rig, and not the interaction between the drill bit and rock. On the contrary, the dependent parameters are dependent on the interaction between the rock mass and drill bit. These parameters include penetration rate, torque pressure, rotation pressure and dampening pressure as well as water flow and pressure. Navarro et al. (2018), studied the inter-correlation between the MWD-parameters and suggested that the feeding pressure parameter influenced greatly on the response of other parameters, implying that changes in the feed pressure are indicative of changes in other parameters in the drilling system and can, therefore, be used for rock mass characterization.

4.2 Drill parameter interpretation

In order for the MWD data, which has been readily logged and stored, to be useful in any practical sense, it must be processed, interpreted and presented for the user. This is done by the *drill parameter interpretation* (DPI). These interpreted parameters are usually divided into hardness, fracturing, and water index (water disturbance factor). The actual interpretation are provided by various different software's, such as: GPM+ (Rockma AB, 2011), Bever Team Online/BT3 (Bever Control AS, 2019), Underground Manager (Atlas Copco/Epirock, 2019) and Sandvik iSure (Sandvik AB, 2019).

Generally, these software vendors will be able to provide at least three interpreted parameters: *hardness, fracturing or water disturbance*; but often various other interpreted models are also available, such as geological classes (lithology), rock quality indexes, etc. Some vendors will provide insight into the algorithms which are used for the different interpretation models, while

others are more secretive about their data processing approach (Jakobsen and van Oosterhout, 2018).

4.2.1 Pre-processing of MWD data

A fundamental challenge with measured data is the presence of erroneous and faulty data in the logged data set. These values are not representative of actual conditions, this could be due to human error, uncalibrated equipment, incorrect measuring or irregular measuring conditions (e.g. vibrations, temperature or humidity). These erroneous influences should be removed before further usage, unless dealt with, these data points will obscure the DPI results. An initial step to raw data pre-processing is described by Ghosh (2017). Unrealistic raw data, e.g. negative and/or unreasonably high penetration rates are removed from the data-set by defined filtration intervals, this important step in the data processing is called *filtering*.

Differences in drilling equipment and operators used will result in differences in the measured data. These effects which in many cases can be removed by data normalization. According to van Eldert et al. (2017), there are several unwanted external influences which should be removed by data normalization and filtration:

- The penetration rate parameter decreases with increasing drill hole diameters and hole length due to larger energy dissipation from friction and between the couplings of the extension rods. These are examples of effects that must be normalized, to correlate data collected from different drill sources (e.g. grouting holes and blast holes).
- During extension rod changes, the feed pressure will decrease considerably with a gradual increase towards the average value. Data collected during rod extensions are not representative of actual rock mass characteristics (Vezhapparambu et al., 2018).
- The very beginning of the drilling process for each hole, a reduced drilling pressure and speed are applied. This data is unrepresentative for the true drilling conditions and should, therefore, be removed from the datasets.

Effective DPI algorithms will effectively seek to filter and remove these adverse effects from the data.

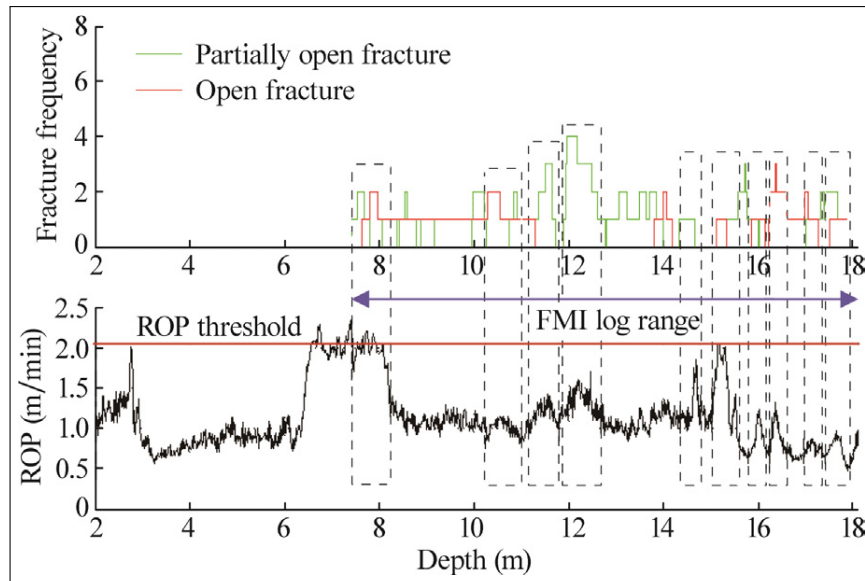
4.2.2 Hardness index

The *hardness index* (HI), is often descriptive of the drillability of the rock mass (Van Eldert, 2018). The parameter can be derived from a large variety of MWD parameters, depending on the software. In Bever Control algorithms, the interpreted hardness is based on normalized penetration rate with respect to variations in both feeder- and hammer pressure (Bever Control AS, 2019). In Underground Manager 2019, it is based on normalized penetration rate, hole depth and percussive pressure (Van Eldert, 2018). HI, unless properly calibrated, will only indicate a relative ranking in terms of hardness. In the case of calibration, this can be done by using: Schmidt hammer, UCS, point load test or Brazil test (tensile strength), which allows for absolute hardness to be estimated (van Eldert et al., 2017).

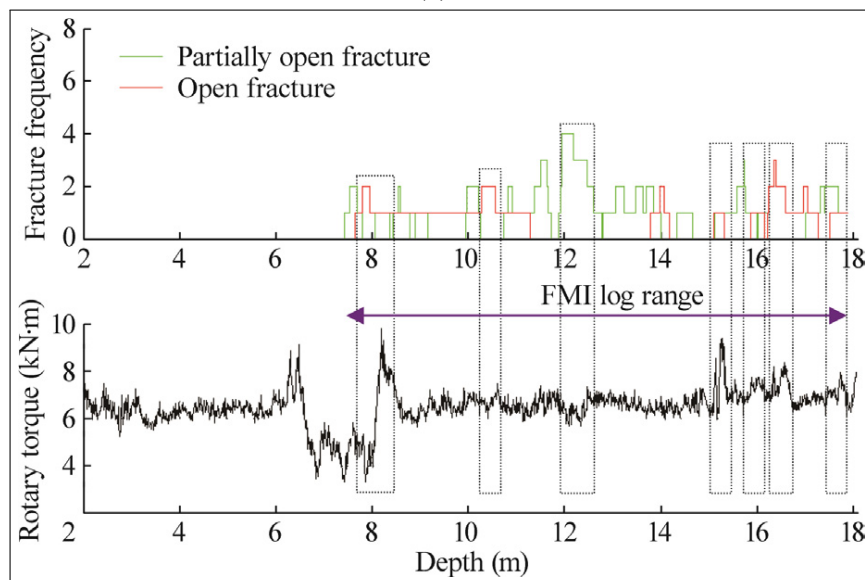
4.2.3 Fracture index

An important DPI parameter derived from the MWD data is the estimated degree of fracturing; namely, the *Fracture index or Fracture factor* (FI). This interpretation is can be derived from the variance of both the normalized penetration rate parameters (PR) and normalized rotation pressure from MWD, according to Bever Control (Bever Control AS, 2019). As these three dependent parameters are found to be most sensitive to variance in fracturing across a borehole and can, therefore, be used for fracture detection (van Eldert et al., 2019, 2017; Khorzoughi et al., 2018). Barr (1985) conducted laboratory drilling trails of an imitated rock mass block (made of a concrete compound) with inbuilt fractures, these tests were able to successfully detect fractures as well as determining whether the fractures had infilling or not. The idea is that when the drill bit crosses an open fracture, an immediate but short-lived increase in PR can be noticed, while an instantaneous drop in torque just as the drill bit enters the fracture void. Upon reconnection with the rock mass, after the drill bit has crossed the fracture void, the thrust, rotation pressure and torque will increase and normalize around values characteristic of the rock mass (Barr, 1985; Khorzoughi et al., 2018).

It should be stated that although these parameters have all been found to respond well to fracturing in a rock mass, variations in other physical properties of the rock mass such as hardness, porosity, and soft rock layers will also produce responses in the same parameters (Khorzoughi et al., 2018). Difficulties in detecting fractures of particularly steep inclination to the borehole ($>60^\circ$), has been reported by both Barr (1985) and Khorzoughi et al. (2018).



(a)



(b)

Figure 4.1: Responses in both PR (a) and torque (b) when the drill bit crosses both partially open and open fractures in a borehole, figures from Khorzoughi et al. (2018).

Figure 4.1, shows the response in the drilling parameters: rate of penetration and torque when fractures of known location and dimensions are crossed by the drilling bit. The fracture densities of the borehole are established by processed FMI logs (Fullbore Formation Microimager; an optical logging method) (Khorzoughi et al., 2018). The FMI can provide data on fracture density, aperture, and orientation. Considering the PR (in 4.1a), the instant but short-lived increase just as the drill bit crosses an open fracture can be seen multiple times at different fracture density peaks as illustrated by the dashed rectangles. A drop in torque as the high fracture

density zones are crossed can also be seen (in 4.1b). The sudden increase and decrease of PR and torque, respectively, at the 6- 8m interval, are due to control system interference; When a certain threshold is reached for these values, the feeding pressure of the drilling system is automatically reduced to compensate for this effect. The feeding pressure will under optimal conditions remain constant through the drilling procedure (Khorzoughi et al., 2018).

4.2.4 Water index

Interpreted water or Water Index (WI) is normally based on normalized water flow and changes in water pressure during drilling, and will give indications of where water is present and flowing from the rock (Bever Control AS, 2019). Høyen and Nilsen (2014), compared fold-out tunnel profiles of both DPI water factor from MWD and manually mapped water leakages. Based on the comparison, it was found a fairly good relationship between the water factor and mapped water leakages. However, the manual leakage mapping was conducted after the grouting was completed, which entails that the initial water conditions were obscured and quite possibly not representative of the water conditions indicated by the interpreted Water factor.

Because water is also commonly used as a flushing medium in rotary percussive drilling (top hammer - drilling method used for most modern drill jumbos in the tunneling industry), the Water Index could be obscured by the introduction of pressurized flushing water from the drilling rig into the borehole. Therefore, potentially limiting the reliability of the WI interpretation.

4.2.5 Presentation of MWD data

In terms of data presentation, there are many possibilities. For simple graphical presentation of MWD and DPI, both 2D and 3D options are used. Drill rigs are often equipped with monitoring solutions that can be used for real-time assessment of the drill parameters. Figure 4.2, is a screenshot taken from the GPM+ software (Rockma AB, 2011), it shows how graphical logging of each borehole can be done. Bever Team Online module allows for specifying chainage intervals for extraction of any raw MWD or DPI parameters. An example of 3D visualization of MWD DPI's by *Bever Control*, can be seen in figure 4.3.

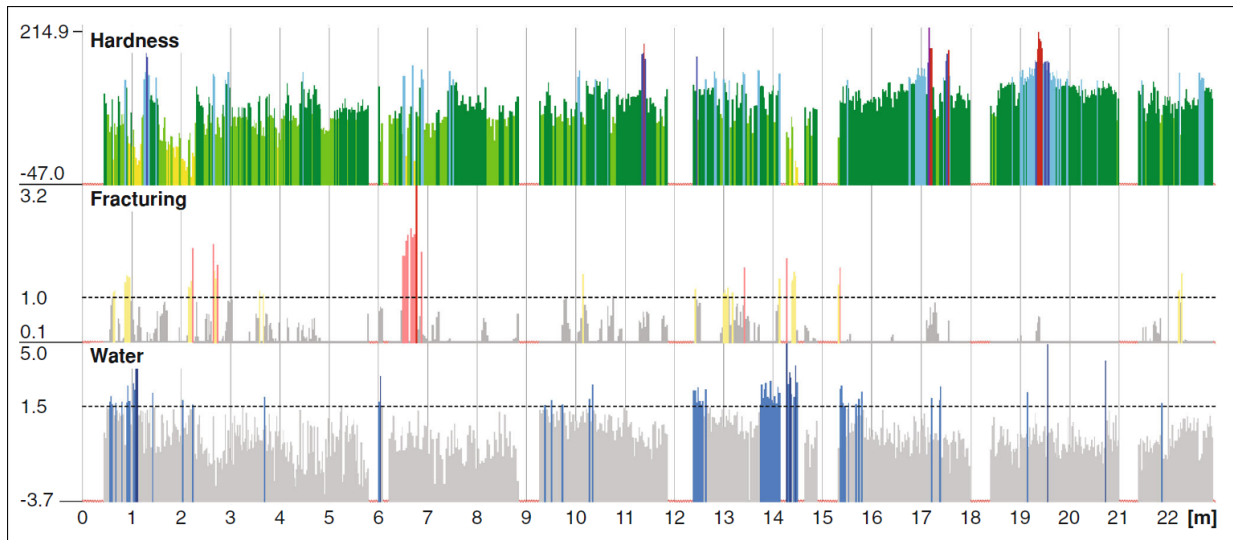


Figure 4.2: Graphs of different interpreted indices of the same borehole as done in the GPM+ software (taken from Høyen and Nilsen (2014))

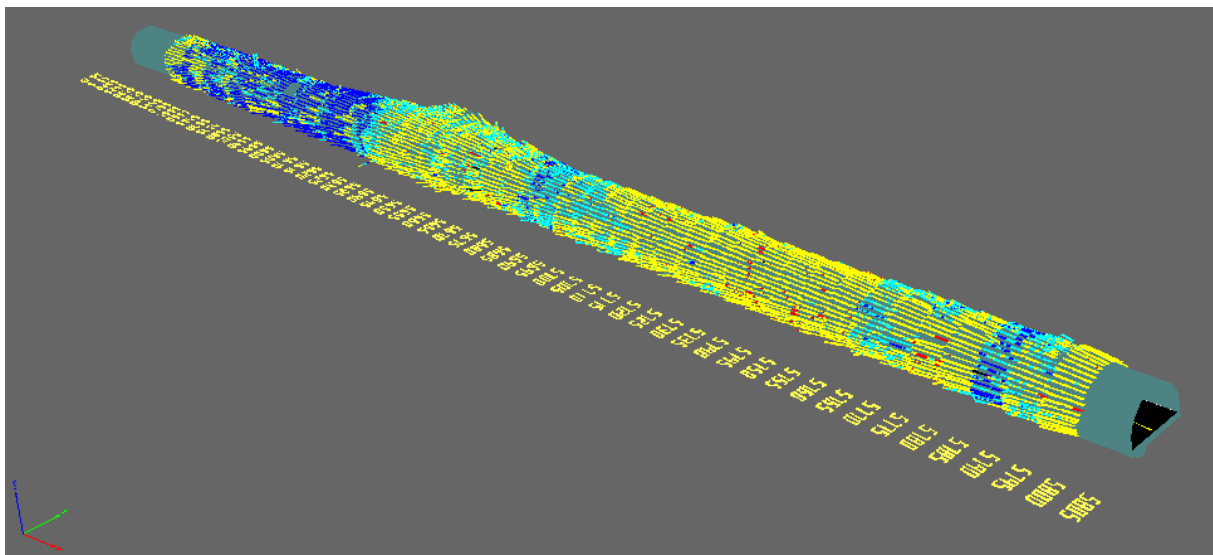


Figure 4.3: 3D visualisation of MWD DPI gathered at each blast round for approx. 250 m of tunnel. Color gradient indicate interpreted hardness, yellow indicate lower int. hardness (rel. weaker rock mass) while blue colors indicate higher int. hardness. (rel. stronger rock mass). Figure taken from Bever Team Online module, Fv. 659 project.

4.3 Limitations of MWD technology

The MWD parameters gathered from the drilling jumbos require proper calibration based on variations due to hole length, hole diameter, drill rig, and operator. Adequate calibration of the equipment, and project-specific tuning is a important for the ability to represent actual rock mass conditions with MWD DPI. Another concern regarding the practical use of MWD, especially in real time applications, is its reliance on fast and lossless data transfer solutions. An

increasing number of modern tunneling projects are now capable of providing a wireless connection at the tunnel face. This allows for real-time processing and transfer of the drilling data to off-site operators, as well as the on-site drilling operators (van Eldert et al., 2017).

There is also a lack in industry standardization, as well as secrecy surrounding how the interpreted parameters are calculated by the different MWD software providers, which often will make it difficult to compare data from different software. The resolution of MWD data with regards to sampling frequency, is an important aspect when considering the usability of the data gathered. For applications such as fracture detection, a very high sampling frequency is required. Van Eldert (2018), also discuss the differences in sampling frequencies, wherein different projects, the sampling frequency was ranging from 2-3 cm to 10-20cm between each sample. Low sample frequency may cause the loss of important properties regarding the rock mass.

Multivariate statistical methods

The different MWD parameters represents a discrete set of values collected at equal depth intervals at each borehole. While the grouting data are a set of values collected for each borehole as a discrete time series. For the purpose of analyzing these two data sets together, converting the discrete time- and depth series for each borehole to singular values for each borehole is necessary. Furthermore, it is desirable to investigate the statistical relationship between the MWD DPI- and grouting data. It becomes apparent, that a large number of data will be included for this purpose. This, along with the relatively large number of different variables with unknown interdependencies, justifies the use of multivariate analysis.

The general goal of a statistical analysis, is to evaluate the presence of a statistical relationship between a set of *response variables* (also known as dependent or outcome variables), and *predictor variables* (also known as independent or explanatory variables) (David Hosmer and Sturdivant, 2013). The response variable will produce a certain outcome, based on its relation to the predictor variable(s). In the following chapter, different multivariate statistical methods are presented for analyzing data.

5.1 Simple- and multiple linear regression models

5.1.1 Simple linear regression

To investigate the simplest form of relationship between a response variable Y and a predictor x , consider the linear relationship:

$$Y = \beta_0 + \beta_1 x + \epsilon \quad (5.1)$$

Where β_0 and β_1 are the intercept and slope parameters (also known as the *regression coefficients*) of the *simple linear regression model*, while ϵ is called the *random error* which associates the model with some uncertainty and keeps the model from being a simply deterministic model. An important aspect in a simple regression analysis, is estimating the regression coefficients, noted: b_0 and b_1 , and thus deriving the *fitted regression model* described by the regression line:

$$y = b_0 + b_1 x + e_i \quad (5.2)$$

Where y is the predicted value according to the linear regression model and e_i are the residual error which essentially is a reflection of the fitting error. It is expected that the fitted line lies close to the true regression line (5.1) when a large number of data points are analyzed (Walpole et al., 2011).

5.1.2 Multiple linear regression

Multiple Linear Regression (MLR) becomes a relevant approach when more than one variable is considered in the model (multivariate). In the case of k -number of independent variable: $x_1, x_2, x_3, \dots, x_k$, the estimated response variable y is given by the regression equation:

$$y = b_0 + b_1 x_1 + \dots + b_k x_k \quad (5.3)$$

Here, similarly to linear regression (equation 5.2), b_k are estimated from the data using least squares approximation.

5.1.3 Correlation

The strength of relationships between one response variable and one (or more) predictor variables can be established through *correlation analysis*, which seeks to derive a singular value

named the *correlation coefficient*, quantifying the statistical strength of the relationship. Widely used correlation coefficients in regression modeling, are the *Pearson correlation coefficient* - r_p , *Spearman correlation coefficient* - r_s and the *sample coefficient of determination* or simply *R-squared* - r^2 (Walpole et al., 2011).

Pearson correlation coefficient

One common method for quantifying the strength of any linear dependency, is by establishing the *Person correlation coefficient* r_p . The basic purpose is to draw a line through some x and y scattered data, so that the total distance between the line and all the scattered data are kept as small as possible. Establishing the coefficient r_p between two arbitrary variables x and y , is defined by:

$$r_p = \frac{\sum_{i=1}^n x_i y_i}{\sqrt{\sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i^2}} \quad (5.4)$$

Equation 5.4 implies that when the plotted points lie close to a straight line, r_p will be high (closer to 1.0 or -1.0) and vice versa (Walpole et al., 2011). The interpretation of correlation coefficients is somewhat different depending on which context and data they are representing, but a general "rule of thumb" approach can be seen in table 5.1.

Correlation coefficient	Interpretation
1.0 to 0.9 or -0.9 to -1.0	Very high correlation
0.7 to 0.9 or -0.9 to -0.7	High correlation
0.5 to 0.7 or -0.7 to -0,5	Moderate correlation
0.3 to 0.5 or -0.5 to -0.3	Low correlation
0.0 to 0.3 or -0.3 to 0.0	Negligible to very low correlation

Table 5.1: General basis for interpreting correlation coefficients.

Spearman rank correlation coefficient

Spearman rank correlation coefficient r_s , is an example of a *rank correlation coefficient*. The basis for finding r_s is based on the same equation as for r_p , only with x and y observations ranked 1,2,...,n, by order of magnitude (Walpole et al., 2011). If no ties (similar values) are present in the ranked data, r_s can be simplified to:

$$r_s = 1 - \frac{6}{n(n^2 - 1)} \sum_{i=1}^n d_i^2 \quad (5.5)$$

Where d_i is given by the difference between x_i and y_i at each corresponding rank, and n is the number of data pairs (Walpole et al., 2011). This method becomes useful when dealing with *monotonic* relationships rather than strictly linear relationships. A monotonic function is a function which either always increases or decreases, in either a linear or nonlinear way. The idea is that this non-parametric method will capture any non-linear monotonic trends between two variables. The r_s value will often be similar to r_p (if the relationship is linear), and can be interpreted in a similar way (see table 5.1).

R-squared

R-squared or r^2 , is a measure of how much of the variability in it's response (y) is explained by the model, defined by:

$$r^2 = \frac{S_{xy}^2}{S_{xx}S_{yy}} = \frac{SSR}{S_{yy}} \quad , \quad S_{xy} = \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) \quad (5.6)$$

Where *SSR* is called the *regression sum of squares*, and indicate the amount of variation explained by the y -variables (Walpole et al., 2011). r^2 values close to 1.0, means that close to 100% of the total variation observed can be explained by the linear relationship between the two variables i.e. the model is able to predict with high accuracy.

T-test statistics are usually performed to check the statistical significance of the linear regression model parameters, that is its slope and intercept. Usually, the test is deemed significant at p-values < 0.05 .

5.2 Logistic regression

Often the response/outcome variable will be discrete and categorical, taking on either two possible values or *binary* e.g. (yes, no or true, false) or a multiple set values or *dichotomous* e.g (low, medium, high). Fitting a regression model to these variables together with some continuous predictor variable (or multiple continuous variables the case of multiple logistic regression), the use of *logical regression* becomes applicable (David Hosmer and Sturdivant, 2013).

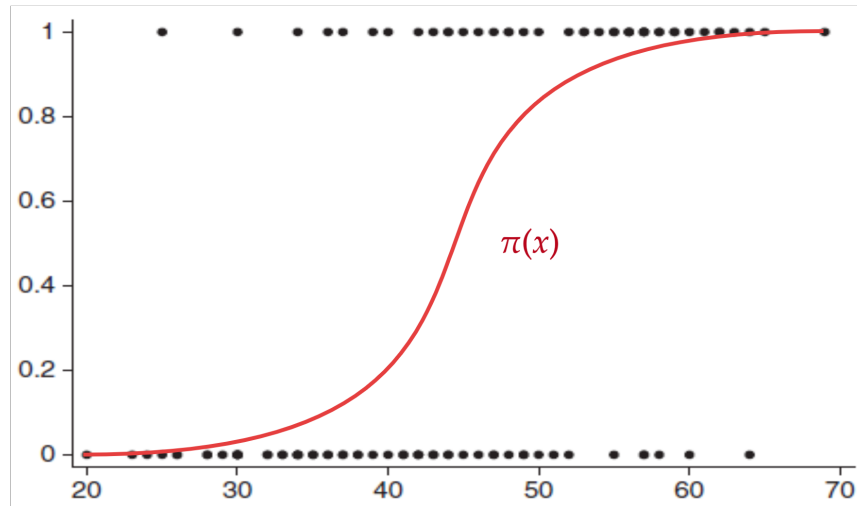


Figure 5.1: Example of fitting a logistic function $\pi(x)$ to a scatterplot of binary response variable (0 or 1) and continuous explanatory variables along the x -axis. Figure modified from David Hosmer and Sturdivant (2013).

Considering figure 5.1, the fitted regression line takes on the shape of a *logistic function*. The logistic regression function is defined by:

$$\pi(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}} \quad , \quad g(x) = \ln \left[\frac{\pi(x)}{1 - \pi(x)} \right] = \beta_0 + \beta_1 x \quad (5.7)$$

The transformed logistic function $g(x)$ in equation 5.7, is also referred to as the *logit function*, it allows the regression model to be constrained to yield values between zero and one, which satisfies the binary nature of the outcome variable. Many of the same principles used in simple linear regression also translates to logistic regression, however, there are differences in terms of fitting the regression model in logistic regression. When fitting the model In linear regression, it is common to rely on the method of *least sum of squares* approximation to approximate values for β_0 and β_1 , as previously stated. In logistic regression the same method does not apply, the method for estimating the parameters of a logistic regression model relies on the *likelihood function*, which derive maximum likelihood estimates that agree mostly with the observed data (David Hosmer and Sturdivant, 2013).

Testing statistical significance of logical regression models, is usually done using *chi-square distributions*, *Wald's test* or the *Score test*. This involves testing if the response variable is *significantly* related to the predictor variables (David Hosmer and Sturdivant, 2013).

Multiple logistic regression

Logistic regression models can also be applied when dealing with more than *one* predictor variable, just like when considering linear regression models. Similar to equation 5.7, the logit function for multiple logistic regression becomes:

$$g(x) = \ln \left[\frac{\pi(x)}{1 - \pi(x)} \right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (5.8)$$

Where n is the number of predictor variables x , and β_n the regression coefficients which we want to estimate through model fitting. The method for fitting involves estimating the β -coefficients, using likelihood functions as previously described. Testing for statistical significance for multiple logistical regression models is essentially the same as previously stated as for the univariate models (David Hosmer and Sturdivant, 2013).

5.2.1 Logistic regression as a predictive tool

Logical regression modeling is widely used as a machine learning application, more precisely, it is used as a *supervised binary classification tool*, to help predict some binary outcome variable using continuous predictor variables. For implementing logical regression as a binary classifier, *scikit learn's* `linear_model.LogisticRegression()`, Python module can be used (Pedregosa et al., 2011).

The basic idea is to fit logistic model based on some *training data*, which is represented by the n -number of predictor variables x (also referred to as *features*), together with its corresponding response variables - y (also referred to as *target*). The trained model is then used to predict values that are compared to the *test data* (Albon, 2018). Usually, the dataset is split in two, in which 75% is used as training data (x and y variables) to train the model, then the remaining 25% of data is used as test data (data the model has not seen before) to evaluate the performance of the model. Where a good model is a model that is able to accurately predict a large portion of the test data. The test data is not involved in actual training of the model, and is important to establish a benchmark for the overall performance of the model.

0's correctly predicted (<i>True negative</i>)	0's wrongly predicted(<i>False positive</i>)
1's wrongly predicted(<i>False negative</i>)	1's correctly predicted (<i>True positive</i>)

Table 5.2: Confusion matrix, showing the number of correct and wrong predictions for each case. Blue cells indicate correct predictions.

According to (Albon, 2018), the fitted models predictive power can be evaluated by investigating multiple metrics, such as: *confusion matrix*, *recall*, *precision*, and *accuracy*.

- A *confusion matrix* will give some information on the accuracy of the model in terms of which observation in the test data that were accurately predicted, and likewise which observations were wrongfully predicted; In the same way as presented in table 5.2, blue cells (main diagonal) are indicating the number of correct predictions.
- The *precision* metric relates to the confusion matrix and shows what percentages each instant (1 or 0) that were accurately predicted. Top right and lower left are also called type I and type II errors, both representing unwanted prediction outcomes. Both false negatives or false positives could represent the most unwanted prediction outcome depending on the target variable.
- The *accuracy* metric is given as a value between 0 and 1, where values closer to 1 are better, indicating the models overall prediction accuracy.
- *Recall* is a measure of the model's ability or "confidence" in correctly predicting positive targets (i.e. 1's). With a high recall metric, the model is highly confident in predicting the target in question.

Another useful method for evaluating the overall quality of a binary classifier, which includes logistic regression, is the *Receiving Operating Characteristic curve (ROC curve)* (Albon, 2018). This curve visualizes the performance of the model by showing the rate of which the model makes wrongly predicted 0's (False positive) and correctly predicted 1's (True positive) (i.e. right top and bottom values in the confusion matrix 5.2). An example of a ROC curve can be seen in figure 5.2. The orange stapled line shows the linear trend of a random predictor i.e. a model which does prediction based on pure guessing. The gray line illustrates the perfect predictor, which predicts with 100% accuracy. The blue line is the ROC curve representing the model, the closer it aligns with the gray line and the more it deviates from the orange line, the better predictive performance of the model.

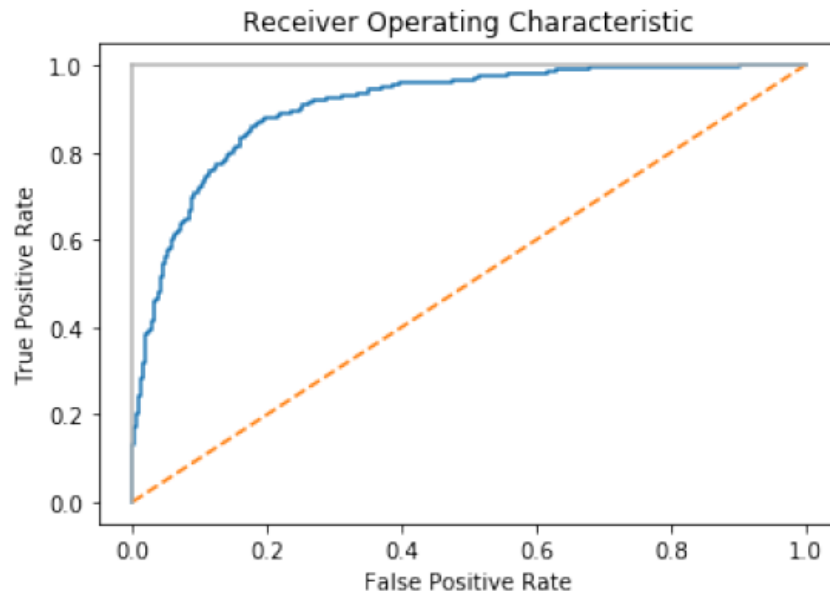


Figure 5.2: ROC curve in blue, gray line indicates 100% predictive accuracy. ROC curves with large deviations from the linear trend line (orange) indicate good predictive performance of the model. Figure taken from Albon (2018).

The model parameters can then be tuned in an attempt to improve its predictive performance. Tuning binary classifiers are mainly done through *regularization*, regularization techniques prohibits the models from becoming too complex by *penalizing* or constraining them. In other words, it is a minimization technique to reduce the overall variance of the model. The main parameter for tuning regularization strength is the C -parameter, which establishes how strong the applied regularization is, with high values corresponding to less regularization (more complex models) and low C -values corresponding to stronger regularization (less complex models). Regularization will follow a specified penalty function, called $l1$ and $l2$ (Albon, 2018).

Limitations of logistic regression models

Limitation of using logistic regression as binary classifier includes:

- Sensitivity to *overfitting*. Overfitting is the term used when the model becomes too complex in fitting a model according to some training data, i.e. not being able to detect underlying tendencies in the data. This effectively limits its robustness in predicting future observations. This is often due to the presence of too much noise in the predictor variables, or simply too many predictors. Regularization is a method to penalize the overfitting by minimizing the complexity of the model (Albon, 2018).

- The performance of the fitted model tends to *not perform* very well when the explanatory variables are not correlated to the response variable, and if the explanatory variables are too similar to each other i.e. highly correlated. The solution to this is often to simply remove one of the explanatory variables that are highly correlated with each other (Albon, 2018).

5.2.2 Cross validation for model testing

A robust method for evaluating the performance logistic regression, including any other machine learning model, is *K-fold cross-validation*. Cross-validation allows for testing a model's performance by splitting the data into K -number of *folds* of data into testing- and training data, and then proceeding with testing based on each of the splits through iteration. E.g. test run with 5 K-Folds, this means that data will be divided into 5 parts, with $1/5$ of the data set of for model training and the remaining $4/5$ used for testing. This is done through iteration such that all of the data sets are tested through i.e. 5 iterations yielding 5 different performance metrics (see figure 5.3). This allows for testing the model multiple times on different parts of the data and is, therefore, often considered more robust than simply training and testing on a given portion of the data set (Müller et al., 2016).

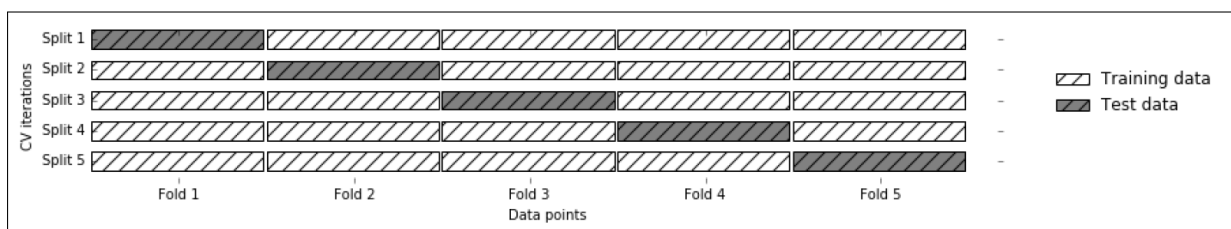


Figure 5.3: Example of 5-fold, where the sample data is split into 5 parts, resulting in model train/testing 5 times through iteration. Figure taken from Müller et al. (2016).

5.3 Principal component analysis

Principal component analysis (PCA) is a widely used statistical method for analyzing multivariate scenarios, as it has many useful appliances when dealing with many variables. The PCA utilizes algebraic transformation of initial correlated variable distribution, into uncorrelated principal components based on the original variables. The main goal is to condense the variables into new factors or components which explain a maximal portion of the total variance between the initial variables. Thus, retaining the maximal amount of information explained by the variables, while at the same time reducing the number of variables (Wackernagel, 2013). PCA has many applications, including:

- *Dimensionality reduction*, PCA can greatly reduce the number of variables that is to be used in further analysis through transformation into uncorrelated components (Barnett, 2017).
- *Data correlation*, PCA can be used to investigate the correlation matrix and loading plots to evaluate the correlation between a large number of variables.
- *Data visualization and outlier detection*, by interpreting the PCA score plots, detecting similarities and outliers among the observations is possible.

The PCA performs rotational transformation to define a new coordinate system for the original data, called *principal components*, preserving as much of the variance or *information* from the initial variables as possible. Before applying PCA, *standardization* of the initial variables is needed, which involves transforming the variables to have a mean of 0, and variance of 1. A visual example of the PCA transformation is shown in figure 5.4, in this example, the dimensionality of the initial 3-dimensional data is not reduced but preserved through three principal components. The Figure shows the rotation of initial variables into a new coordination system. The same principle can be used for higher-dimensional data (more than 3), where visualization becomes difficult. The principal components that contribute little towards variability explained can, in that case, be dropped. To help consider which principal component should be dropped, one can utilize the *scree plots*. The scree plots show the amount of variance explained within the different principal components. Figure 5.5, shows an example of a *scree plot* corresponding to figure 5.4, it can be seen that PC1 and PC2 together contribute to about 90% of the total variance explained by the model, suggesting PC3 can be dropped without loss of too much information.

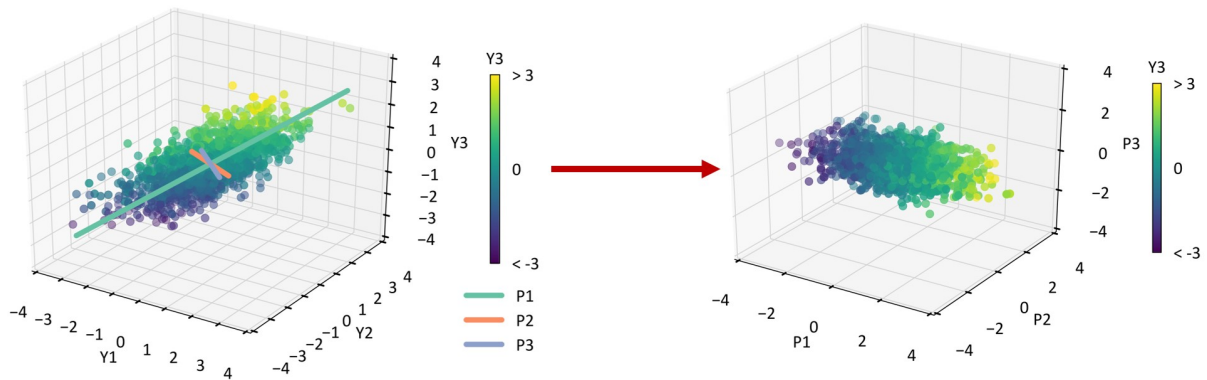


Figure 5.4: Figure visualizing the PCA transformation of data: from original data on the *left*, to principal components explaining the most variance in data (PC1) to least variance (PC3) on the *right*. Note the new orientation of the data, in this PCA example, dimensionality is not reduced. Figure taken from Barnett (2017).

The result of running PCA on a data set is called the *scores* (see right plot of figure 5.4). The scores are the actual results of the PCA transformation on the dataset (Bro and Smilde, 2014). The scores represent the same observations present within the original data set, after PCA transformation, and can be interpreted and visualized in many ways. A plot over the PCA scores is called a *score plot*, and will often reveal clustering and similarities within the data, and is very useful for data visualization. The principal component *loadings*, are unit vectors explaining which linear combination of variables relates to a particular principal component (Bro and Smilde, 2014). In other words, the loadings reflect how much variance each initial variable represent

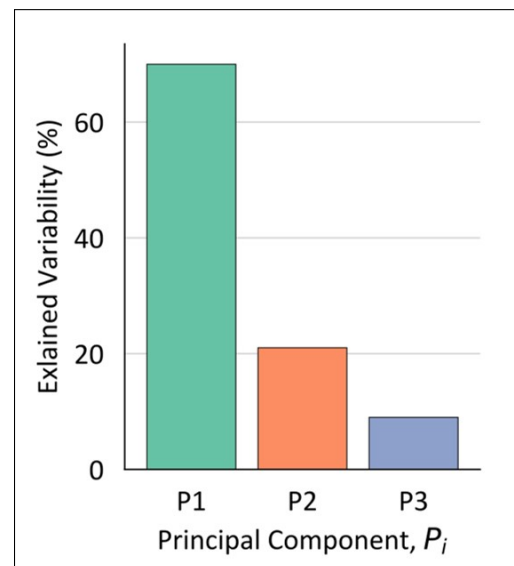


Figure 5.5: Example scree plot, showing the explained variance for each principal component. Figure taken from Barnett (2017).

in terms of the different principal components, an example of loading vectors visualized in the same principal component space can be seen in figure 5.6. Loadings are useful to better understand what initial variables the different components represent. A *biplot* is essentially combining the loading vectors with the scores in the same plotting space.

5.3.1 PCA assumptions

To assess if PCA is applicable for any given dataset, some assumptions must be evaluated before moving forward with PCA. Schumacker (2015), discusses some assumptions that need to be assessed:

- As an obvious prerequisite, the dataset should consist of multiple variables with continuous values. One can argue that the full strength of PCA is realized when a large number of different variables are considered. There should also exist a certain *linear relationship* between these variables, even if the correlation is very low. This is because PCA is based around the Pearson correlation coefficients to reduce the number of variables (dimensionality reduction). To evaluate this assumption, one can check if the determinant of the *correlation matrix* - M is positive ($\det(R) > 0$). Where R is the correlation matrix, a positive determinant indicates that there is some linear dependency present between the variables. In the unlikely case of perfect linear dependency (correlation of 1 between all the variables), $\det(R)$ would be zero, indicating that multicollinearity is likely present i.e. the independent variables are highly correlated with each other. To evaluate if a statistically significant correlation is present, it is also suggested to check the *sphericity* by using the *Bartlett Test*. This test statistic checks if the correlations are present in the correlation matrix, and if they are statistically significant ($p - value < 0.05$).
- The dataset should have *sampling adequacy*, meaning that in order for PCA to produce a reliable result, a large enough sampling space should be available. The sample adequacy is often tested using a test called KMO - *Kaiser-Meyer-Olkin*, which is a criterion for sampling adequacy. There exist different rules of thumb for what is considered "adequate" sampling, the general belief is that a $KMO > 0.5-0.6$ is considered adequate and reflects that there is a sufficient sample size for conducting PCA.
- The dataset should not have a significant amount of *outliers*, this is because a large number of outliers will have an irregular influence on the PCA results. However, there exist methods to detect and exclude outliers in datasets. In this thesis, *Support Vector Machines* (SVM), is used for outlier detection of the PCA results. SVM is a machine learning technique used for outlier/novelty detection, based on learning the expected distribution of any given dataset Meyer and Wien (2001). SVM needs tuning of some key parameters which have to be set properly if it is used for outlier detection, namely *gamma*— and

nu -parameter. the $gamma$ -parameter helps the algorithm to approximate the distribution in which to base the outlier detection on, where a value of 0 tells it to approximate the distribution. nu tells the algorithm what percentage of outliers that can be expected from the dataset, a value of 0.05-0.06 is often used for outlier detection.

That being said, a violation of any of these assumptions does not reject the use of PCA as a whole. E.g. for data visualization and discovering patterns in the data. When using PCA for dimensionality reduction, these assumptions become more important, as the analysis outcome becomes more stable and reliable if the assumptions are validated. For this thesis, PCA was done using the Python library *scikit-learn*. KMO and Bartlett's test was done using the *factor-analyzer* Python module.

5.3.2 PCA limitations

Some limitations to consider when applying PCA, include:

- *Interpretation challenges*: Due to the process of scaling, normalizing, and transformation into principal components. The data is transformed many times, both through initial scaling of variables and the subsequent transformation of variables into principal components. This makes the final PCA result somewhat difficult to compare to the initial variables, especially when dealing with many variables.
- *Information loss*: When using a large number of variables, the transformation into principal components will result in a lot of information loss. Even though the main goal is to preserve a large portion of the *explained variance* of the original dataset, there will often be a considerable information loss due to dimensionality reduction.

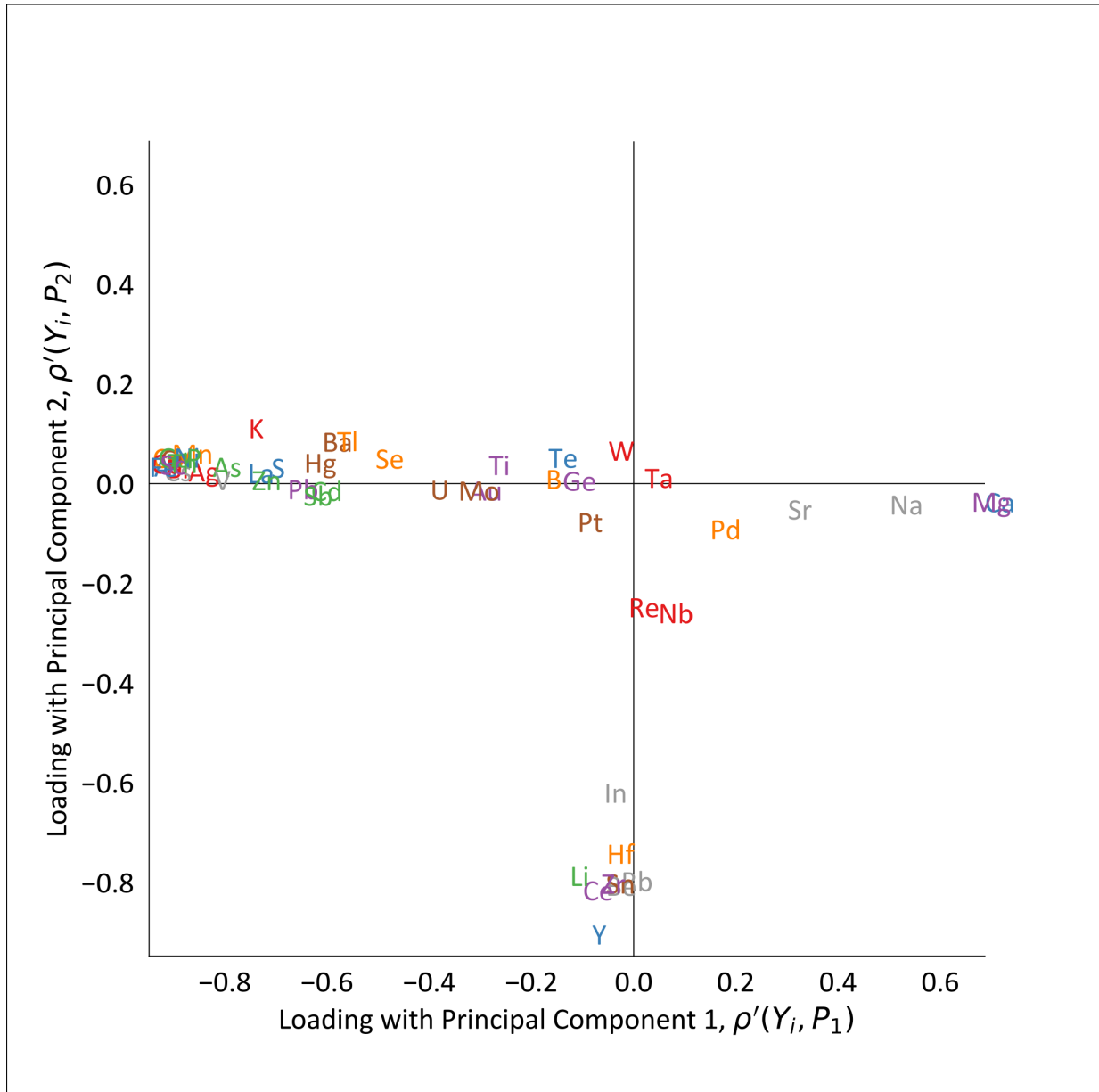


Figure 5.6: Example loading plot, showing the loading vector (without arrows), depicting each variables influence on the principle components (in this example being the influence from each element). Figure taken from Barnett (2017).

Project site description and methods for data gathering

6.1 Project description

To gather MWD- and grouting data for further data analysis, data from an ongoing (2020) infrastructure project is used, namely *Fv.659 Nordøyvegen*. The project is located in the "Møre og Romsdalen" county in northwestern Norway (see figure 6.1). It is a large infrastructure project comprising of new roads, land reclamation, three bridges, one smaller landbased tunnel, and three subsea tunnels. This will serve as mainland connection for about 2900 residents of the five islands: Lepsøya, Haramsøya, Skuløya, Fjørtoft, and Harøya. For this thesis, data from two different worksites were gathered, namely: *Longva*, which is the north-going tunnel worksite at "Nogvafjordtunnelen", and *Austnes*, which is south-going tunnel worksite at "Haramsfjordtunnelen" (see figure 6.1).

The project comprises a total of 6 contracts, of which the main contract -K5 (which also includes all the tunnels), is engaged by the turnkey contractor *Skanska Norge AS*, other smaller contracts from this project are mainly represented by smaller, local contractors. The building was started in 2017, and it's estimated to be completed by 2022. The total cost for the whole project is estimated to be around 4.9 BN NOK (NPRA, 2010).

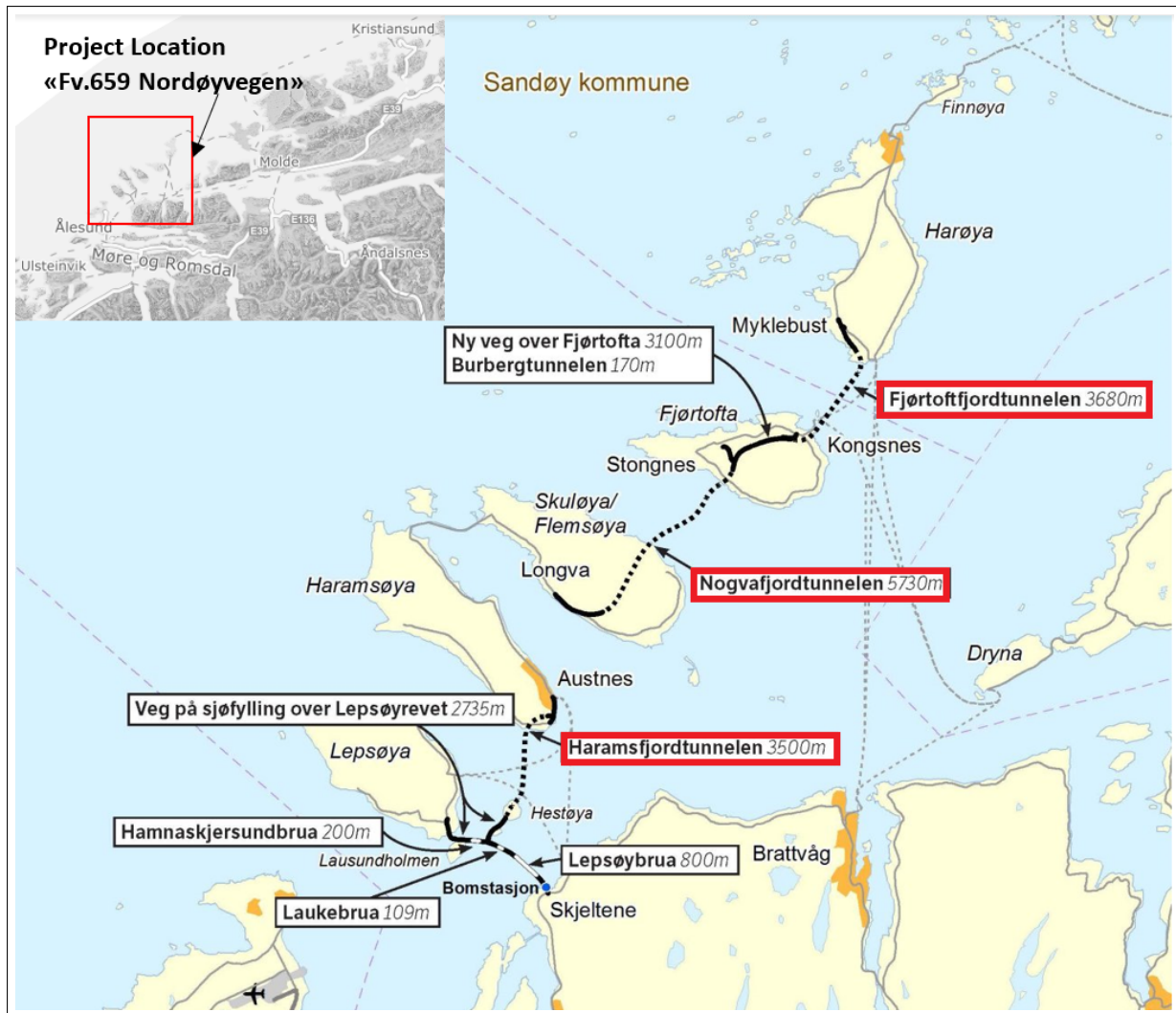


Figure 6.1: Location of the project Fv.659 Nordøyvegen, including location and names of the three subsea tunnels shown in red markings. Map modified from NPRA (2010).

6.1.1 Regional geology and engineering geology

In conjunction with the planned tunneling activity that this project included. Structural geological and bedrock mapping was carried out as early as in June 2011, by Norwegian Geological Survey (NGU) on behalf of the Norwegian Public Roads Administration (NPRA) (Ganerød and Lutro, 2011). The bedrock geology of these islands is characteristic of the *Western Gneiss Region*. The islands were first mapped systematically by NGU in the years between 1995 and 2002, and bedrock geology in the preliminary NGU rapport is mainly based on these mappings.

The bedrock of Skuløya consists of very deformed rock which can be described as "dioritic and migmatitic gneiss". The bedrock of the three southernmost islands: Skuløya, Hamsøya, and Lepsøya also consist of "granitic gneisses" with "eclogite lenses" and sporadic introduc-

tion of "mafic intrusions" (Ganerød and Lutro, 2011). Since these rock types are so heavily deformed, it is estimated that the variation in terms of rock mass quality and rock mechanical properties of the different rock types are difficult to estimate. Problematic rock mass conditions for the tunnel construction include unfavorable sub-vertical orientation of the rock mass foliation/intrusions, which could lead to increased inflow of water where tunnel overburden is small (Ganerød and Lutro, 2011). Full bedrock geology map can be seen in figure 6.2.

In addition to the preliminary geological mapping, more detailed knowledge of the geological properties and features including soil thickness along the seabed, was gathered by geophysical mapping carried out by NGU. The geophysical methods included airborne magnetic surveying and interferometric bathymetry surveying (John F. Dehls and Rønning, 2012). The magnetic method was mainly for weakness-zone interpretation, localization, and characterization. Interferometric sonar was used to map the seabed bathymetry oriented around the 3 planned subsea tunneling paths. In addition to this, results from refraction seismic conducted prior to this mapping were used in establishing potentially problematic areas and weakness-zones. Important concluding remarks from the geophysical report, include the identification of at least three larger interpreted weakness-zones that intersects with the planned tunnel paths (see figure 6.3). One of these adverse zones was identified at the crossing between Skuløya and Fjørtoft (Nogvagjord-tunnel), two zones were identified at the crossing between Fjørtoft and Harøya (Fjørtoft-tunnel), and multiple smaller zones at the crossing between Haramsøya and Lepsøya (Haramsfjord-tunnel). The three zones are characterized as "poor quality rock mass", with seismic velocities ranging from 3400 to 4000 m/s (see figure 6.3) (John F. Dehls and Rønning, 2012). One of these interpreted weakness-zones will be used to verify the response of the MWD DPI (see section 8.1).

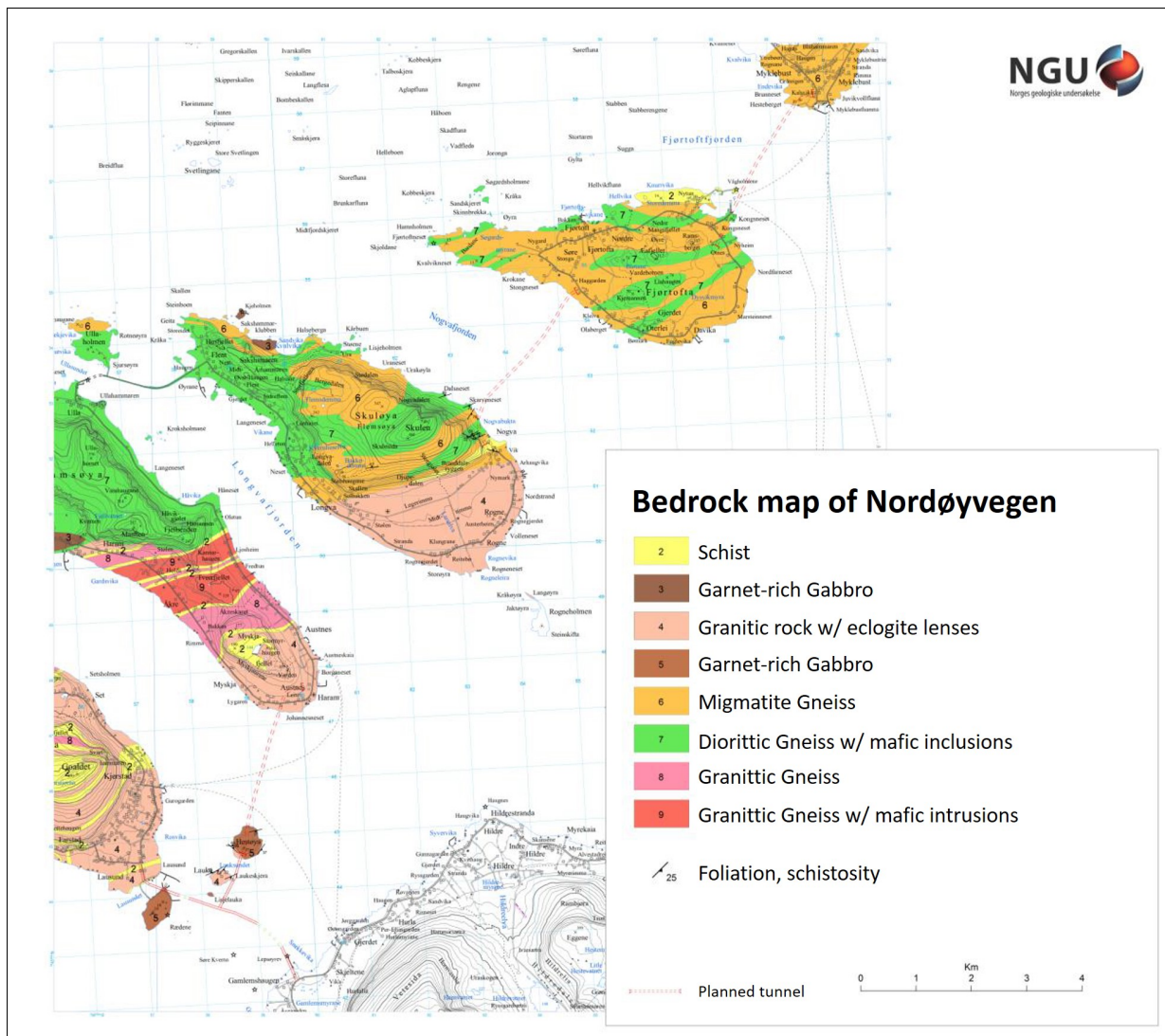


Figure 6.2: Bedrock geology of the area relevant to Fv.659 Nordøyvegen. Figure modified from Ganerød and Lutro (2011).

6.2 Data gathering, processing, and management

A database for both MWD- and grouting data was established in *Excel* for easy data entry, which was then converted to a .csv-file for further analyses. The database entries included descriptions on each hole: worksite, chainage number, hole number, and logging depth, including different columns for actual MWD DPI- and grouting data. The full database is presented in appendix A. An important aspect of the data analysis was the ability to collect as much data as possible, as well as retrieving representative data for each borehole, without missing or defective data. To combine the two data sets, both the MWD DPI- and grouting data needed to be matching their respective borehole. Data gathering and processing for both MWD and grouting data are presented in the next two subsections.

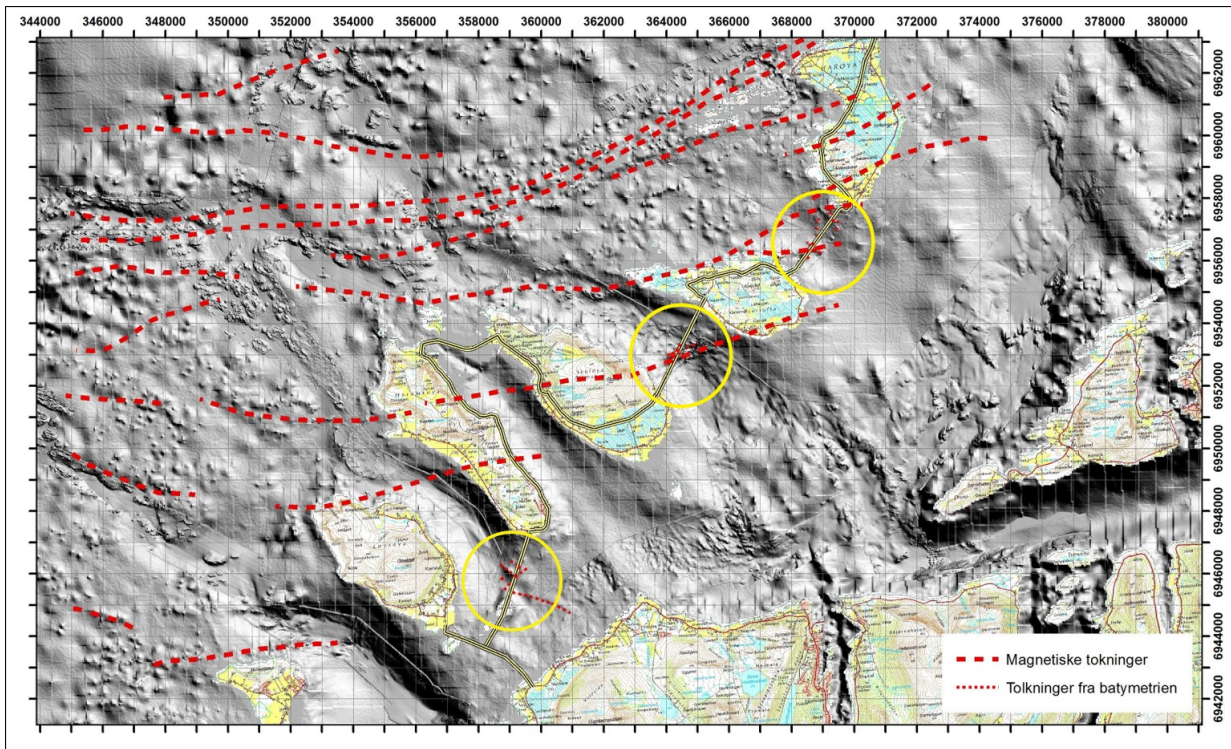


Figure 6.3: Schematic map illustrating positions and lateral extent of interpreted weakness-zones, intersection with planned tunneling paths are indicated with green circles. Map taken from John F. Dehls and Rønning (2012).

6.2.1 MWD data

The MWD data used are gathered from the Fv.659 project via the Bever Team Online (BTO) project module of Fv.659 Nordøyvegen, provided by Bever Control (Bever Control AS, 2019). BTO is a web-based solution for storing and visualizing as-built project data, which are available within the web browsing environment (see figure 6.4). BTO provides real-time monitoring of the production advance, as well as access to as-built geometry-files and drilling logs for each blast rounds and grout curtains.

The drilling logs include a hole description for each hole, including the actual MWD data logged with a typical sampling resolution of ca. 3 cm between each measurement. MWD logging is typically started after 0.6 m of drilling, this is done to minimize the influence of rock mass disturbed by blasting, and to avoid the unrepresentative measurements at the start of drilling. A summary of the data available in the drilling logs is shown in table 6.1.

The Excel drilling logs were organized in such a way that drilling data for each hole, were presented on different Excel-sheets. Each borehole (Excel sheet) consisted of data series with around 800 data points for each parameter (column 2 and 3, table 6.1), depending on the length

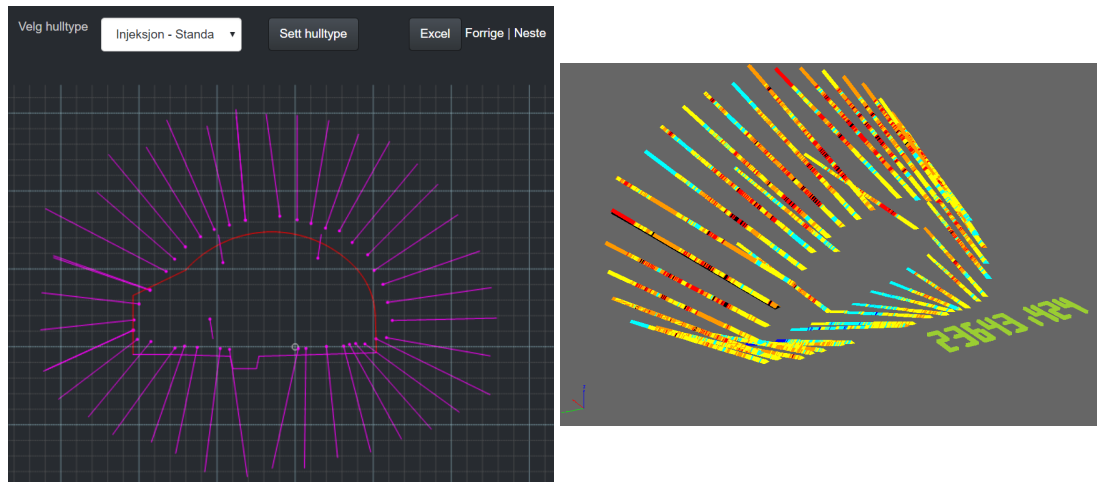


Figure 6.4: Snippet from BTO, left figure showing 2D presentation of a grout curtain at chainage nr. 23643. Individual or multiple borehole can be selected for export to *Excel* as drill logs. Right figure shows the same grout curtain visualized in 3D with interpreted hardness as colored texture for each borehole.

of the borehole (which is usually between 24 and 30 meters for grouting holes). A visual inspection of the MWD data for each hole was made to ensure that the drilling logs were not lacking data. An example of a borehole with insufficient logging together with a sufficiently logged hole can be seen in figure 6.5. Boreholes with approximately $> 70\%$ missing data were *excluded* altogether for further use. The hole-numbering of the MWD data had to be compared with that of the grouting reports, to ensure that all holes were present and matched the hole numbering which was described in the grouting reports (see figure 6.6).

To ready the MWD DPI data for the data analysis, it had to be efficiently collected and processed from the *Excel* drilling logs. A Python script using *PyCharm* as IDE, was written to read a whole *.xlsx*-file, iterate through each sheet, and extract the MWD DPI data (see table 6.1, column 3). As previously stated, it was desirable to condense each borehole to a *singular value*, similar to the methods presented in Høien and Nilsen (2014). The script allows for much

Hole description	Raw drilling parameters	Interpreted parameters
Tunnel chainage (nr.)	Depth (m)	Depth (m)
Hole type (e.g. blasthole)	Penetration (m/min)	Int. Hardness
Hole coordinates (X,Y,Z)	Rotation pressure (bar)	Int. Fracturing
Start- and stop data and time	Feeder pressure (bar)	Int. Water
	Hammer pressure (bar)	
	Rotation speed (rpm)	

Table 6.1: Table of the different MWD DPI-parameters available in the drilling logs.

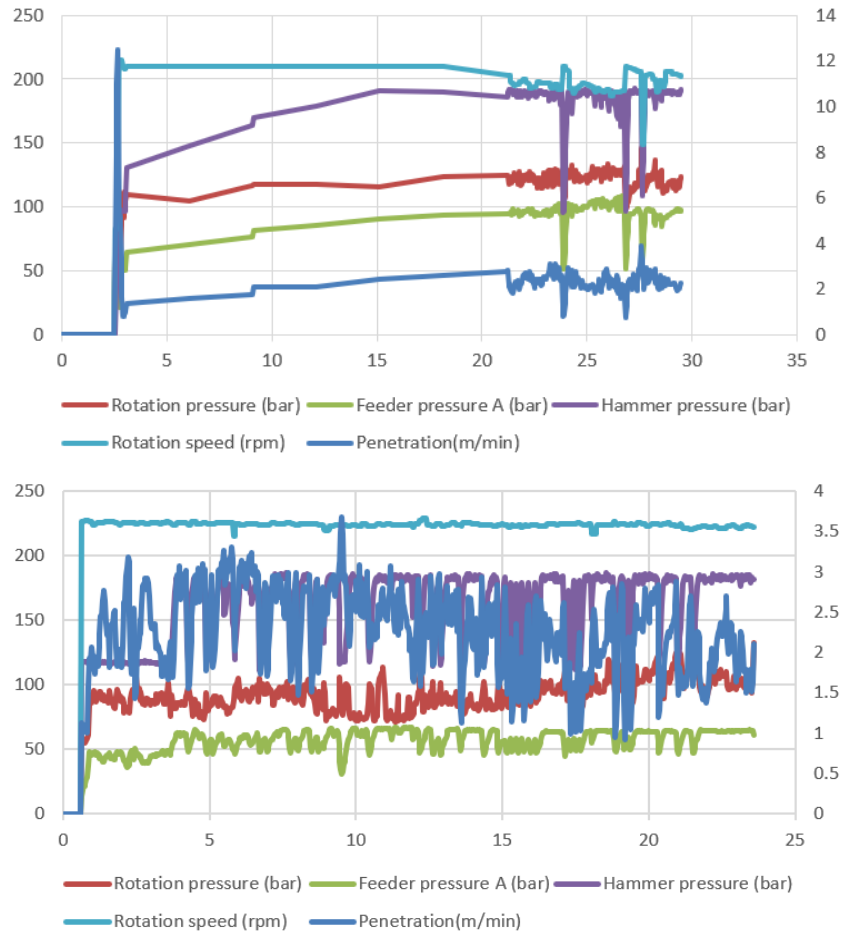


Figure 6.5: The top figure shows a typical drill log with lacking data, the bottom figure shows a drill log with complete data. Data example is showing MWD raw data, not DPI's. Graphs taken from the Excel drilling logs (Bever Control AS, 2019).

flexibility in terms of extracting and processing the data as wished. The output of the script provides singular descriptive values for each interpreted parameter for each borehole in a grout curtain, including: *hole number, mean, max, min, standard deviation, and quartiles*, for each interpreted parameter. The full Python source code for the MWD DPI data gathering algorithm is available in Appendix B. The processed data retrieved using the script was then inserted into the Excel database (appendix A).

Both the *mean* and *max value* from each of the MWD DPI parameters were selected to be used further in the data analysis. Mean and max values were considered to be the most representative values, in terms of representing the MWD DPI data for each borehole with a singular value. Condensing up to 900 samples per borehole, to 1 singular value, will naturally offer some limitations in regards to how well each borehole is described. It is conceivable that a mean value

would yield higher values for holes with high fracture density, but it could also potentially mask some important responses such as very large fractures in a relatively competent rock mass, and that the hole potentially could be better described by a max value. Zero values were excluded from the data in the function which provided the descriptive stats, this is because zero values in the drill logs represent voids in the dataset due to the lack of logging (as seen in figure 6.5), which occurs quite often. The data voids are neither descriptive and will potentially obscure the data analysis.

6.2.2 Grouting data

Grouting data are continuously monitored and logged from grouting rigs during the whole grouting procedure. The logged parameters consist of: volume, pressure, and flow against time, the logs also include start- and stop time, date, hole number, hole length, w/c, and recipe number for each hole. All these variables are stored in the grouting *log-files*, which are .txt-files of raw data taken during grouting.

The grouting-technicians are required to provide a *grouting report*, after each grouting round. The grouting report contains an overview of the cement amounts and time used, including more detailed information on each grouted borehole: stop pressure, recipes, and comments made by the rig operators. In Norwegian practice, information regarding variations in penetration rate, color of flush water, and other problems/observations made during drilling should also be registered in the full grouting rapport (Arnstein Aarset and Frogner, 2010). An example of a grouting report summary page (first page) taken from the Fv.659 project, can be seen in appendix C. Another important addition in the grouting report is the hole numbering overview (see figure 6.6), this overview is used to define the boreholes that are to be grouted. The same hole-numbering was also used in this study, to visually compare the MWD- and grouting data to match the individual holes.

For all the different worksites in this project, systematic pre-grouting is performed, with a general hole-length of 24m, and primarily standard Portland industrial cement grouts are used. Maximum grouting pressure is set at 80 bars for both the crown and invert of the tunnel. An overview of the grouting procedure used for this project is presented in appendix C. For the purpose of this research, the properties of the different grout recipes, such as w/c ratio, cement

types and, additives, are not considered.

Because Bever Control didn't have grouting data stored and available for this project, all information with regards to grouting had to be gathered from *Skanska* as they became made available from the different worksites. Preferably, the information for each grout curtain included both a grouting report and log files. The grouting logs were very important for analysis purposes, as they included all the raw data from the grouting rig: volume, flow, and pressure as time series with approx. 10 seconds sample intervals. Including general descriptions of the grouting round: tunnel site, recipe, hole number, and date. An example of a typical grouting log file can be seen in figure 6.7.

Bever Team 3 (Bever Control AS, 2019) was initially used to import the log-files, but due to some limitations with this software, such as not being able to group and add values within same hole numbers, extract values of moment flow and problems importing log-files which have missing information, an alternate approach had to be found. After discussions with Bever Control representatives, it became clear that this was not possible to find an immediate solution to this. Due to these problems, a Python script was written to extract all the appropriate values from the

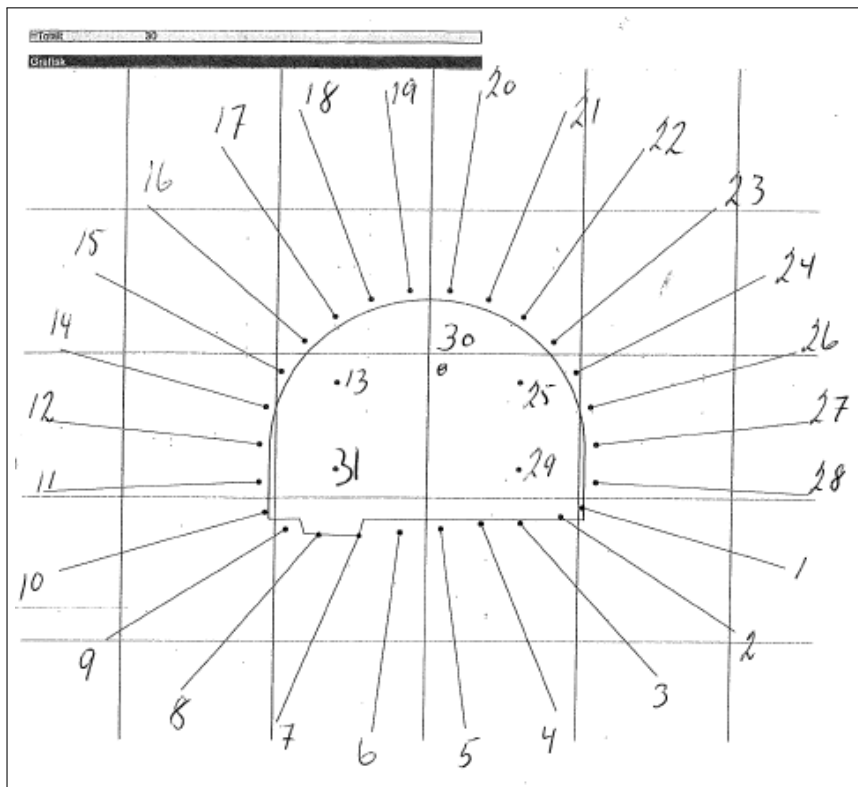


Figure 6.6: Example taken from a grouting report, showing hole numbering overview.

raw data in the log-files, process them accordingly, which would then allow the data to be used readily in the analysis. Full Python source code is available in Appendix B.

The grouting variables extracted from the log-files were: *total volume*, *end pressure*, *mean momentary flow* and *grouting time*. An overview on how each value was gathered is presented in table 6.2. Including these main four variables, general descriptive information, such as: grouting recipe, hole number, worksite, chainage, and date were also gathered. The output from the script was then compared with the grouting reports to verify that the data was processed and retrieved correctly by the Python script, including that the log-files were complete and not lacking any information. The finished processed grouting data could then be inserted into the main database (see appendix A).

```

Worksite;LONGVA
Section;23615
HoleNo;1
HoleLen;24.0
Stage;1
Recipe;1
Injection;1
Date;2020:01:23
Time;Pressure;Mom.Flow;Volume
HH:MM:SS;Bar;Liters/minute;Liters
10:35:56; 0.2; 0.0; 0.0
10:36:06; 0.2; 0.0; 0.0
. . . .
. . . .
. . . .
12:04:25; 59.7; 12.5; 951.4
12:04:34; 58.8; 13.3; 953.1
Checksum;1615

```

Figure 6.7: Snippet from an output log-file from the grouting rig.

6.2.3 Detection of jacking events using the PF Index

Among the different methods for detecting HJ-events described in section 3.4, it was decided to use the PF index developed by Strømsvik (2019) to locate possible HJ-event in the grouting data. The PF index was chosen as the preferred option for analyzing jacking events, because it is developed and optimized according to Norwegian tunneling conditions and grouting pressures. A prerequisite for using the PF index to detect HJ events, is a sampling frequency of one sample each 10 seconds (recall from section 3.4.1). This assumptions was validated for all grouting logs gathered from the Fv.659 project.

Similar to the methods of gathering grouting data from the log files, another Python script was written to calculate PF index for all holes. This script took the grout logs as input (.csv-files), did all the required filtering and processing of the data as described in section 3.4.1, and

outputted the graphs for each borehole which then could be visually interpreted. It was decided not to implement the full PF index algorithm for this study, but rather rely on visual interpretations of graphs consisting the flow, filtered pressure, and PF index. Since chainage 6045 did not include flow data, it was excluded in all analyses involving HJ cases. Full Python source code for calculating the PF index is available in appendix B.

Interpretation of the graphs were done using the tools for visual interpretation discussed in section 3.4.1. Figure 6.8 shows an example of a grouted hole from the Austnes worksite, depicting several characteristics of a grouting graph. Most notably, the onset of a potential jacking event can be seen at point A, this is due to the large momentary increase in flow while the pressure remains relatively constant, which is also reflected by a clear response in the PF index at the same point. The graph shows two periods of a temporary pause in the grouting procedure, this is normally done during grouting to allow the hole to "rest". This is often done after a potential jacking event has been observed, or to better facilitate that the target pressure is achieved in a controllable manner (Strømsvik and Grøv, 2017). Note also the large responses in the PF index at each point the grouting is resumed, this is because of the large momentary flow relative to the pressure happening at the start of grouting, and is not related to jacking events. The last period can be seen as stable pressure buildup while the flow remains constant, which also produces a stable response in the PF index which is as expected in this scenario. End pressure is achieved for this hole at the end.

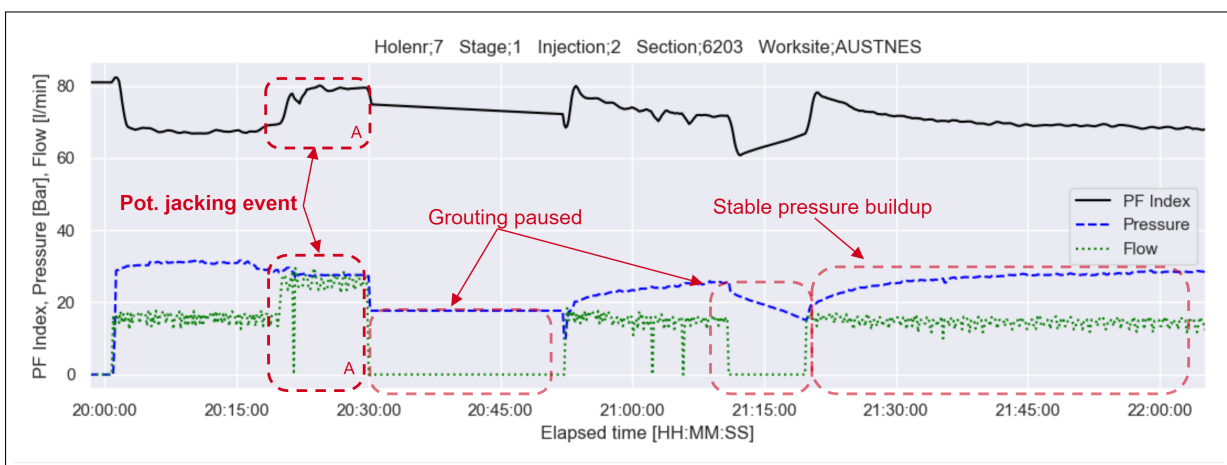


Figure 6.8: Interpretation example of grouting graphs. Boxes annotated 'A' show the onset position of possible HJ event.

6.3 Analysis of MWD and grouting data

Following is a summary of all data used further in the data analysis, along with information on how each data parameter is gathered (see table 6.2). Each borehole investigated was represented by *one value* for each variable, meaning one reading per borehole for each of the MWD DPI and grouting variables. Including this, some hypothetical assumptions on the relationships between variables are raised prior to conducting the analysis (section 6.3.1).

The full dataset consisted of 10 variables with 368 observation per variable (one per borehole), data was taken from 13 different chainages and two different worksite. A full overview of the used data is included in appendix A.

6.3.1 Hypothetical assumptions on MWD and grouting relationships

Some *hypothetical assumptions* are made on the presumed relationship between the variables, this is done in order to have a basis for summarizing and discussing the results. These assumptions are based on both experiences made from the litterateur review and logical reasoning. These assumptions will be discussed later in light of the research results (see section 8.6).

The assumptions are as follows:

1. It is expected that the MWD DPI parameters (FI, HI, and WI), are able to produce adequate responses according to the actual rock mass conditions.
2. Relatively high correlations between some of the different MWD DPI parameters are expected, especially FI and HI, seeing as these are dependent on partly the same input parameters. A correlation between the WI and FI is expected, since water disturbance is considered to be mainly bound to the fracture characteristics of the rock mass.
3. Considering the grouting variables, significant correlation between total volume and grouting time is expected, considering larger grout takes requires more time. Correlation between volume, time and mean flow is also expected.
4. Correlation is expected *between* MWD DPI's and grouting variables. Particularly between HI and total volume, time, and flow. It is presumed that higher overall fracturing of the rock mass (high FI values), will correspond to a systematic increase in grout con-

sumption, grouting time and mean flow rate.

5. It is expected that HJ cases will cause an increase in both time and grout consumption.

MWD DPI data	
<i>How gathered</i>	<i>Variable</i>
Mean of all non-zero samplings across the total borehole length.	HI mean FI mean WI mean
Calculated max value of all sample points across the total borehole length.	HI max FI max WI max
Grouting data	
<i>How gathered</i>	<i>Variable</i>
Accumulated volume, equal to last entry in 'volume' column of grouting logs.	Total volume [l]
Max value of 10 last entries from the 'pressure' column of the grouting logs.	End pressure [bar]
Subtracting stop data and start date for each hole, then converting to minutes.	Pumptime [min]
Mean of all non-zero values in the mom. flow column of the grouting logs.	Mean flow [l/min]
By visual interpretation of PF index, flow and pressure, see section 6.2.3.	HJ detected
Descriptive Data	
<i>How gathered</i>	<i>Variable</i>
Tunnel worksite (Austnes or Longva).	Worksite
Relevant chainage number of the grout curtain.	Chainage number
Hole number taken from the grouting reports (matched with drill report).	Hole number
Hole depth taken from the drilling logs (not used in analyses)	Hole depth

Table 6.2: Summary of all relevant MWD DPI- and grouting variables involved in the data analysis, including how they were gathered.

6.4 Limitations and challenges of the data gathering

The most important prerequisite for the data analysis was the availability of both MWD and grouting data for each borehole. Where information was lacking from a borehole on either MWD- or grouting-data, the same borehole had to be excluded from the analysis. Due to this fact, several had to be excluded altogether. MWD data were abundantly available, and the amount of data gathered was mainly limited by the amount of grouting log-files available. A problematic aspect regarding the grouting data, was that the log-files from the grouting rigs often were sometimes deleted altogether by the rig operators. This had a significant impact in regards to how much data was made available for analysis purposes.

Another significant challenge regarding the data gathering, was combining the two datasets (MWD and grouting) for each borehole. This is because each borehole did not have a unique standard id-number or any other feature in which they can be identified by in both datasets, this means that the hole-number indicated in the grouting logs not necessarily coincides with that of the drill reports. This complicates the process of combining the two datasets (MWD and grouting) and makes it a very time-consuming process. It also leaves room for a significant source of error because the hole distribution of the drilling logs had to be visually compared to the grouting logs to match the data. The amount and of data that could be gathered were also limited to a great extent by this issue.

Results

7.1 Detection of weakness-zones using MWD DPI's

To investigate the ability of the MWD DPI parameters to respond to actual geological features, it was of interest to see if the various MWD DPI's *fracturing (FI)*, *hardness (HI)* and, *water (WI)* parameters were able to produce notable responses, matching the interpreted weakness-zones as indicated by the preliminary geophysical mapping (figure 6.3). To do this, a basic visual comparison was done of the mapped MWD DPI's, as provided by BTO, with the interpreted weakness-zones (figure 6.3). Due to the limited advance of the tunnels at the time of this research, only *one* of the four weakness-zone as indicated by the geophysical mappings had been potentially intercepted by one of the advancing tunnel, namely the *Fjørtofta North* subsea tunnel.

7.1.1 Fjørtofta North, subsea tunnel

Figure 7.1, shows the advancing tunnel face shown in pink at the Fjørtofta tunnel. The area marked in green, indicates approximately where the interpreted weakness-zone is expected to intercept with the tunneling advance, i.e. at somewhere between chainage 32000 and 32400. Looking at a profile section of the same tunnel in figure 7.2, an apparent weakness-zone is present between approx. chainages 32100 and 32300. This is indicated by the distinct response in the DPI parameter HI, where red and darker colors indicate lower interpreted rock mass hardness.

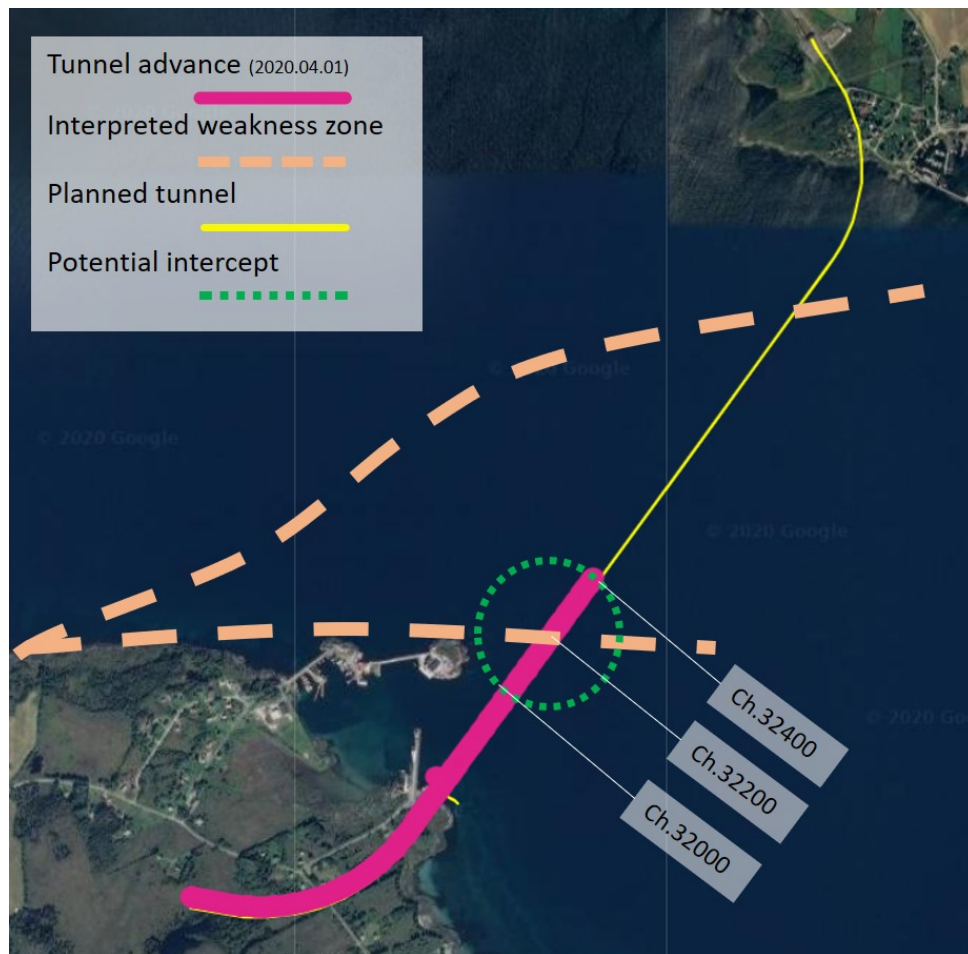


Figure 7.1: Map showing tunnel advance as of 1 April 2020, including interpreted weakness-zones as seen in figure 6.3. Potential intercept is estimated between ch. 32000 and 32400. Figure modified from the BTO as-built project module, showing real time tunnel advance.

A closer look at this section can be seen in figure 7.3, here all interpreted parameters are included as color gradients on fold-out tunnel geometries, all sections is taken from ch. 32100 to 32300. The response in the HI (top figure in figure 7.3) is particularly evident in this section, with a large portion of this section being classified as relatively soft rock mass. The same pattern can also be seen by the FI response, although not quite as apparent, there is a relatively higher density of yellow to red colors in this section, indicating a zone with higher fracture density. The WI parameter shows no extensive water is present at the weakness zone, however, areas indicating water disturbance seem to follow some narrow zones the same manner as the FI on the right and left side of the image (white markings in the bottom image in figure 7.1). This could indicate that "larger" water-bearing structures in the rock mass, are captured to some extent by the WI- and FI parameter.

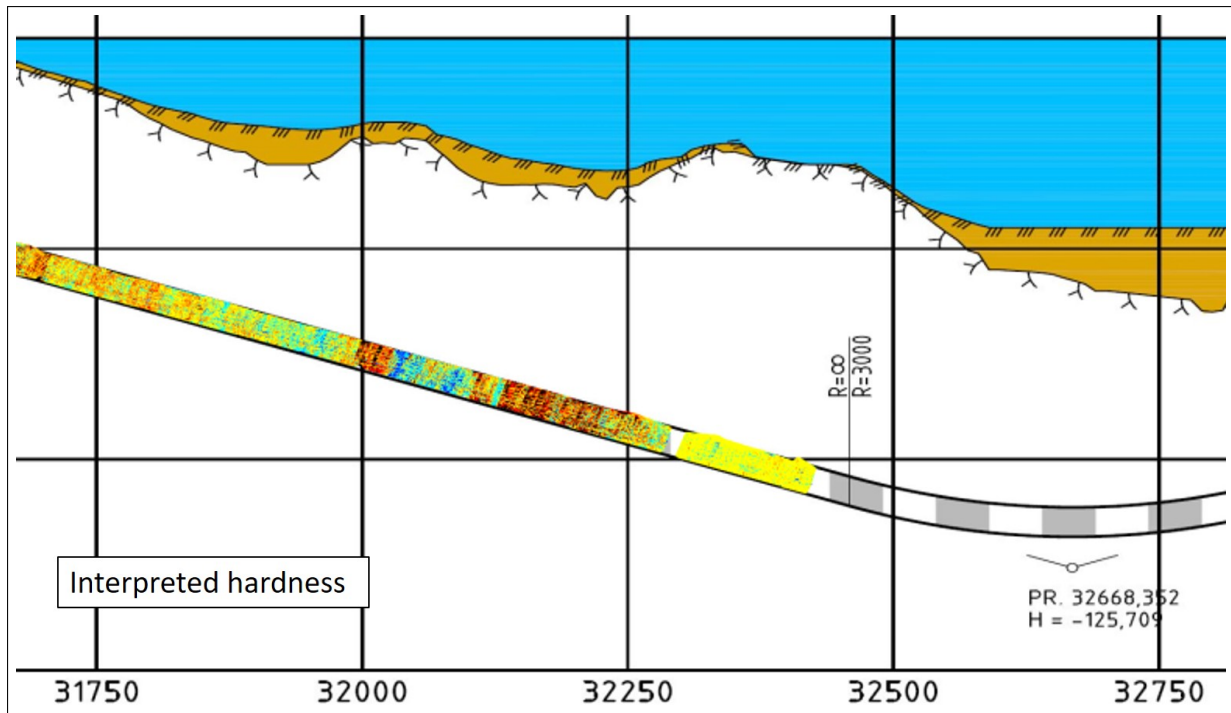


Figure 7.2: Profile view of Fjørtofta Nord, showing the interpreted weakness-zone intercepted by the tunnel as indicated by response in HI, marked by the red box. Figure modified from the BTO as-built module.

Judging from a visual interpretation of the MWD maps, it appears that the MWD DPI's are able to detect the interpreted weakness-zone, as indicated by the preliminary mapping. Most notably by the HI parameter, as can be clearly seen in both figure 7.2 and 7.3. There also seems to be some connection between where the WI shows indications of a water-bearing structure, and where the FI responds to a fractured structure.

Many systematic vertical and horizontal linear features can be seen from both the FI and HI DPI's. The vertical features could be an effect produced by the onset of drilling for each blasting and/or grouting rounds, while the horizontal features likely show the contour of each borehole. Keeping in mind that there is some extrapolation used in *between* each borehole, to allow for colorization of the whole tunnel contour.

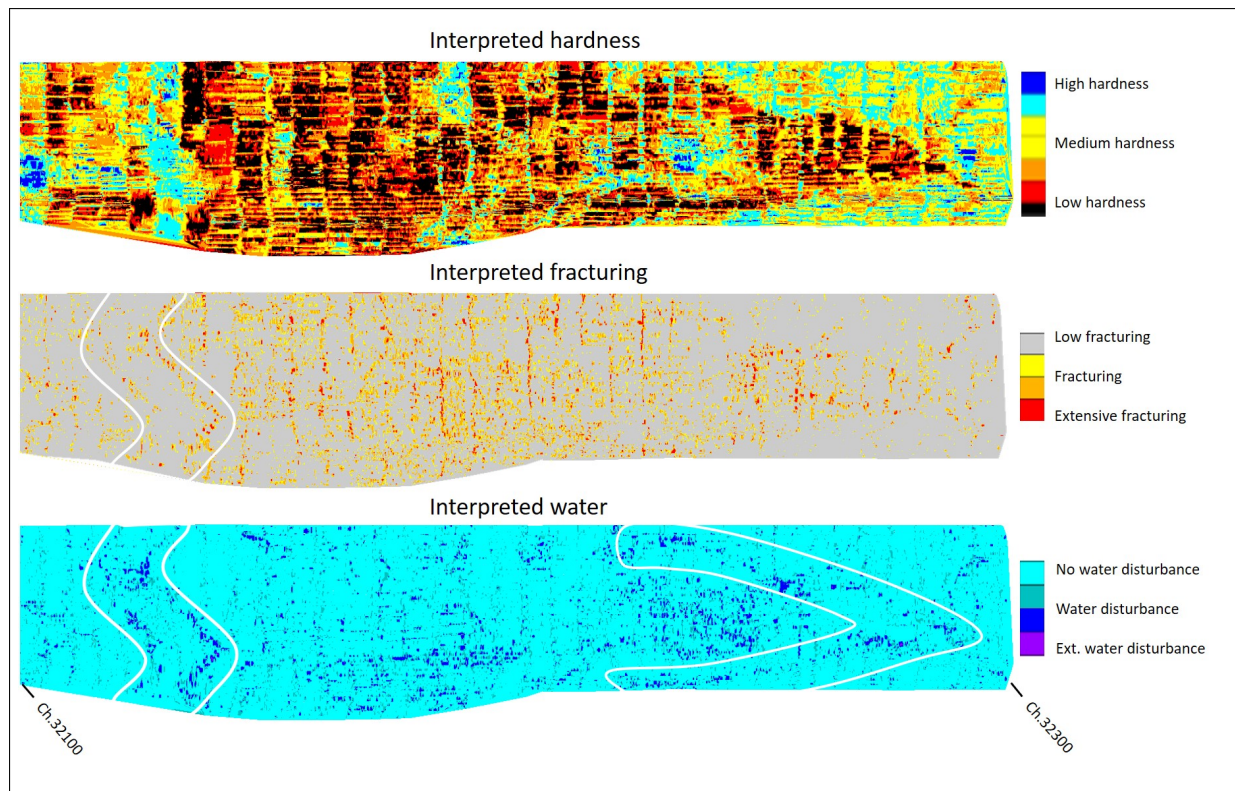


Figure 7.3: Images of fold-out tunnel geometries with colorized textures, comprising all MWD DPI parameters, sections taken between ch. 32100 and 32300 (200m section). Possible water bearing structures are indicated in white markings. All MWD DPI images modified from BTO as-built module.

7.2 Detection of hydraulic jacking

As previously described in section 6.2.3, detection of jacking events was done using the PF index. Following are the results of the visual interpretation of the PF index graphs for some boreholes exhibiting one or more indication of hydraulic jacking events. Evaluation of jacking was done for all grouting rounds, but interpretation is only presented from three different chainages in the following section (see figures 7.4, 7.5 and 7.6). A full overview of detected HJ cases can be seen in the full dataset (appendix A). Two of the presented chainages, are taken from the *Longva* worksite, and one from the *Austnes* worksite.

For data analysis purposes, holes with multiple indications detected are not explicitly presented in the full dataset. HJ events are indicated simply by binary values - *True* or *False*, i.e. potential HJ detected or no HJ detected. A summary of cases for each chainage is presented at the end of this section in table 7.4.

7.2.1 Chainage 5892, Austnes worksite

Figure 7.4a, shows a relatively short grouting round of about 30 minutes, with one potential HJ event as indicated by the red box. After a period of stable and constant pressure and flow conditions, the pressure drops while the flow remains constant. This also results in a clear response in the PF index. This hole achieved the target end-pressure at approx. 40 bars.

The next graph shown in figure 7.4b, shows indications of two potential HJ events in the same grouting round. In *event A*, a clear increase in flow is followed by a slight pressure increase and is therefore not characterized as an HJ event. *Event B* is seen as a momentary drop in pressure while the flow remains constant over a longer period, this is identified as a potential HJ event. Target end-pressure was achieved at approx. 90 bars, following a longer stoppage at the end of the second grouting round (not shown here).

The last graph, shown in figure 7.4c, shows on potential HJ event marked as *event A*, after a long period of relatively stable pressure and flow conditions. Just before the onset of *event A*, there is an event that gives a very clear response in the PF index. This event is interpreted as an artificial disturbance in the logging over a few samples, where the flow alternately jumps from 0 to very high levels during a smaller time period, and is not considered as a potential HJ event. This type of logging disturbance is a quite common false indicator that can be revealed by considering the sampling intervals in the raw log files. In this hole successful end-pressure at approx. 60 bars was achieved at the end of this grouting round.

Number of HJ events	0	1	2+
Number of holes	19	6	1
Percentage of holes	73%	23%	4%

Table 7.1: Overview of potential HJ events detected at ch. 5892.

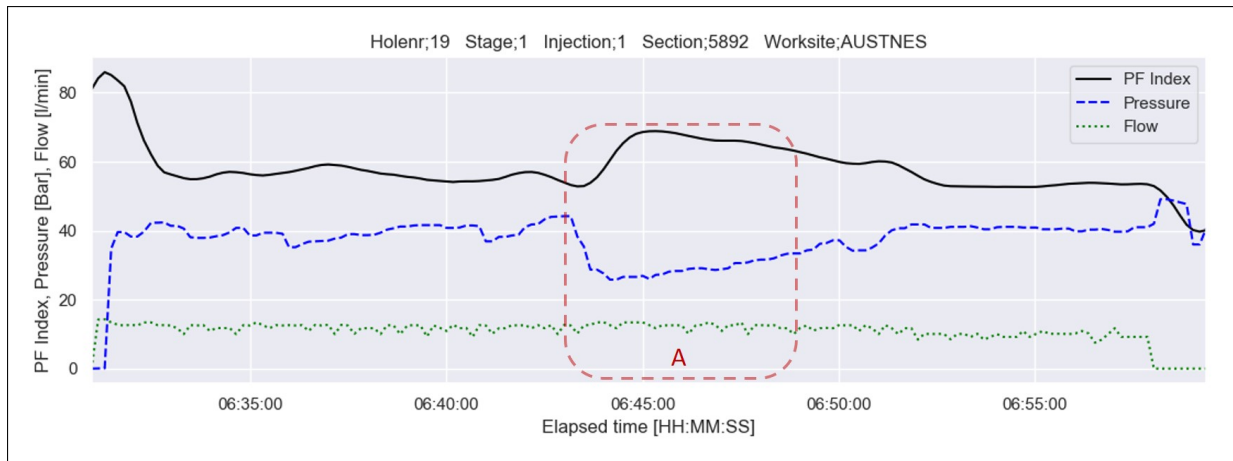


Figure 7.4: Grout pressure, flow and calculated PF index with time for three boreholes from the Austnes Worksite, ch. 5892. These are some examples where indications of HJ events were found, marked by red boxes.

7.2.2 Chainage 6203, Austnes worksite

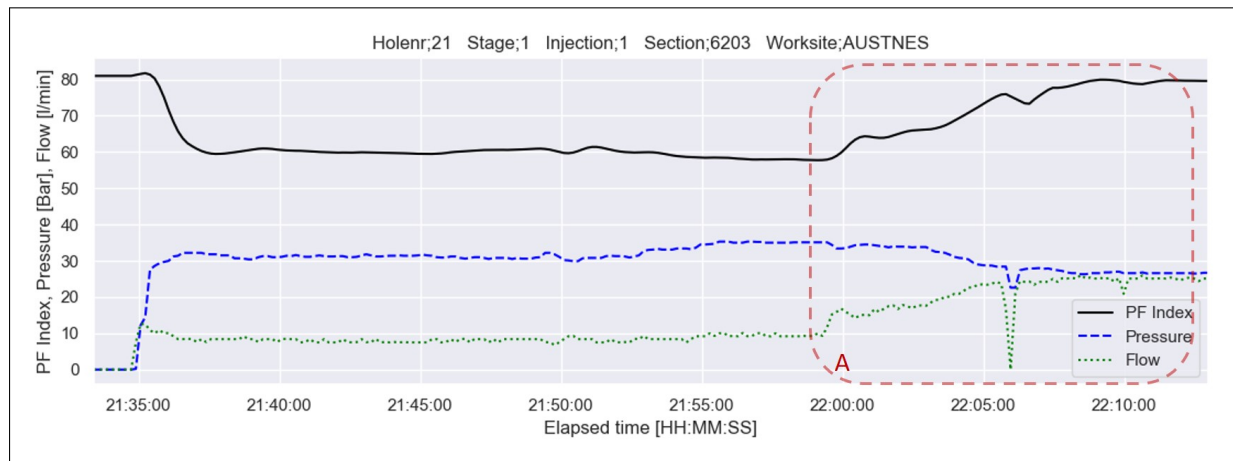
In figure 7.5a, the graph depicts a very stable grout progression with very small fluctuations in both pressure and flow, and this is also reflected by the stability in PF index response, from the start of grouting (21:35), until the onset of the potential HJ event marked as *event A* (22:00). This area shows both decrease in pressure and an increase in flow, which is a strong indicator of a possible HJ event. The PF index shows a clear response to this and normalizes around the end. At this particular hole, the grouting was stopped and resumed the next day with satisfactory end-pressure achieved.

Figure 7.5b, shows the second injection round of a hole and the possible onset of an HJ event, annotated *Event A*. This HJ event is indicated by a clear drop in pressure while the flow remains constant, which also gives a corresponding response in the PF index. The event occurs after a small period of pressure increase and is followed by a short paused period. After this, relatively stable conditions are achieved with clear pressure increase with some fluctuations towards the end where end-pressure is achieved successfully.

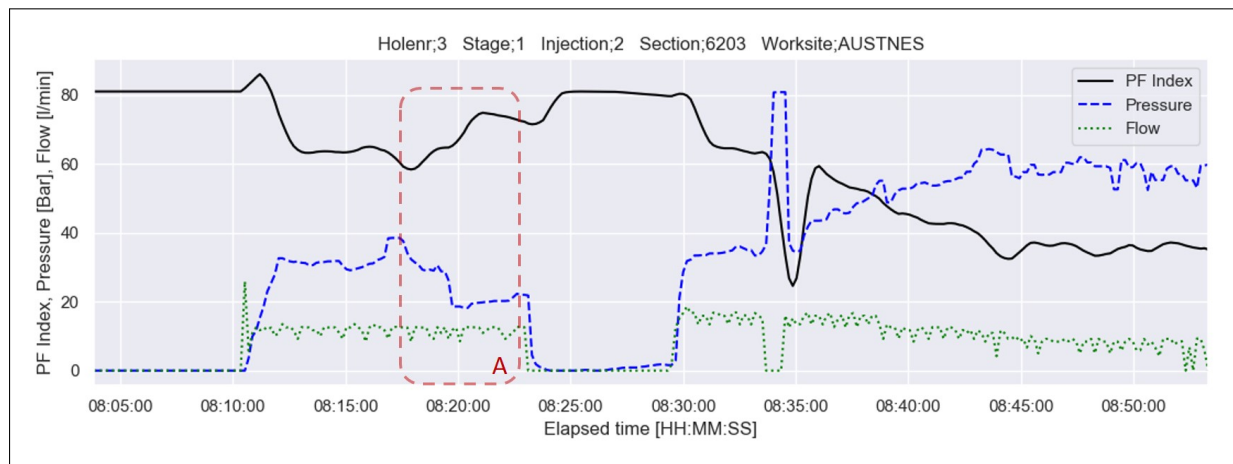
Figure 7.5c, shows three plausible HJ events, both *events A* and *B* are relatively short-lived momentary pressure drops with constant pressure. However, because these events are short-lived with a fast regain of pressure, they are likely not related to HJ events, but rather due to other effects. *Event C* shows a pressure decrease over a longer period with constant flow, and is more likely to represent an HJ event.

Number of HJ events	0	1	2+
Number of holes	20	7	1
Percentage of holes	71%	25%	4%

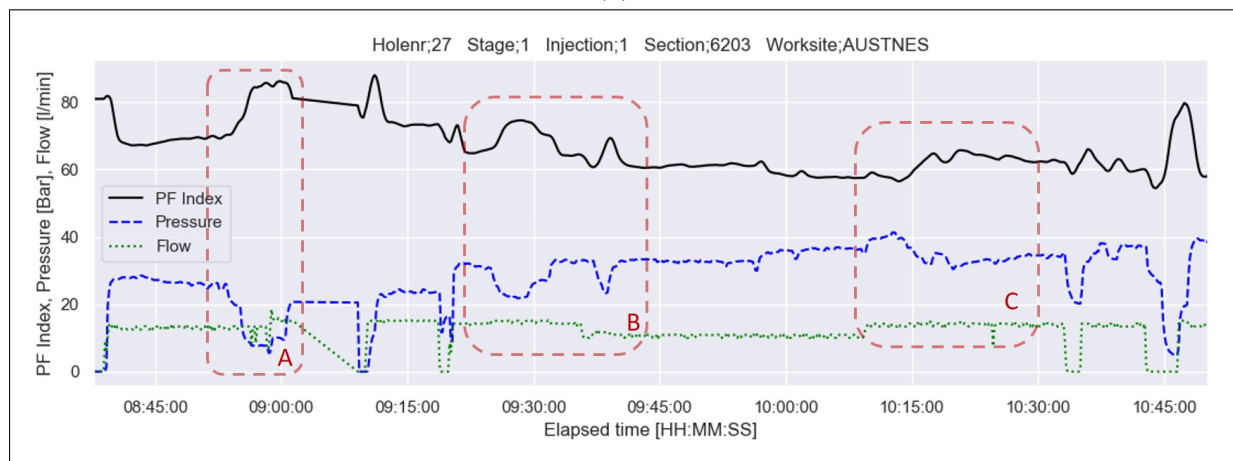
Table 7.2: Overview of potential HJ events detected at ch. 6203.



(a)



(b)



(c)

Figure 7.5: Grout pressure, flow, and calculated PF index with time for three boreholes from the Austnes Worksite, ch. 6203. These are some examples where indications of HJ events were found, marked by red boxes.

7.2.3 Chainage 23615, Longva worksite

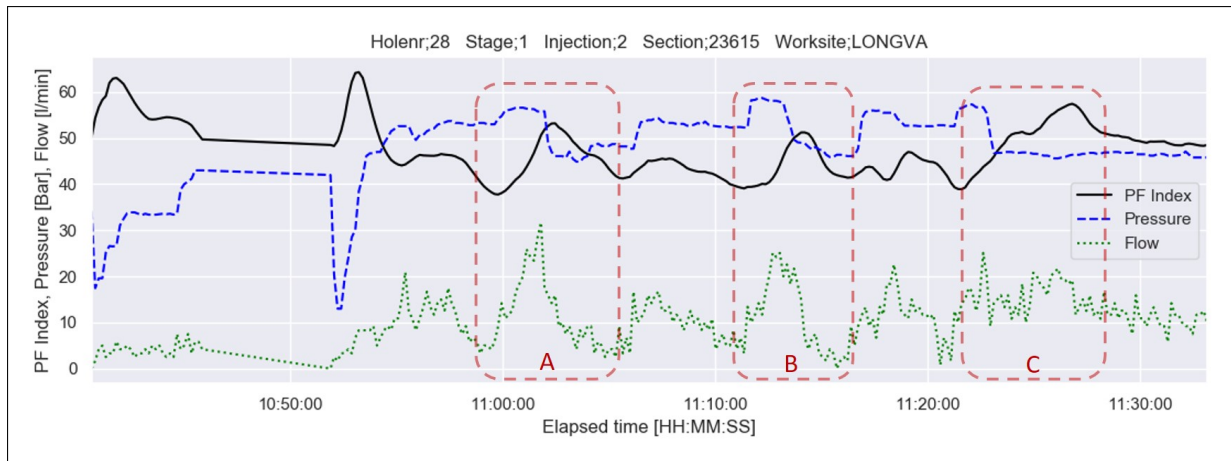
Figure 7.6a, shows multiple plausible jacking events, shown here as *events A, B, and C*. All these events share a very steep momentary flow increase, which also signified with clear responses in PF index. However, this particular grouting exhibits high fluctuations in the flow progression, making the interpretation of actual behavior difficult. Regardless, it is reasonable to believe at least one or two of these indicators are potential HJ events. The grouting was paused at the end of this graph and resumed 30 minutes later, where stable pressure increase and end-pressure was achieved successfully.

The next graph, shown in figure 7.6b, demonstrates a potential HJ event at *event A*. Here, pressure decreases while flow remains constant and even has a slight increase, until the grouting is temporarily stopped at the end of *event A*. The PF index resonates with this event, shown by a steady increase starting from the onset of the event. This hole also had a second possible HJ event at a later grout stage not shown here. end-pressure was not achieved for this hole and was stopped by volume restrictions after multiple rounds. According to the grouting report, a special grouting component *-mauring* was used, suggesting difficult grouting conditions at this particular hole.

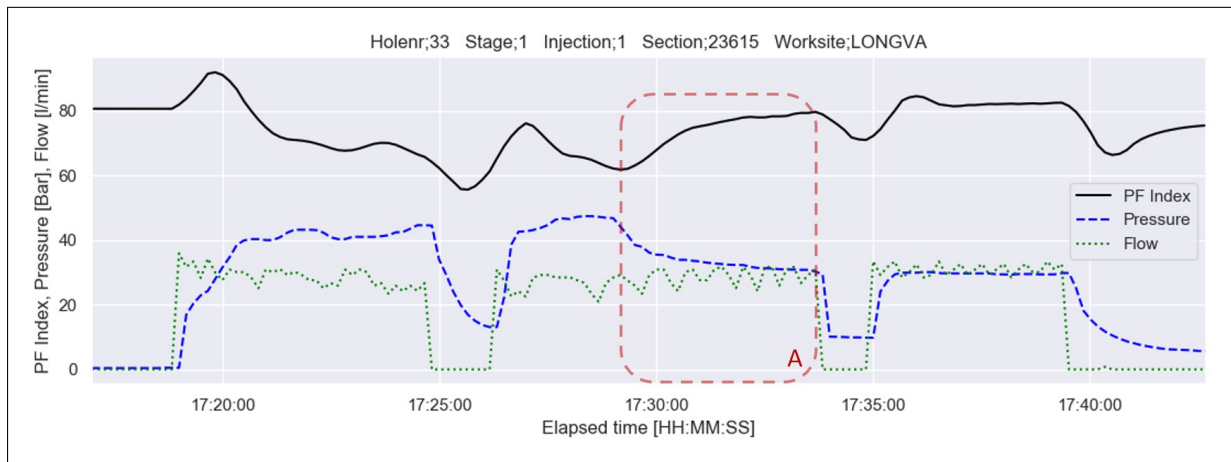
The last graph shown in figure 7.6b, shows a more difficult interpretive case of a potential HJ event. After a period of stable pressure increase accompanied with by a slight decrease in flow, the pressure drops momentarily while flow remains stable over a longer period. Both constant pressure and flow after a period of pressure increase, can also be considered a potential HJ event (see section 3.4.1). Despite this, a stable pressure increase was achieved without a temporary stoppage in grouting, beginning from the end of *event A*. Successful end-pressure of approximately 60 bar was achieved at the end of grouting for this hole.

Number of HJ events	0	1	2+
Number of holes	30	7	4
Percentage of holes	73%	17%	10%

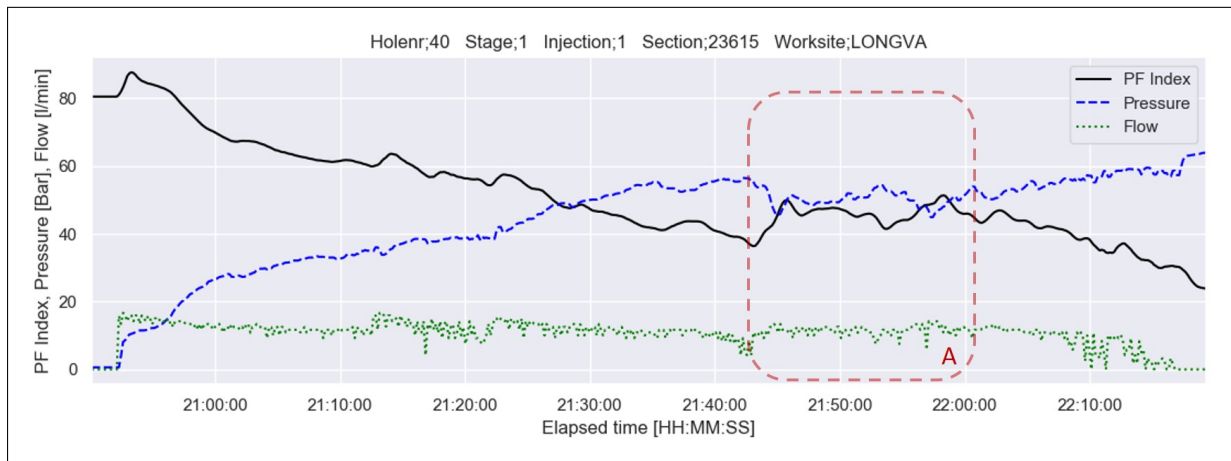
Table 7.3: Overview of potential HJ events detected at ch. 23615.



(a)



(b)



(c)

Figure 7.6: Grout pressure, flow and calculated PF index with time for three boreholes from the Longva Worksite, ch. 23615. These are some examples where indications of HJ events were found, marked by red boxes.

Worksite	Chainage	HJ events detected	% of total holes
Austnes	5506	5	25%
	5523	7	25%
	5856	3	15%
	5892	7	27%
	6203	8	27%
Longva	23498	6	24%
	23528	6	27%
	23545	6	21%
	23577	5	16%
	23615	11	28%
	23654	7	17%
	23707	6	20%

Table 7.4: Summary of potential HJ events detected for all analyzed chainages.

7.3 Principal component analysis

In this thesis, PCA was used to gain more insight and overview of the dataset. Both by visually identifying clustering and tendencies in the dataset, and to determine how these variables differ or conform with each other.

7.3.1 PCA on MWD DPI data

The mean value of the MWD DPI parameters: hardness, fracturing, and water were used as initial variables in this PCA analysis. The dataset used consisted of 3 columns x 369 rows of data, comprising MWD measurements for 369 boreholes across 13 different chainages. The PCA was done to compress and visualize the dataset, and to evaluate if the different chainages and worksites were fundamentally different or similar in terms of the MWD DPI parameters.

Assumptions

Assumptions were investigated in compliance with that presented in section 5.3.1. The correlation matrix \mathbf{R} , of the three standardized MWD variables is shown in matrix 7.1. The correlation matrix shows some weak linear dependency is present between the three variables. The determinant of \mathbf{R} is also positive, validating the first assumption.

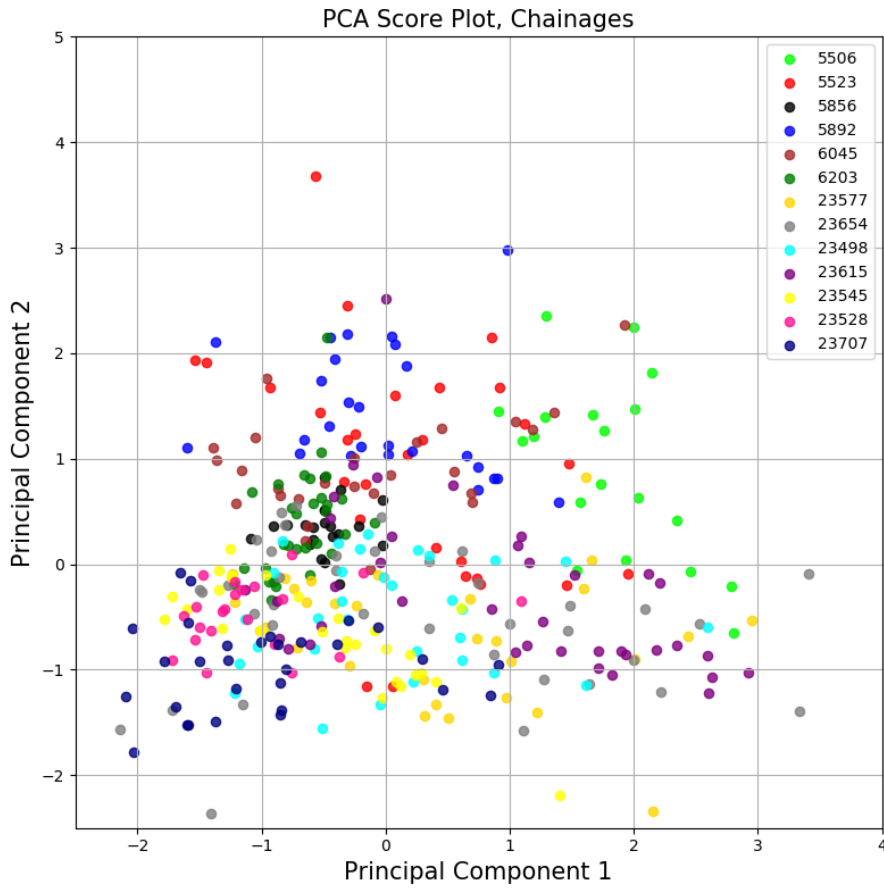
$$\mathbf{R} = \begin{bmatrix} 1 & 0.08522 & 0.24713 \\ 0.08522 & 1 & 0.26394 \\ 0.24713 & 0.26394 & 1 \end{bmatrix}, \quad Det(\mathbf{R}) = 0.87311 \quad (7.1)$$

The KMO test for sample adequacy considering these DPI variables, concludes in a KMO value of 0.538, which barely validates the assumption of sampling adequacy. Bartlett's test for sphericity indicates a statistically significant test result, with a $p - value \ll 0$. Outliers was filtered using the SVM-method, as described in section 5.3.1, tuned with parameters $gamma = 0.01$ and $nu = 0.05$, which seems to be appropriate for outlier detection of the PCA score results. In conclusion, all assumptions are validated, keeping in mind a low KMO test result.

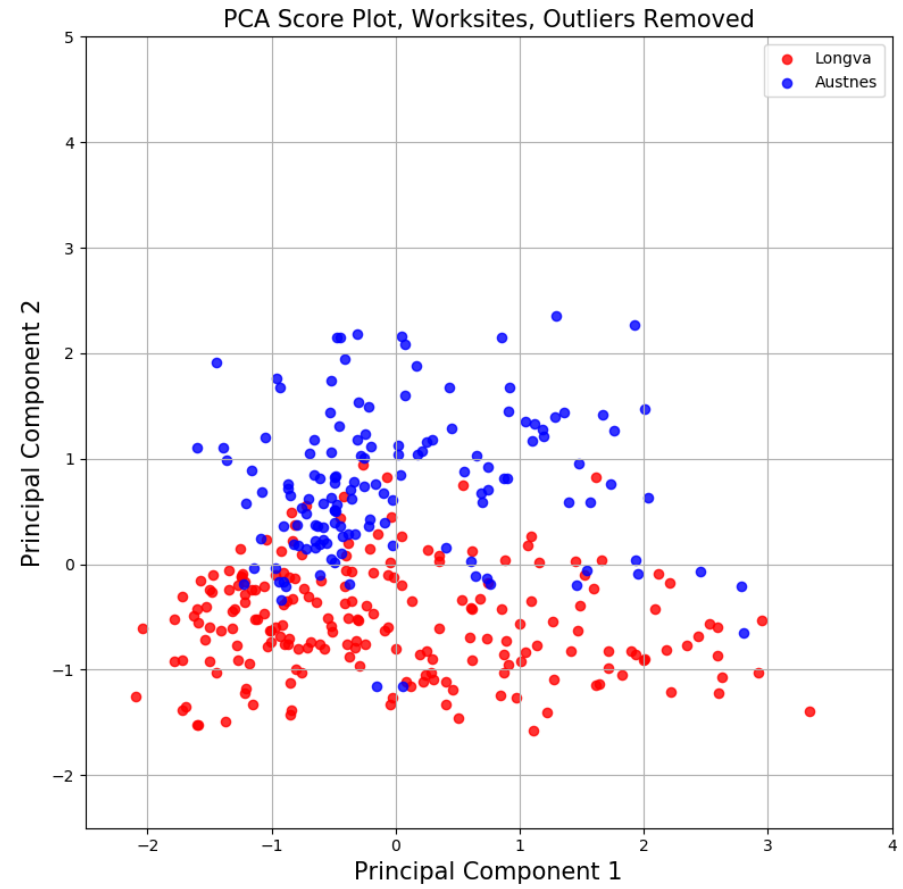
Analysis

PCA for the MWD DPI data was done reducing three variables to two principal components. A test for explained variance (scree test) gives a result of 0.469 for principal component 1 (PC1), and 0.305 for principal component 2 (PC2). This means that by reducing the three variables to two principal components, the PCA model is still able to account for about 77% of the total information from the three initial variables. This also implies, that about 23% of the total variance is left out in this analysis.

Figure 7.7, shows the score plots from the PCA analysis of both the individual chainages (7.7a), and the chainages grouped together by worksites (7.7b). Looking at the PCA score plot of the chainages (7.7a), it becomes apparent that there is generally a large variance of MWD measurements within many of the individual chainages, e.g. ch. 5523 and 23654. While other chainages exhibit more distinct and tighter clustering, e.g. ch. 6203, 23528, and 23707, indicating more constant measurements over their respective chainage. Another useful observation from this plot is the distinct differences between many of the chainages (e.g. ch. 5506 and 23707), suggesting that geological differences between chainages are captured by the MWD measurements. This observation becomes even more evident looking a figure 7.7b. In this score plot, the different chainages are grouped together by their respective worksites, and outliers removed by using the SVM-method. The score plot shows distinct clustering of both Austnes and Longva worksites (occupying different spaces of the plot), suggesting that these two worksites are distinguishable in terms of their MWD DPI measurements, which again could reflect their differences in geological domains.



(a)



(b)

Figure 7.7: MWD PCA score plots grouped by chainages (7.7a), and grouped by worksites Longva and Austnes (7.7b), where outlier filtering is applied.

To get more insight into what these principal components represent in terms of influence from the input variables (HI, FI and WI), the loading scores of the PCA analysis can be interpreted (as discussed in section 5.3). The individual loadings are presented in table 7.5, it shows that the water parameter (WI mean) has the strongest influence on PC1, while the hardness (HI mean) and fracturing (FI mean) parameter represent somewhat equal influences. Considering PC2, its shown that the hardness parameter has the most influence on PC2 while the water parameter has a negligible influence on PC2. This implies that the vertical axis (PC2), will be more indicative of differences in the hardness and fracturing. This also means that the clustering between work-sites Longva and Austnes, as seen in figure 7.7b, are mainly due to differences in fracturing and hardness parameters from the MWD variables. This is because the separation of these two groups occurs mainly along the PC2 axis, and not PC1 where more information on the water parameter is mostly explained.

The individual loadings are also visualized in figure 7.8. Here, the loading vectors from table 7.5, are plotted as scaled vectors showed by green arrows over the score plot. The same observation as previously discussed, can be visualized here. The water parameter does not influence greatly on PC2, implying that the variation seen along PC2 is mostly influenced by the hardness and fracturing parameter.

Principal component	HI mean	FI mean	WI mean
1	0.516947	0.539663	0.664477
2	0.732657	-0.680375	-0.017415

Table 7.5: PCA loading scores for the MWD parameters.

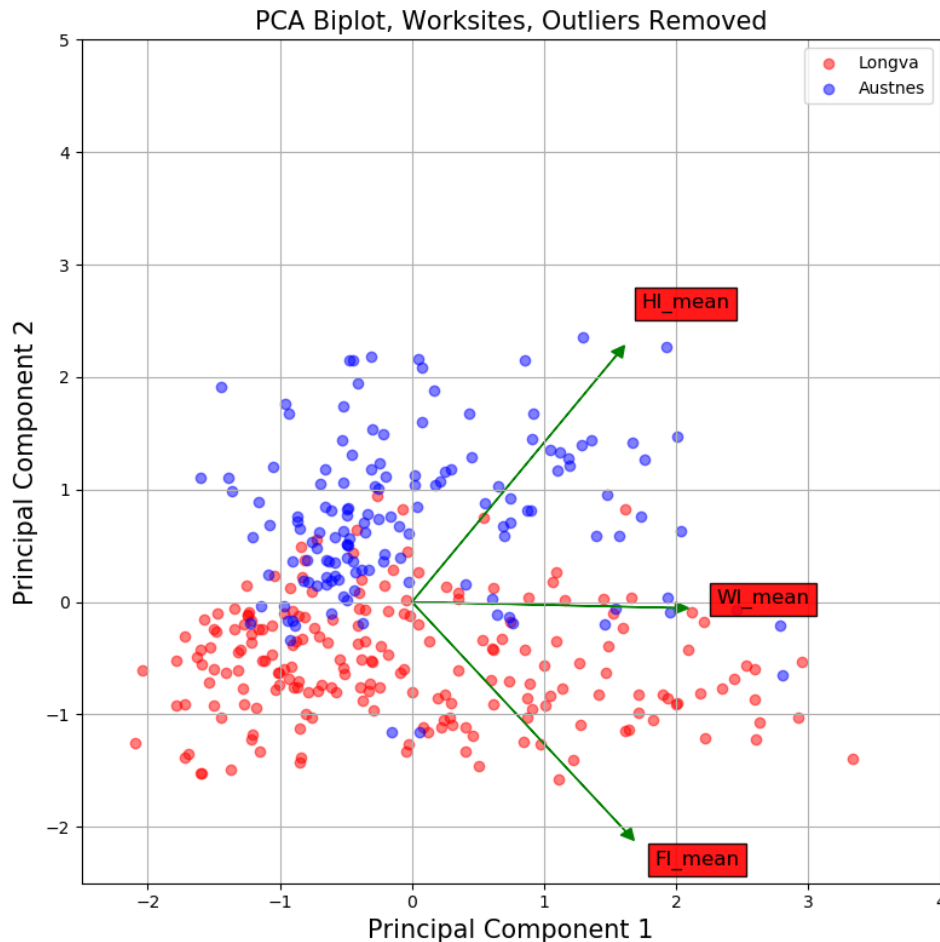


Figure 7.8: MWD DPI PCA biplot showing both scores grouped by worksite, and loading vectors for each input variable shown as green arrows.

7.3.2 PCA on grouting data

PCA was also done on the grouting variables: *total volume*, *end-pressure*, *grouting time*, and *mean flow* (in that order). The dataset used for this analysis consisted of 4 columns x 334 rows of data, comprising grouting measurements for 334 boreholes across 12 different chainages. The reason for this dataset being smaller than the MWD DPI dataset is because of missing grouting data for some chainages due to corrupted or lacking LOG-files. The PCA was done to compress and visualize the dataset, and to evaluate if the different chainages and worksites were fundamentally different or similar in terms of the grouting data.

Assumptions

Assumptions for conduction PCA were investigated in compliance with methods presented in section 5.3.1. Considering first the correlation matrix \mathbf{R} , of the four initial variables (7.2). The determinant of \mathbf{R} is positive, validating the first assumption of linearity. Note also that the determinant is much smaller for the grouting data than for the MWD data. This is because the overall correlation within the grouting variables is larger than for the MWD parameters. Looking at the correlation matrix (7.2), there is a particularly strong correlation present between the first variable (total volume) and the third variable (grouting time), which is very much as expected, considering that more grouted volume requires more time to pump.

$$\mathbf{R} = \begin{bmatrix} 1 & 0.08342 & 0.83529 & 0.41338 \\ 0.08342 & 1 & 0.10600 & -0.05221 \\ 0.83529 & 0.10600 & 1 & 0.24284 \\ 0.41338 & -0.05221 & 0.24284 & 1 \end{bmatrix}, \quad Det(\mathbf{R}) = 0.23575 \quad (7.2)$$

The KMO test for sampling adequacy resulted in a value of 0.5147, which barely validates the assumption of sampling adequacy. KMO is even less than for the MWD data, but with even fewer samples for the grouting data, this is as expected. The Bartlett test for sphericity resulted in a statistically significant test with a p -value $\ll 0.05$. Outliers was filtered using the SVM-method described in section 5.3.1, tuned with parameters $gamma = 0.01$ and $nu = 0.05$, which seems to be appropriate for outlier detection of the PCA score results. In conclusion, all assumptions are validated, again keeping in mind a low KMO test score.

Analysis

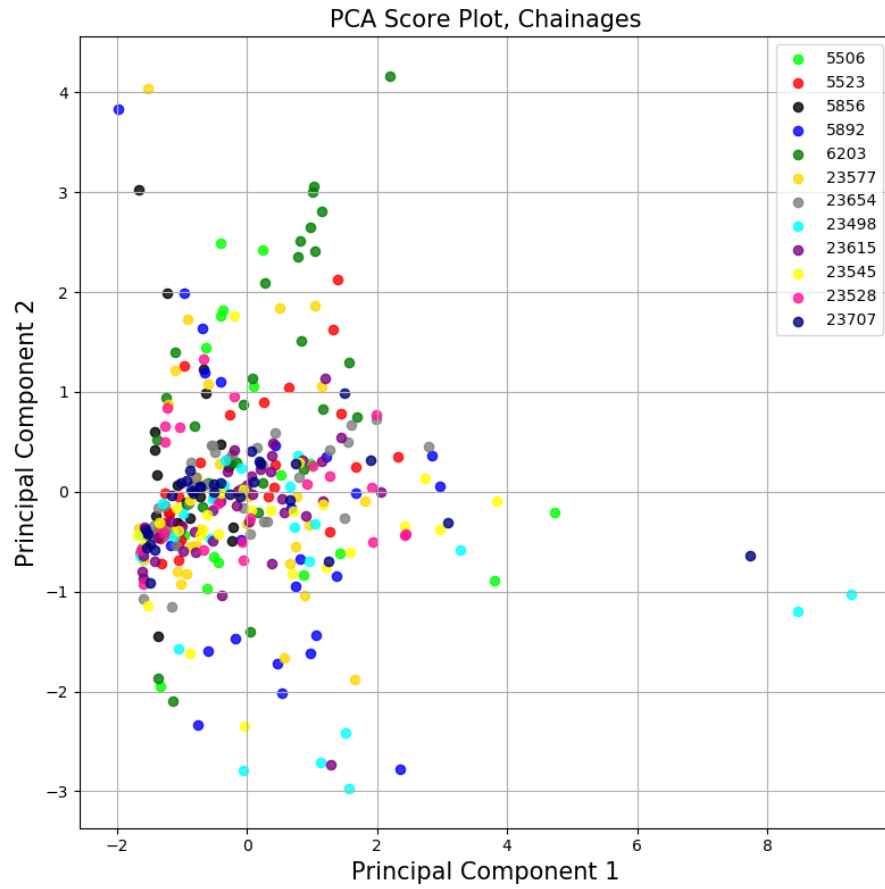
Initially, all four principal components were considered to evaluate what percentage of variance the initial variables they account for. The explained variance between the four principal components (scree test), was: 0.513 , 0.259 , 0.191 and 0.036 . Dropping the last two components (PC3 and PC4), resulted in a variance explained between PC1 and PC2 of approx. 77%, which is about the same variance explained (with even more initial variables), compared with the MWD DPI PCA. It was decided to use two principal components for the ease of plotting, visualizing, and interpretation of the PCA results.

Figure 7.9, shows score plots from the PCA analysis. It shows the PC scores of both the individual chainages (7.9a), and the different chainages grouped together by worksite (7.9b). Looking at figure 7.9a, the clustering of individual chainages is less apparent compared with that seen of the MWD data (figure 7.7a). Some very extreme outlier measurements can be seen (e.g. ch .6203, 5892, and 23498), this is due to some holes taking in very high volumes of grout which also directly affects the grouting time. The variance in PCA scores for individual chainages seems to be relatively large for all chainages, suggesting that the general variance in grouting measurements is large. Considering figure 7.9b, there is no obvious clusters differentiating the two worksites, suggesting that both the worksites are relatively similar in terms of what grouting measurements they represent. The Longva worksite seems to have a more favored orientation of samples along the PC1 axis than the Austnes worksite, but that could be due to lack of samples for the Austnes worksite.

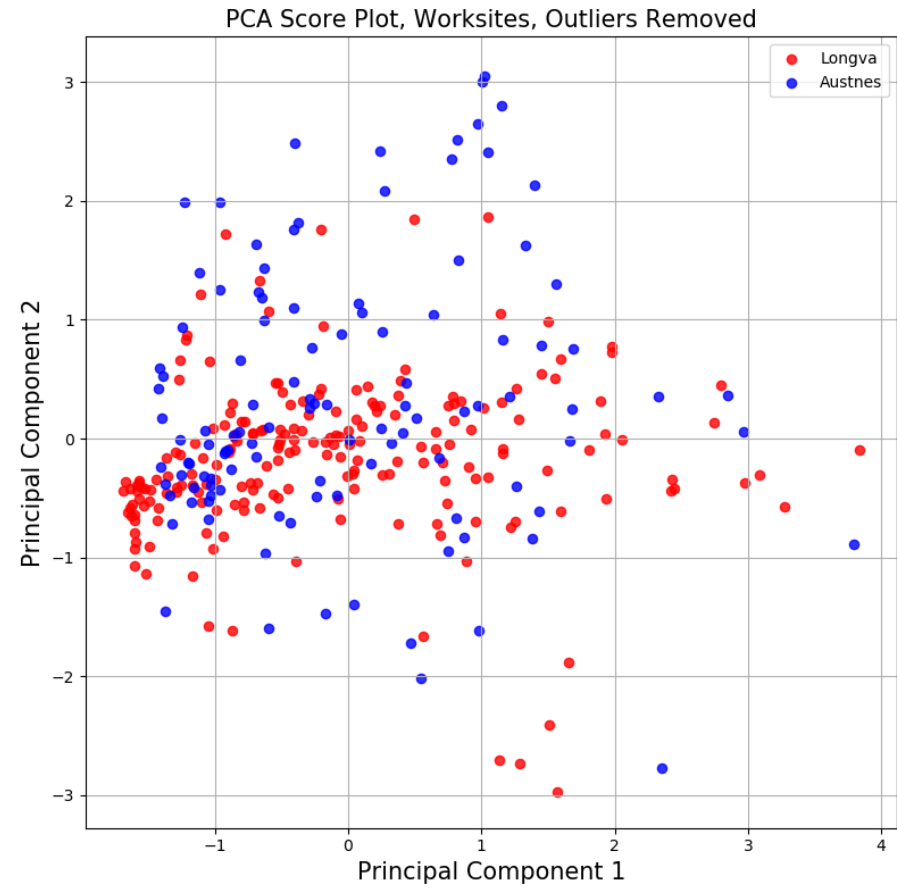
Table 7.6, shows the loading's each grout variable represents in terms of the principal components. It can be seen that both the *volume* and *time* has a large influence on PC1, which are also the two variables with the highest correlation. *Mean flow* is also relatively well represented in PC1, while information on *end-pressure* is not very well preserved in PC1. Likewise, considering PC2, very much information on *end-pressure* including a relatively large portion of the *mean flow* is preserved in this component. Looking at the loading vectors in figure 7.10, the influence of each variable on the two PC's is visualized. The orthogonality between time, volume, and end-pressure vectors, emphasize the lack of correlation between the variables. It should be noted that the interpretation of the loading vectors are rather limited in this PCA, seeing as no distinct clustering and groupings are present in the score plot.

Principal component	total volume	end-pressure	grouting time	mean flow
1	0.66186	0.09573	0.62691	0.39970
2	-0.00985	-0.90451	-0.11350	0.41096

Table 7.6: PCA loading scores for the grouting parameters.



(a)



(b)

Figure 7.9: Grouting PCA score plots grouped by chainages (7.9a), and grouped by worksites Longva and Austnes (7.9b), where outlier filtering is applied.

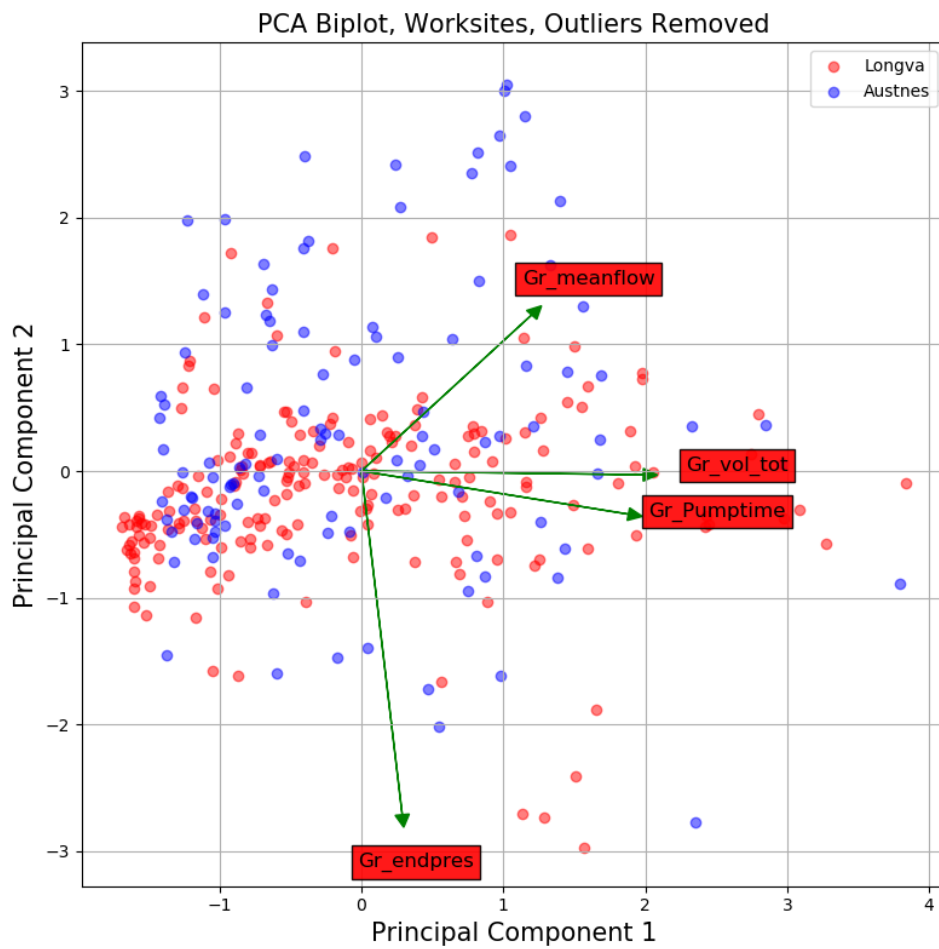


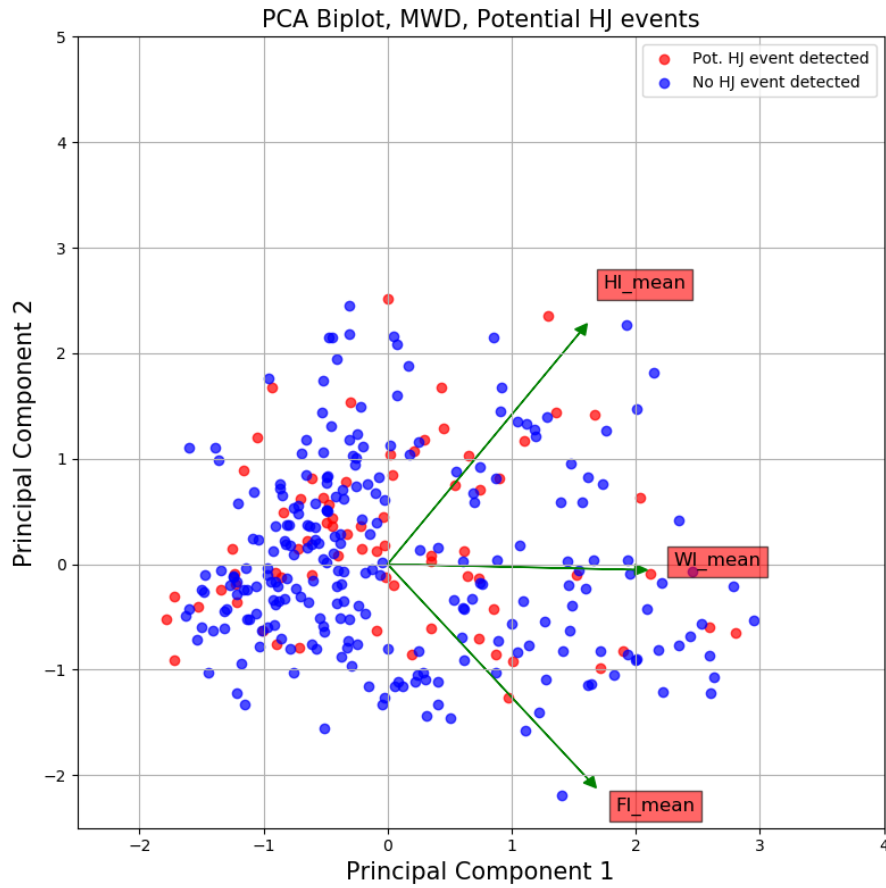
Figure 7.10: Grouting PCA biplot showing both scores grouped by worksite, and loading vectors for each input variable are shown as green arrows.

7.3.3 PCA on HJ events (grouting and MWD)

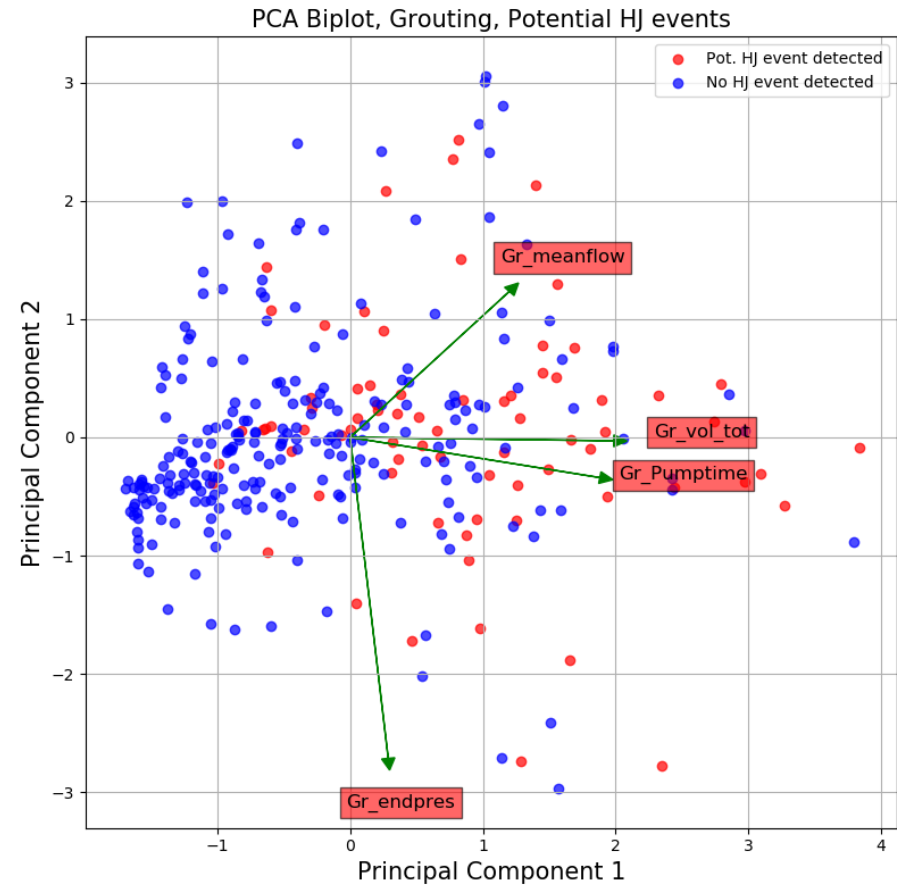
It was of interest to gain insight on the distribution of potential HJ event across both the MWD DPI- and grouting data, using the same PCA results from section 7.3.1 and 7.3.2. This was done grouping the results after potential HJ events, as previously found by using the PF index (section 7.2). Biplots are used for both cases, which enables visual interpretation of both the score orientation and evaluation of the respective loadings. Resulting plots are presented in figure 7.11.

The scattered borehole measurements of MWD DPI data, shown in figure 7.11a, shows no apparent clustering or similarities in terms of where the HJ holes orientate in the principal component space. The holes where HJ were indicated show no distinctive differences compared to the rest of the measurements. Figure 7.11b, shows a biplot over the grouting data grouped by measurements with potential HJ events. This biplot shows more distinctive tendencies in terms of where borehole with potential HJ events orientates, compared with that of the MWD biplot (figure 7.11a). There is an apparent tendency of the pot. HJ borehole to orientate further up along PC1, compared with boreholes with no HJ. Thus, suggesting that HJ events are potentially better explained by the grouting parameters *volume* and *time*.

Interestingly, there seems to be no favored orientation of the pot. HJ boreholes along the negative PC2 axis, where the information on end-pressure is mostly explained. This result points towards that the boreholes with pot. HJ events, does not tend to favor higher end-pressures. On a more general note, there seems to be a large variation and few clustering in the measurements where potential HJ events are found. But a weak tendency of HJ cases favoring *higher* volume and time consumption, can be seen.



(a)



(b)

Figure 7.11: PCA biplots of worksites indicated by holes where potential HJ events were found including remaining holes where no potential HJ events were found. The left figure is of MWD data, while the right figure is of grouting data. Outlier filtering is done using the SVM method in both cases.

7.4 MWD and grouting data comparative analysis

To investigate the *statistic relationship* between the MWD and grouting data, an initial correlation analysis was done followed by a comparative study on various machine learning algorithms (ML). The different ML models were evaluated in terms of their ability to train regression models, using the MWD DPI- and grouting data.

7.4.1 Correlation analysis

Spearman correlation coefficients were found for all numeric variables in the dataset (see table 7.7). Spearman was relied on rather than Pearson, to better detect monotonic relationships between the variables. For these variables, the Spearman correlation coefficients did not diverge significantly from the Pearson correlation coefficients, but did show higher coefficients between many of the variables (see Appendix C for Pearson coefficients). The correlation coefficients are presented using a heatmap matrix, shown in figure 7.12. In this heatmap, the correlation between any variable is indicated both by color and number in each cell. Each number representing the calculated Spearman correlation coefficient between each pairing of variables. Associated p-values, indicating the statistical significance of the coefficients, are shown in figure 7.13.

Looking at the correlation coefficients between the different MWD variables in figure 7.12, it becomes evident that the max values for each of the MWD DPI variables seem to be moderately correlated to each of their respective mean counterpart, with coefficients of 0.44, 0.65 and 0.66, respectively. Generally, higher correlations coefficients are seen within the max values compared to the mean values of MWD variables. Some significant correlation is seen between FI max and HI max (0.69), on the contrary, no correlation is seen between FI mean and HI mean (0.06). The low correlation between FI and HI mean can be partly explained looking at the differences between the two worksites (Austnes and Longva), as seen in figure 7.14. Together, these two worksites exhibit low correlation as previously discovered. However, looking at Longva worksite as an isolated case, a considerable higher correlation is found (0.542), compared to the Austnes worksite (0.039).

MWD variables	Grouting variables
HI mean	Total volume
FI mean	Grouting time
WI mean	end-pressure
HI max	Mean flow
FI max	
WI max	

Table 7.7: All MWD DPI- and grouting variables involved in the correlation analysis.

Considering the four different *grouting variables* in figure 7.12, a very strong correlation is seen between total volume and grouting time (0.89). High correlation is seen between flow and total volume (0.71), while some moderate to low correlation is seen between time and flow. Notably, end-pressure show no correlation to any of the other grouting parameters.

The most important observation that can be made from figure 7.12, is the lack of any significant correlation between any of the MWD DPI- and grouting variables. A test on statistical significance on the Spearman correlation coefficients (figure 7.13), also reveals that almost all coefficients ≤ 0.10 are to be considered *insignificant*, as indicated by p-values > 0.05 . It also shows that all the correlations discovered are can be considered statistically *significant* p-values < 0.05 .

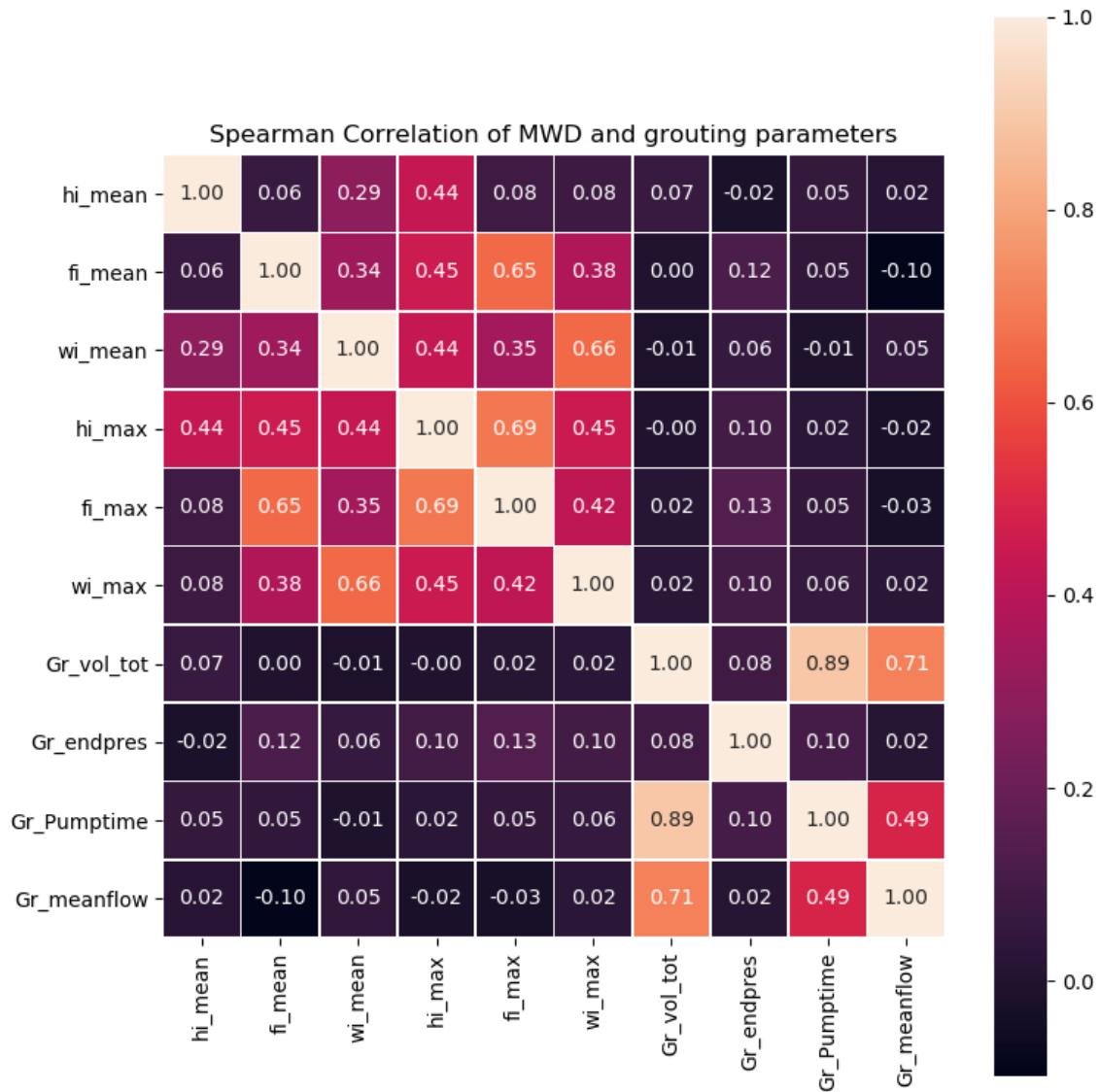


Figure 7.12: Heatmap showing Spearman correlation coefficients between all involved variables (see table 7.7), color gradient ranges from light (positive correlation) to dark (0 to negative correlation).

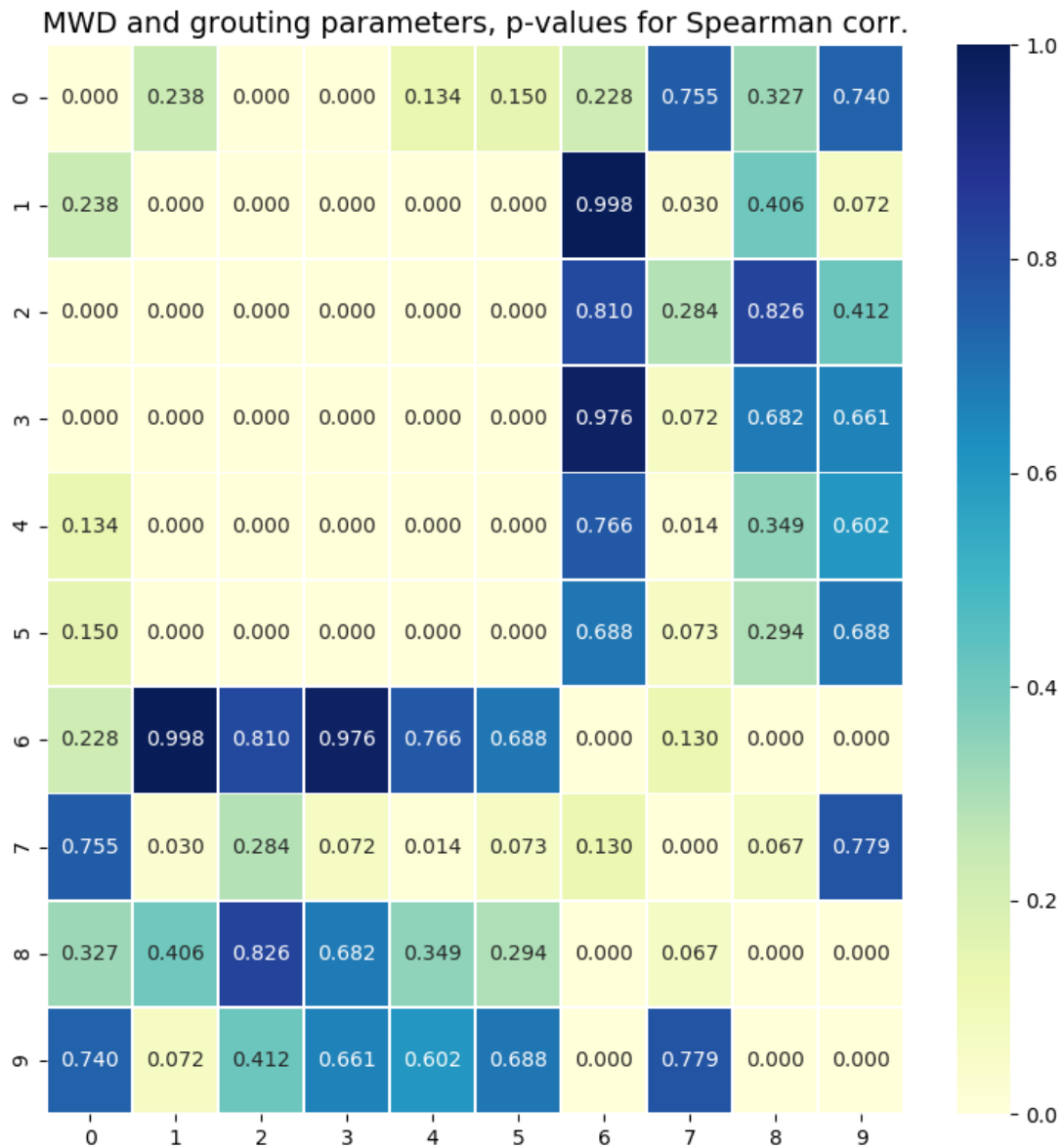


Figure 7.13: Heatmap showing p-values of Spearman correlation coefficients between all involved variables as in figure 7.12. Light cells depict significant correlation in terms of p-values, while light green to blue depict statistically insignificant correlations.



Figure 7.14: Scatter plot of int. hardness and fracturing grouped by the two worksites. Linear association incl. Spearman correlation coefficients between the respective groupings are annotated.

7.4.2 Testing ML algorithms on MWD and grouting data

Although no apparent relationships were found between the MWD DPI- and grouting parameters from the correlation analysis, it was of interest to verify this observation through other methods. To do this, various machine learning regression algorithms were tested and evaluated using *cross-validation*. The `cross_val_score` module from *scikit-learn* was used for this purpose. Python source code for the cross-validation can be seen in Code Listing 4 (Appendix B). The cross-validation method allows for testing the performance of multiple ML-algorithms (see section 5.2.2). The method returns the performance metrics for each model in terms of their predictive accuracy, which in this case, using regression models, is the R^2 -score. The R^2 -value serves an indication of the goodness of fit between the model's prediction and actual values (see section 5.1).

As target variables (response variables i.e. what is to be predicted), all the four grouting variables are used, to test the performance in predicting each of the four variables. Features variables used are the *mean values* of the MWD DPI parameters. namely: mean fracturing, hardness, and water. All the models used have different theoretical approach in terms of how they fit the data, and will not be discussed in detail for the purpose of this basic comparative study. The reader is referred to Pedregosa et al. (2011), Müller et al. (2016) for further reading on this subject. The regression models used in this comparative study, including their resulting R^2 -value on each of the target variables are presented in table 7.8.

Figure 7.15, shows four plots (one for each target variable) with box plots describing the median and 95% confidence interval of each of the tested algorithms in terms of R^2 -score. A higher positive R^2 -value (with 1.0 being the highest), corresponds to a model that better explains the data. It becomes obvious looking at figure 7.15, that all models fail to fit the data, indicated by their negative R^2 for all models across all the tested target variables. It should be noted that none of the models are tuned in any way before the cross-validation, only default settings are used for all of the ML models. Never the less, using only default settings, the models are still expected to respond positively when they are able to learn and fit from the data in some way.

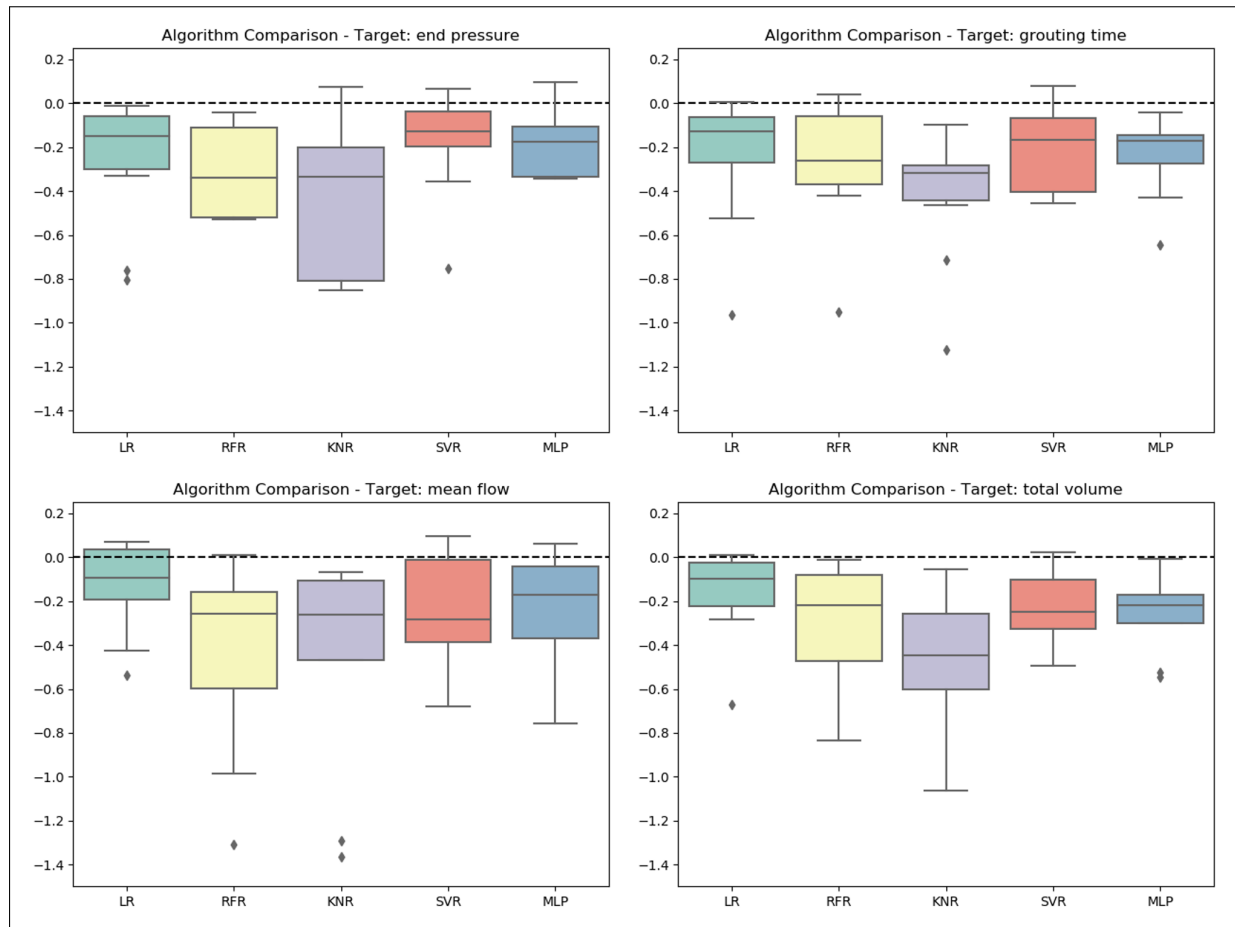


Figure 7.15: Box plots showing the distribution of R^2 -values (y-axis), for each of the regression models (LR, RFR, KNR, SVR and MLP, see table 7.8), with one plot for each of the four target variables.

Regression model	R^2 -values			
	Volume	Time	End-pressure	Mean flow
Linear Regression (LR)	-0.164	-0.242	-0.258	-0.135
Support Vector Regression (SVR)	-0.236	-0.200	-0.173	-0.243
K-Neighbors Regression (KNR)	-0.465	-0.413	-1.430	-0.452
Random Forreest Regression (RFR)	-0.299	-0.275	-1.166	-0.439
Multi-layer Perception Regression (MLP)	-0.253	-0.238	-0.545	-0.239

Table 7.8: Resulting mean R^2 -values from the tested regression models on different target variables.

7.5 Prediction of HJ event using logistic regression

It was of interest to establish a predictive model for detecting potential HJ events from the gathered grouting data. To see if the holes where indications of HJ was found could be predicted based on the gathered grouting data alone, and possibly revealing new relationships between HJ cases and the grouting variables in the process. This was done using logistic regression as a *binary classifier*, as previously described in section 5.2.1. The data selected to predict potential HJ events as indicated by the PF index (see section 7.2), was the grouting parameters as the predictor variables or *feature variables* (i.e. what is used to predict), and potential HJ detected as the response variable or *target variable* (i.e. what is to be predicted). Both the features and target variables validate the assumptions of continuous and binary data types, respectively. The target variable is represented by Boolean values: **1** for potential HJ event detected, and **0** for no potential HJ event detected according to the PF index.

7.5.1 Establishing a model

In order to assess what explanatory variables or *features* to include in the model, the findings from the PCA of grouting parameters previously found in section 7.3.2, was used. By assessing the PCA result, it became apparent that the most variance was explained by the total volume and time, and to some extent the mean flow. While the end-pressure did not contribute to PC1 (recalling that differentiation between HJ events occurred mainly along PC1). Because the feature variables total volume and grouting time exhibited a very high correlation, the latter is excluded as an input variable in the logistic classifier model. The model therefore consisted of two feature variables: *total volume* and *mean flow*. Training data was set at 60% of the initial data amount, while 40% of the total data amount was used for model testing. After some model testing, the model was set with parameters $C = 0.001$ (penalizing complexity), penalty function set to $l2$ (default). The final model is established with logit parameters: $\beta_0 = -0.0156$, $\beta_1 = 0.0355$, and $\beta_2 = 0.0334$.

7.5.2 Evaluation of final model

Beginning with the confusion matrix (see figure 7.16), a relatively large number of the **0**-cases (no HJ-cases) were accurately predicted by the model, with 79 correct predictions. While 29 **0**-cases was wrongly predicted. On the contrary, the model was able to accurately predict 16 of the total 26 cases of **1**-cases (HJ-cases) in the test data.

Target	Precision	Recall
0	0.89	0.73
1	0.36	0.62
Accuracy	0.710	

Table 7.9: Classification report showing performance metrics of the model.

The performance stats of the final model are comprised in table 7.9. The stats show a much higher prediction accuracy for the **0**-cases (no HJ events) than the **1**-cases (pot. HJ event), the *recall* values, i.e. how confident the model is in its predictions. Shows a relatively fair result for the **0**-cases with a value of 0.73, but are less confident in predicting the **1** cases, with a recall value of 0.62. The overall model accuracy is 0.71.

Assessing the ROC curve shown in figure 7.17, the model is clearly performing better than pure guesswork. The area under the curve (AUC) is 0.745, where a value of 1 would represent a perfect predictor model, and a value less than 0.5 would represent a worthless predictor. The curve shows the rate of true-positives (i.e. **1**'s correctly predicted) vs. rate of false-positives (i.e. type I error, **1**'s wrongly predicted).

Taking a closer look at the actual correct predictions made by the logistic model, it seems that the model has problems distinguishing particularly the **1**-cases, with as many as 29 being wrongly predicted (false positives). Because accurately predicting the **1**-cases is considered the most important ability that the model should have, the rate of which the model predicts false-positive results (type I errors) is of particular interest. It is fair to say that this model is somewhat insufficient in predicting the potential HJ events, with respect to the gathered grouting data. Nevertheless, the model is able to fit and predict to a certain degree, using the feature variables mean flow and volume. Thus suggesting that there *might* be some relation between these feature variables, and cases of HJ.

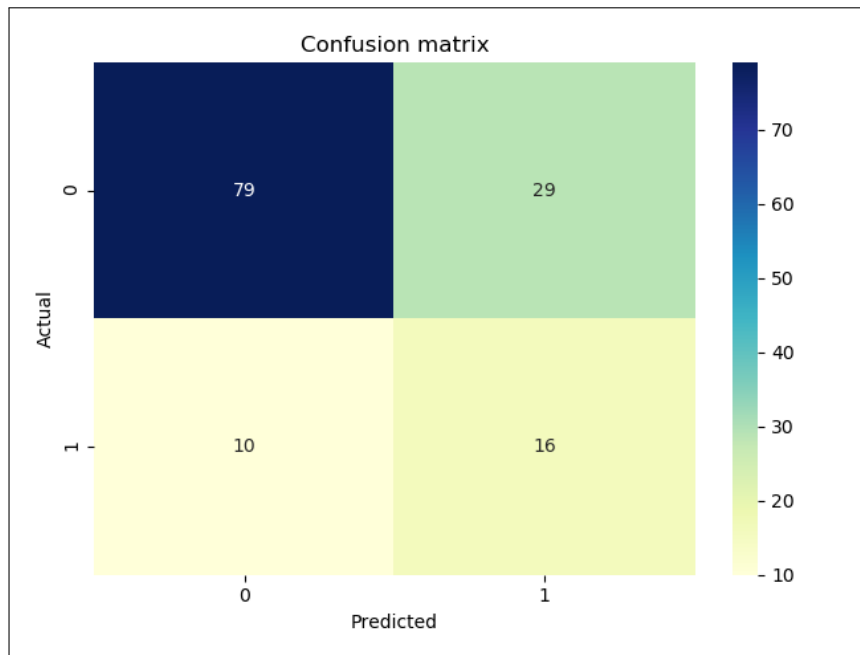


Figure 7.16: Confusion matrix of final model, main diagonal shows number of correct predictions for each case (79 and 16).

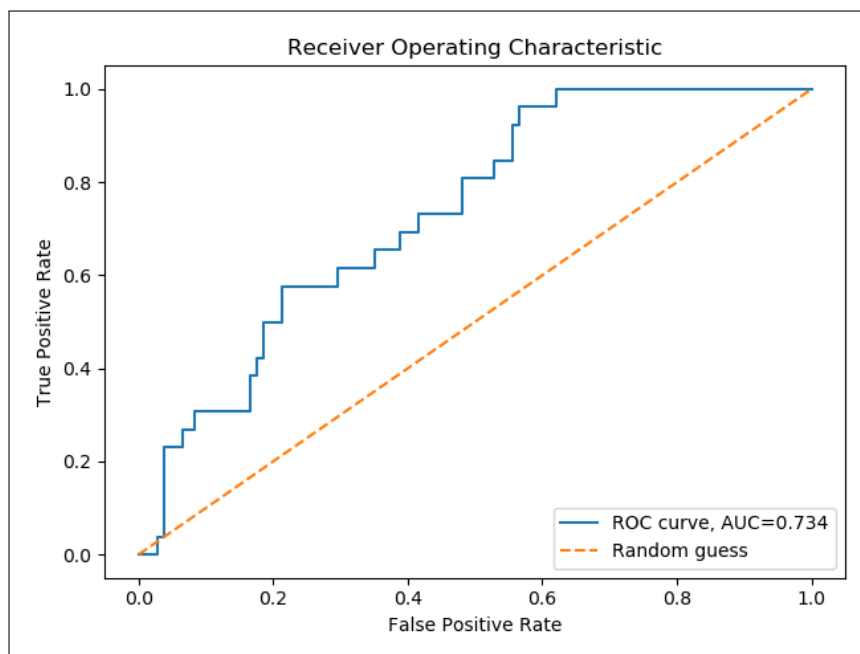


Figure 7.17: ROC curve showing the overall performance of the model compared to pure guesswork.

Discussion

The general usability of MWD data in establishing a grouting strategy is the question of main interest in this study. In this chapter, the research results and findings are discussed. A summarized review of the main findings is presented in section 8.6. A review of the main limitations including discussions on further work is presented at the end of this chapter.

8.1 Ability to detect geological features based on MWD

To verify the ability of the MWD DPI of detecting actual geological features, the response in these parameters when intersecting a prominent weakness-zone as indicated by the preliminary geophysical mapping by John F. Dehls and Rønning (2012), was analyzed. As previously stated, only one of the interpreted weakness-zones had been intersected by the tunnel advance within the time frame of this thesis, namely Fjørtofta North.

As seen from figure 7.2, the intersection of an apparent weakness-zone occurred around chainage 32100 to 32500 of the Fjørtofta North tunnel. This is similar to what was expected, judging from the weakness-zones as indicated by the geophysical mapping. In conclusion, the mapped weakness-zone, was quite clearly indicated by a response in the MWD DPI *hardness* and *fracturing*, but with a limited response in *water disturbance* (figure 7.3). Some water-bearing structures were also found by looking at both the fracturing and water disturbance textures of the fold-out tunnel geometries (figure 7.3). Considering these observations, it can be concluded that it is possible to detect large-scale geological features based on the MWD DPI's. However, this does not conclude on the MWD DPI's ability to detect smaller-scale features in the rock

mass, such as smaller fractures and water-conductive zones.

8.2 Using PF index to detect hydraulic jacking

To detect potential HJ events, visual interpretation of time series with PF index including corresponding flow and pressure was done. Some of the graphs, including their respective interpretations, are shown in section 7.2, the results from the HJ analysis are comprised in table 7.4. Detection of HJ events was done to supplement the data basis for this research, thus providing an additional basis for which potentially interesting relationships could be unveiled. The HJ cases are therefore used both in the PCA (section 7.3.2), and in the logistic regression (section 7.5).

Looking at table 7.4, potential HJ cases was detected in approximately 24% of holes across all chainages at the Austnes worksite, and 22% of holes across all chainages at the Longva worksite. Suggesting that a relatively even amount of HJ events has occurred at both worksites. The number of HJ events seems reasonable when considering studies on similar Norwegian tunneling projects. Strømsvik (2019), analyzed 7 different D&B tunnels in Norway for HJ events (using the PF index), and found HJ cases in approximately 23% of all grouted holes. In a master thesis done by Moe (2016), HJ events in two Norwegian railroad tunnel projects were analyzed (not with the PF index), and HJ cases were found in approximately 25% of all holes. Compared to these two comprehensive studies on HJ in Norwegian tunnel projects, it appears that a proportionate number of HJ events has occurred in all of them, between 23-25%.

As previously discussed in section 3.4.1, there are also events which exhibit similar or equal behavior to HJ events during grouting, but is rather caused by other effects. This naturally makes the indications of HJ very interpretive, and this is important to keep in mind when using the PF index. It is not possible to validate any results regarding detected HJ events, as is the case for many aspects of grouting research. The limited amount of usable data that was available for this research, made it possible to base the detection of HJ events on visual interpretation of the PF graphs. For larger datasets, it is suggested to automate the procedure by implementing the full algorithmic PF index method for HJ detection as proposed by Strømsvik et al. (2018).

8.3 General findings from the PCA

PCA was done to detect and visualize trends, clustering, and tendencies in the data. As well as a method for establishing which of the parameters, contributed most to the overall information explained. The PCA allowed for a deeper understanding of the data and the relationship between the different variables. Three Principal Component Analyses was done, two where the MWD DPI and grouting data were treated as isolated cases, and a third where the same grouting and MWD variables were used to investigate their relation to the HJ events.

8.3.1 PCA on MWD DPI data

Considering the PCA on MWD DPI's as an isolated case (figure 7.7b), some weak clustering of data points could be seen between the different chainages involved in the analysis, but overall the observation from each of the chainages seemed quite variable, with no apparent tendencies. Furthermore, the most apparent tendency became evident when the individual observations were grouped according to their respective worksites.

Grouped by *chainages*, there was a large variance of observation within many of the chainages, which also suggests that the variance in terms of rock mass quality was considerable within many of the individual chainages. This is a logical response, in that sense that the rock mass quality can change to a great deal even within the confined area of a few meters, certainly when taking into account that the "Eastern Gneissic Region", in which all these tunnels are constructed, is a geological domain which is often characterized by its high geological complexity. Looking at the PCA grouped by *worksites*, the clustering of the individual tunnel worksites became apparent, clearly showcasing the overall differences in rock mass characteristics between these two areas. This also supports the ability of the MWD data in differentiating the overall geological characteristics between two areas.

From the PCA biplot in figure 7.8, the importance of the MWD parameters fracturing and hardness in differentiating the two worksites clustering, became evident. This clearly shows that the differences between these two worksites are due to overall differences in the rock mass characteristics, that are captured by these two parameters. This further supports the ability of the MWD interpreted parameters *fracturing* and *hardness*, to quantify geological conditions relatively. The resulting clustering also suggests that the worksite *Austnes* was consistent with

overall higher rock mass quality (in terms of fracturing and hardness) than the *Longva* worksite. Suggesting that even though both the tunnel worksites are consistent with the same geological domain according to the bedrock geology (granitic rock with eclogite lenses, see figure 6.2), the relative rock mass characteristics of this region can change greatly within the same geological unit.

It should also be stated that the validity of all these observations, only holds if reliable calibrations are assumed for all the drilling jumbos. Meaning that what is indicated by the data is representative of the actual rock mass conditions at the different worksites, and not due to false effects such as equipment not being calibrated properly.

8.3.2 PCA on grouting data

Considering the PCA on grouting data as an isolated case, less apparent clustering could be seen from the score plot grouped after chainages (figure 7.9a), compared to the MWD DPI PCA results. No apparent clustering or tendencies was differentiating the two worksites (figure 7.9a), as was seen by the PCA on MWD DPI's. The most interesting perspective resulting from this observation, is that the clear difference in rock mass quality as indicated by the MWD PCA result, did not translate to any notable differences in terms of grouting parameters between the two worksites, as may would have been expected. Another observation from the grouting PCA is that the similarities in total volume and grouting time became evident (which was also found in the correlation analysis), including the orthogonality (i.e. no correlation) between end-pressure and grouting time/total volume. Most of the total variance in this dataset was caused by the total volume, time and to a certain extent mean flow, while the end-pressure provided a lesser amount of variance explained on PC1. This is as expected considering that the end-pressure is set at a predetermined value (40, 60, or 80 bar), and reached successfully for most of the grouted holes. Other than this, the PCA on grouting parameters was rather inconclusive, and did maybe suffer to some extent by the lack of data (especially from the Austnes worksite). As was also indicated by the KMO test (0.5147), which barely validated the assumption on sampling adequacy.

8.3.3 Evaluation of potential HJ events (grouting and MWD data)

PCA was also done using results from the two preceding PCA's, grouped after observation (holes) where indications of HJ events were found and not. No clear tendencies or clusters were discovered from the MWD PCA biplot (figure 7.11a), while a certain tendency of HJ cases to orientate further away along the PC1 compared to the observations with no indications of HJ, was found for the grouting PCA. The latter observation suggesting that holes with HJ events indicated, have a weak affinity towards higher values of the interdependent variables *time* and *total volume*, and to a certain extent *flow*. This observation is also in conjunction with the general belief that hydraulic jacking causes higher grout takes and increased time consumption of grouting (Stille, 2015; Strømsvik, 2019).

8.4 Relationship between MWD and grouting variables

Investigating the statistical relationships between the MWD DPI- and grouting variables represents an integral part of this study. As the result from this would help gain a deeper understanding of how the MWD parameters could potentially relate to the grouting parameters. For this purpose, a correlation analysis comprising all the MWD DPI data and the grouting data was conducted (see section 7.4). Subsequently, a comparative study using *cross-validation* of various different machine learning models was done (section 5.2.2).

8.4.1 Correlation analysis

A correlation analysis was conducted to measure the strength, direction, and statistical significance of any association between the different variables. The main emphasis was put on the relationship between the MWD- and grouting variables. Results from the correlation analysis visualized as a heatmap matrix can be seen in figure 7.12, while their corresponding p-values are presented in figure 7.13. The main results from the correlation analysis were as follows:

- Some weak to moderate correlations were found within the MWD DPI's of the dataset. The highest correlation was found between the max and mean values of each variable (0.44, 0.65, 0.66). Generally, high correlations were found within the max values than the mean values of MWD DPI's. Notably, no correlation was found between the mean of fracturing and hardness, when both worksites were analyzed together (0.06), but a moderate correlation was found between the same variables when only data from Longva

worksite was considered (0.542, see figure 7.14).

- Within the four grouting variables of the dataset, a very high correlation was found between time and grouted volume (0.89). A considerable correlation was also found between total volume and mean flow (0.71), while a moderate correlation was found between mean flow and grout time (0.49). No correlations were found between the remaining pairings.
- Between both the MWD DPI- and grouting data, *no correlations* were found.

Since both of the interpreted parameters, FI and HI, are both partially derived from the same normalized penetration rate parameter from the raw MWD data, as previously explained in section 4.2. It would also be reasonable to believe that a fractured and weak rock mass would produce a somewhat equal, or at the very least comparable response in these two parameters, including that these two exhibits some correlation. The two variables were shown to be uncorrelated when the full dataset was used, as seen from the correlation map (figure 7.12). However, the correlation is deemed *insignificant*, judging by its corresponding low p-value = 0.238 (see figure 7.13). As figure 7.14 suggests, there is a large difference in correlation between the two worksites (0.06 and 0.542), contributed by an observable high sampling variance at the Austnes worksite. This could be because its geological domain being more fluctuating and varying, compared to that of the Longva worksite. As was also seen previously in the MWD PCA (section 7.7). Figure 7.14, also suggests that there is generally a higher degree of fracturing and harder rock mass (lower hardness index) at the Longva worksite, compared to Austnes worksite, which resonates well with the results from the MWD PCA biplot (7.8).

The most important finding obtained from the correlation analysis is the lack of any linear or non-parametric relationships between any of the MWD DPI- and grouting variables. An initial hypothesis for this research was an observable dependency between grout consumption and particularly the fracturing parameter (FI). Even though no correlation was found between these variables, it is still believed that the overall grout take is largely dependent on the fracturing of the rock mass, as established by many researchers Stille (2015); Gunnar Gustafson (2012). As an initial approach for a PhD on grouting parameters and HJ events, done by Strømsvik (2019), the correlation between MWD and grouting was investigated. However, no correlation was found in this research either, and the approach was discarded after a few months. The PhD

study also suggested that the MWD parameters were insufficient in detecting and describing smaller fractures and water-conductive zones, similar to the results of this study

The lack of correlation could be due to how the fracturing parameter was gathered. To investigate a large number of boreholes across many chainages, the mean and max value of the 700-900 samplings *per* borehole was taken. It is conceivable that the information loss was too great in terms of establishing accurate and representative estimates for these DPI's when considering that up to 900 samplings were compressed to a singular value for each borehole. Another matter which obscures the interpretation of the FI is fracture infilling. Fracture infilling such as clay, will often significantly reduce permittivity of an otherwise fractured rock mass. It is not possible to establish whether fracture filling is present or not based solely on the FI DPI. Suggestions for alternative methods for establishing the MWD DPI data, is discussed later in section 8.7.2.

It should also be stated that correlation coefficients were also established for the Longva and Austnes as isolated datasets, in the same manner as done in figure 7.14. However, still no significant correlations between the MWD DPI's and grouting variables were found using this approach.

8.4.2 Testing ML algorithms on MWD and grouting data

Even though no inherent relationships were found between any of the MWD DPI's- or grouting variables, it was of interest to check the performance of some machine learning algorithms. To see if the ML models could detect any relationship between these variables, and produce an appropriate predictive response. To do this, four different target variables (all grouting variables) with corresponding mean MWD DPI variables as feature variables: FI mean, HI mean, and WI mean was used in five different ML regression models (see table 7.8). The performance of each model was evaluated through *cross-validation*.

As figure 7.15 shows, none of the used models are adequate in establishing a relation between the two sets of variables. This further supports the previous observation that no inherent relationship exists between the two variable groups.

Although few studies on the relationship between geology in terms of MWD DPI- and grouting data are conducted, Strømsvik (2019) and Høien and Nilsen (2014), offers some perspective on this subject.

In the first study conducted by Strømsvik (2019), grout consumption is compared with engineering geological mapping reports from a Norwegian tunneling project, relying mainly on the Q-system (rock mass classification system). This study also concludes with no obvious relationship between grout consumption and geological conditions. However, a limitation in this study, was that the Q-values were obtained *after* the grouting procedure was done. This could have altered the rock mass conditions on-site, in terms of some of the input parameters to the Q-system.

In another study by Høien and Nilsen (2014), the grouting performance of an urban tunnel was evaluated in terms of gathered MWD DPI variables. In this particular study, a distinct relationship was discovered between the mapped water leakages and the water disturbance factor (WI), while some rather indistinct relationships were found between *grouted volume* and the DPI factors *water and fracturing* (WI, FI), for some sections of the tunnel. It should also be stated that this research was conducted with MWD DPI provided by another software (GPM+ Tunnel, Rockma AB, 2011), which is not necessarily comparable to the MWD DPI provided by *Bever Control*.

It is also important to keep in mind that *correlation does not imply causation*. This means that any relationship found by either means of simple correlation analysis or more complex machine learning models, high correlation or predictive accuracy does not necessarily mean that the used variables are inherently related by nature. This also implies that one must be careful to assume a causal relationship beyond a strictly statistical relationship when interpreting these results. A critical point is that the statistical measures presented do not explain *why* or *how* the data are related, this means that there must also exist some sound logical reasoning behind them.

8.5 Prediction of HJ events using logistic regression

Logistic regression was used as a binary classifier for predicting potential HJ events based on the grouting data. The goal of this exercise was to investigate the predictive power of a classifier in accurately predicting HJ-cases in the dataset, relying only on the gathered grouting variables. And potentially gaining a deeper understanding of the relationship between HJ cases and the grouting variables.

The final model was able to predict 79 of the 108 1-cases in the test data, and 16 of the total 26 1-cases in the dataset. With an overall accuracy of 0.710. The ROC-curve was established with an AUC of 0.734, which is an improvement compared to pure guesswork (0.5). This in itself does not qualify the binary classifier as a good predictive model, which was not the purpose of this model. Nevertheless, the results signalize that the classifier model is able to detect a logistic relationship between the variables grouted volume, mean flow, and cases of HJ. This also supports the findings of Strømsvik (2019), where holes with HJ events were found to be correlated to an higher grout consumption.

As could be seen, it is not sufficient to base the detection of HJ event in grouted holes, solely on a predictive model such as logistic regression. However, applying ML methods on entire *grouting logs* time series to predict HJ events, could potentially return positive results. But this problem was not treated in this study. For computerized detection of HJ events, it is suggested to implement the PF index algorithm (Strømsvik et al., 2018).

8.6 Review of raised assumptions

To provide a critical and summarized review of the results, the raised assumptions from section 6.3.1, are discussed in light of the results, and previous discussions.

Assumption 1: *It is expected that the MWD DPI parameters (FI, HI and WI), are able to produce adequate responses according to the actual rock mass conditions.*

Based on the findings from the weakness-zone analysis and the PCA on MWD DPI variables, this assumption has been *validated*. The weakness-zone could be detected from the MWD DPI maps with quite high accuracy, based on the extent of the weakness-zone indicated by previous geophysical mappings. The two analyzed worksites: Austnes and Longva, exhibited consistent differences in terms of MWD DPI variables HI and FI. Further supporting the ability of the DPI's to relatively distinguish different rock mass characteristics. However, the ability to detect *small scale features* of the rock mass is still inconclusive, based on the research results.

Assumption 2: *It is expected that the different MWD DPI variables exhibit relatively high correlations, notably between: FI and HI, including FI and WI.*

The results from the correlation analysis and PCA only *partly validated* this assumption. Although no Significant correlation between FI and HI was found when both worksites were considered (figure 7.12), a moderate correlation was found between these variables at the Longva worksite (figure 7.14). The PCA result of the MWD variables of both worksites, revealed orthogonality between the parameters HI and FI, also suggesting that no correlations were found between these two. On the contrary, some weak correlation was found between both FI, HI, and the water disturbance, WI.

Assumption 3: *Significant correlation between total volume and grouting time is expected since larger grout takes requires more time. Correlation between volume, time and mean flow is also expected.*

The PCA and correlation analysis on the grouting variables validated this assumption. As expected, a high correlation was seen between grouting time and total volume. A moderate correlation was also seen between total volume and mean flow.

Assumption 4: *Correlation is expected to be found between MWD DPI's and grouting variables.*

This assumption was *rejected*, based on the findings from the correlation- and ML analysis. No apparent correlations could be derived from this dataset. Contrary to these results, it is still believed that relationships between MWD and grouting parameters could be established through alternative approaches, and prove a valuable resource in establishing grouting strategies. This will be discussed further under section 8.7.

Assumption 5: *It is expected that HJ cases will cause increases in both time and grout consumption.*

This assumption was *validated* through the results from PCA on grouting variables grouped by HJ events (figure 7.11a). The observations with HJ cases were scattered further up PC1, which is dominated by both the volume and time parameter. The results from the logistic classifier also support this assumption to some extent. The ability to predict HJ cases with an accuracy 0.710, reflects the model's ability to detect some relationship between observations with HJ events and the grouting variables volume and flow.

8.7 Review of research limitations and future work

Although most of the limitations are addressed in each appropriate section, a summary of the most important research limitations is presented in the following section. Including some recommendations regarding future work, presented at the end.

8.7.1 Research limitations

Because of the data-oriented nature of this research, data gathering and processing represent a great deal of the research limitations. The following comprises a review of the most important limitations in this study, including suggestions on how they could be improved for the benefit of future research. Detailed discussion on data limitations were presented previously in section 6.4.

The *amount of data* was greatly limited by difficulties in matching the hole numbering from the grouting reports and that of the drilling reports; including limited access to grouting log-files, due to files being deleted by the grouting technicians. For future applications, it is suggested to implement a unique hole ID for each borehole, which is used both for the individual drilled holes and the grouted holes. This would allow for greater certainty in matching MWD- and grouting data, and would help facilitate a larger amount of data to be used for research and analysis. This feature would also improve the *certainty* in conducting research on both MWD- and grouting variables. An improved system for data management of as-built data, including that all project data is systematically saved and store for later use, will not only be beneficial for future research but also to evaluate the grouting procedure *after* grouting.

A considerable limitation that is relevant for all the gathered data, whether it is MWD- or grouting data, is the reliance on accurate calibration of all the used equipment, i.e. drilling jumbos and grouting rigs. Incorrect or irregular calibration of equipment will produce skewed responses between different worksites, which are not representative of actual rock mass conditions. This represents a considerable pitfall to this study, which was not possible to evaluate based on the available information.

8.7.2 Recommendations for future work

Although no correlation was found according to the main research question, there are still questions that remain unanswered by this research. Further research is needed to better understand the relationship between MWD- and grouting data.

It is firmly believed that a more profound relationship between these variable groups could be found by alternate approaches to establishing representative values for MWD DPI data. A better understanding in how the different MWD DPI parameters respond to especially water-bearing/conductive fractures, and from that deriving a value for each hole in terms of "fracture conductivity". It is also suggested that the MWD DPI responses is compared to its corresponding engineering geological mapping, similar to methods used by Høyen and Nilsen (2014), to give a better understanding in the MWD DPI's responses to variations in the rock mass.

Furthermore, to better explain the fracturing parameter (FI) with a singular value, more knowledge on how the fracturing translates to overall permittivity is needed. One possible suggestion, is to derive a method for establishing a "fracture density" for each hole, based on *optical televiewer imaging* (OTW). This would lead to a better understanding of what response is produced by the fracturing parameter when fractures of different apertures are crossed by the drill bit (as indicated by the OTW), similar to methods described by Khorzoughi et al. (2018). This would allow for better estimates by establishing more insight on the actual rock mass conditions, and understanding which FI thresholds correspond to actual high resistivity (open) or closed fractures. Understanding the MWD DPI responses to different rock mass characteristics, could be the key to establish a relationship between MWD DPI and grouting parameters. Including deeper insight in terms of grouting applications.

Seeing as the ability of the MWD DPI's to produce detailed information on the rock mass characteristics ahead of the tunnel face, is of utmost importance when seeking to establish a method for utilizing this data in a grouting context. This study verified the ability of MWD to detect large scale features of the rock mass, such as weakness-zones. However, to utilize the MWD data in a grouting context, *highly* detailed information is needed. It could be argued that the sampling frequency of today's drilling equipment (approx. one sample every 3 cm, at best), is inadequate for establishing detailed data on the *fracturing characteristics*, which is the most

important aspect when considering the groutability of the rock mass.

When both MWD data of high quality (high sampling frequency, robust DPI pre-processing, and minor loss of data), and a deeper understanding in the MWD response to various rock mass characteristics have been established. This high-quality MWD data could then be used with greater confidence in various machine learning applications. More specifically, this involves learning models based on detailed and representative data on the rock mass conditions ahead of the tunnel face. In turn, this could allow for accurate predictions of variables related to grouting, e.g. penetrability, volume, flow, and susceptibility to jacking events. These predictions could then be used as supplementary guidelines for the grouting technicians.

Conclusions

The main objective for this thesis, was to evaluate the relationship between the MWD and grouting variables, and in the process, achieving an increased understanding of how these descriptive parameters may relate to each other. This was done in order to detect possibilities of using the MWD DPI data as a supplementary tool in the grouting procedure. This thesis also investigated several data analytical approaches to establish deeper understanding on the different MWD DPI- and grouting variables.

Main conclusions from the research results are summarized in the following list:

1. Results from MWD DPI study, suggest that it is possible to detect large scale features in the rock mass, such as weakness zones, based on the MWD DPI mapping. It should be emphasized that, based on these results, there is still uncertainty in the MWD DPI's ability to detect and respond to small scale features of the rock mass, including the overall water conductivity.
2. It was found that differences in rock mass between two different tunnels was shown through differences in the measured MWD DPI's *fracturing* and *hardness*. Thus, suggesting these two parameters could be used to relatively differentiate between rock masses.
3. It was experienced that the PF index could be used as a visual tool in detecting potential HJ cases from the grouting logs. Furthermore, results from this study indicate that approximately 23% of the grouted holes were influence by hydraulic jacking, suggesting that this phenomenon is relatively common in Norwegian grouting practice. There was

also found a logistical relationship between the cases of HJ jacking and grouted volume, time, and flow. Supporting the assumed relationship between grouting time/volume and HJ cases.

4. Considering the main research question, no significant correlation was found between any of the MWD DPI variables and the grouting variables, using the data from 13 different grout curtains comprising approximately 330 holes. However, moderate to strong correlations were found within the respective MWD DPI- and grouting data groups. Thus suggesting that inter-correlation are present *within* the two different groups, but not *between* the two data groups.

The main findings of this study indicate that no apparent relationships exist between these variable groups. However, it is still believed that the abundantly available MWD data, could still prove useful for grouting purposes in future applications. The ability of the MWD DPI's to establish detailed information on the rock mass characteristics ahead of the tunnel face, is of utmost importance when seeking to establish a method for utilizing this data in a grouting context. This study verified the ability of MWD DPI to detect large scale features of the rock mass, such as weakness-zones. Regardless, to utilize the MWD data in a grouting context, there is a need for *highly* detailed information on the rock mass ahead of the tunnel face. It could be argued that the industry standard MWD technology of today, is inadequate in describing the rock mass at a high enough level detail for it to prove useful for grouting applications. Based on the results from this thesis, it is suggested that further research is done to gain deeper understanding on the presumed relationship between MWD- and grouting parameters.

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Appendices

A Full MWD DPI- and grouting dataset

	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
0	Austnes	5506	5506_1	23.999	1.209170	10.280930	2.532740	39.11316	35.049740	10.56515	1001.3	66.50	2:11:38	14.233305	True
1	Austnes	5506	5506_2	23.985	9.194560	9.991990	2.049380	37.71006	28.750140	6.19756	4142.7	67.50	11:35:47	7.627690	False
2	Austnes	5506	5506_3	23.993	12.919590	9.105810	1.995750	53.43641	26.794130	7.97140	1433.6	30.80	2:15:40	11.290466	False
3	Austnes	5506	5506_4	23.980	10.704680	10.796540	2.114100	56.49632	27.787310	8.17776	1196.6	61.20	2:06:20	7.614469	False
4	Austnes	5506	5506_5	23.993	8.644370	7.403370	2.193090	52.30747	34.661020	19.99814	1883.5	69.70	4:29:09	6.200890	True
5	Austnes	5506	5506_6	23.999	11.634810	10.202340	1.532040	55.42387	46.475560	8.19077	14.1	82.50	0:25:52	1.205970	False
6	Austnes	5506	5506_7	23.982	13.154980	7.966930	1.714710	45.96993	24.470580	10.99512	1948.6	66.90	6:20:39	7.390424	False
7	Austnes	5506	5506_8	24.004	17.137290	6.509670	1.791300	111.66973	46.062970	6.11779	448.2	70.70	1:56:45	3.866014	True
8	Austnes	5506	5506_9	23.731	8.804520	5.588220	1.781400	44.83992	34.342780	11.49967	1237.1	45.00	2:59:39	7.300189	True
9	Austnes	5506	5506_10	23.975	16.778590	6.539030	1.500280	51.02813	17.922180	7.59776	717.6	38.90	1:15:09	10.233183	False
10	Austnes	5506	5506_11	23.979	17.499930	6.344890	2.070370	61.53278	28.156600	20.62389	5503.1	60.20	12:10:18	10.104512	False
11	Austnes	5506	5506_12	15.561	25.791210	6.913520	1.799110	63.84284	29.663650	10.57366	222.3	65.50	0:40:36	5.290650	False
12	Austnes	5506	5506_13	25.492	23.829620	4.636290	1.602060	55.32447	16.909150	10.37057	549.6	39.20	1:51:51	6.289313	True
13	Austnes	5506	5506_16	23.987	30.498230	6.429280	1.616910	70.73870	20.868790	11.86651	1791.8	60.50	3:38:39	11.320786	False
14	Austnes	5506	5506_17	23.979	13.545760	5.643600	1.470710	44.56870	15.959890	6.84139	712.7	39.80	1:06:23	10.290881	False
15	Austnes	5506	5506_18	23.992	9.405130	5.315100	2.323990	50.70096	25.729190	21.40367	438.0	67.70	2:01:39	5.206200	False
16	Austnes	5506	5506_32	24.005	7.240480	7.282910	1.898130	77.13987	21.622200	5.31995	43.0	65.90	0:07:40	5.587500	False
17	Austnes	5506	5506_33	23.985	14.214300	6.619620	1.496760	43.70116	21.178560	7.81214	409.1	71.70	1:31:28	7.558884	False
18	Austnes	5506	5506_34	23.980	2.440090	8.558890	1.815560	36.74090	21.038740	7.80054	513.8	33.70	0:37:29	13.572124	False
19	Austnes	5523	5523_1	29.490	0.153460	1.193820	0.796560	32.18154	19.269220	4.15055	2633.0	60.00	4:55:59	11.256492	False
20	Austnes	5523	5523_2	29.480	1.574190	1.565410	0.757990	31.18157	14.848760	5.96673	583.1	55.80	0:58:04	11.695852	False
21	Austnes	5523	5523_3	23.993	25.452440	0.440500	0.842970	40.82592	11.384470	4.06191	2243.7	47.80	6:10:14	8.071432	True
22	Austnes	5523	5523_4	23.496	14.531460	2.386910	1.065470	44.47186	17.996450	5.96503	212.0	64.20	0:58:01	3.769217	False
23	Austnes	5523	5523_5	23.477	1.174860	2.314150	1.036460	36.43109	26.141430	4.68611	1293.2	51.40	2:17:20	10.378078	True
24	Austnes	5523	5523_6	23.505	-28.268810	5.883920	1.986460	16.30621	34.838760	12.06607	26.3	60.80	0:39:53	1.883333	False
25	Austnes	5523	5523_7	23.996	-9.863890	6.121170	1.950190	39.09559	35.205200	9.38567	2354.6	65.50	4:42:26	7.943887	True
26	Austnes	5523	5523_8	23.987	-1.131660	8.288630	1.915300	39.85940	48.430060	10.64657	1458.4	60.90	2:57:32	8.476879	False
27	Austnes	5523	5523_9	19.508	-10.104120	5.127540	1.952060	51.60145	29.343320	15.28536	2284.7	37.90	5:25:30	9.556402	False
28	Austnes	5523	5523_10	23.497	-5.853540	7.079810	1.725440	40.74712	31.836090	9.52193	2584.3	35.70	4:01:16	13.000891	True
29	Austnes	5523	5523_11	23.486	-25.818330	6.426060	1.971830	29.40437	29.260300	16.06403	1613.4	54.10	1:53:54	14.173520	False
30	Austnes	5523	5523_14	29.482	3.143130	4.381080	1.560050	84.27127	36.982900	10.91521	626.6	60.70	1:00:09	10.596775	True
31	Austnes	5523	5523_15	23.494	-4.448270	6.836460	1.617880	52.72147	31.058600	7.02400	70.1	62.40	0:13:35	5.021687	False
32	Austnes	5523	5523_16	23.483	10.195900	6.646430	1.845320	53.75599	27.400060	24.82154	245.2	59.90	0:31:07	9.148734	False
33	Austnes	5523	5523_17	23.496	13.776210	6.111780	1.542310	54.93369	22.760280	6.63115	230.2	62.40	0:54:57	3.990634	False
34	Austnes	5523	5523_18	23.496	10.082620	4.443860	1.149630	43.29483	18.834570	7.06726	114.1	61.50	0:19:21	6.279487	False
35	Austnes	5523	5523_19	23.499	6.741990	5.678220	1.118040	112.44936	56.303520	6.46711	115.5	65.80	0:30:33	1.990517	False
36	Austnes	5523	5523_20	23.487	14.553050	5.051150	1.544550	64.49162	22.966830	8.36201	305.9	60.40	0:57:13	5.125872	False
37	Austnes	5523	5523_21	23.474	4.304180	4.492370	1.085400	35.41105	20.768510	5.15385	108.1	61.20	0:23:34	4.232168	False
38	Austnes	5523	5523_22	30.394	9.380620	2.243240	2.156650	53.72855	21.153790	27.14358	80.4	68.00	0:18:23	5.983117	False
39	Austnes	5523	5523_23	23.480	12.991780	4.789990	1.267330	67.91149	40.422350	7.18169	3474.3	57.10	6:09:24	10.822162	True
40	Austnes	5523	5523_24	23.494	3.226070	4.471350	1.071260	86.81121	59.278470	7.05775	1106.8	63.10	2:15:35	12.630343	False
41	Austnes	5523	5523_25	23.487	-1.258920	4.912690	1.122620	41.98079	20.475510	5.57606	1026.7	66.30	2:15:00	11.514978	True
42	Austnes	5523	5523_27	21.030	2.614760	3.426230	1.103020	59.13809	30.132840	7.86453	43.2	59.30	0:09:08	4.816071	False
43	Austnes	5523	5523_28	23.499	-0.024740	5.227170	1.161050	32.73629	21.945020	6.23680	116.6	59.70	0:56:41	2.019648	False
44	Austnes	5523	5523_29	23.492	-1.515580	7.759980	2.407360	47.15607	26.895810	17.32058	231.4	42.20	1:04:44	6.173043	False

Continued on next page

	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
45	Austnes	5523	5523_30	23.485	-9.497390	6.456710	1.971110	35.52610	23.859530	17.88044	75.7	62.30	0:36:12	2.018349	False
46	Austnes	5523	5523_31	23.473	-3.453940	5.682160	1.161580	34.53745	19.252310	9.66616	203.8	65.40	1:17:36	2.515665	False
47	Austnes	5856	5856_1	23.981	-11.313740	4.545960	1.446090	31.39699	22.852570	4.99159	865.7	66.80	1:36:34	7.812708	False
48	Austnes	5856	5856_2	23.999	-8.837270	4.238590	1.369600	16.50739	22.792530	7.12667	238.3	61.90	0:38:59	6.114468	False
49	Austnes	5856	5856_3	24.002	-6.007960	3.713230	1.367460	32.77337	16.493850	6.48948	76.0	60.40	0:11:00	6.677612	False
50	Austnes	5856	5856_4	23.986	-6.113140	4.444680	1.604220	39.12859	19.383750	22.85873	75.3	65.20	0:12:09	6.159459	False
51	Austnes	5856	5856_5	23.987	-9.206130	4.558050	1.322040	27.83770	23.474590	6.41899	810.2	65.60	2:22:38	5.645093	True
52	Austnes	5856	5856_6	29.478	-9.934790	4.498100	1.395520	27.83770	23.474590	6.41899	599.4	62.40	0:52:56	11.018495	True
53	Austnes	5856	5856_7	23.990	-12.799190	5.121620	1.344870	46.85620	21.091690	8.21745	199.4	49.60	0:16:18	11.670707	False
54	Austnes	5856	5856_8	24.002	-14.403270	5.497760	1.422240	24.31892	22.481640	7.77781	65.6	54.10	0:23:16	2.781560	False
55	Austnes	5856	5856_9	24.003	-14.759860	4.573220	1.485480	25.24137	16.791950	8.08210	25.0	76.30	0:12:08	1.810811	False
56	Austnes	5856	5856_14	23.984	-6.335630	5.348910	1.019640	25.07506	18.024020	8.21040	263.0	50.00	0:11:13	2.257881	False
57	Austnes	5856	5856_15	24.000	-9.721460	5.019140	1.189500	24.85595	18.386330	3.50780	573.0	45.00	1:48:38	5.788744	False
58	Austnes	5856	5856_16	23.992	-8.670110	5.047880	1.307600	15.49724	17.648660	6.03330	276.0	62.00	0:21:35	13.043511	False
59	Austnes	5856	5856_17	23.976	-7.553430	5.669460	1.440220	36.83755	21.325140	6.83980	320.0	63.70	NaN	NaN	False
60	Austnes	5856	5856_18	23.999	-10.103710	4.444320	1.255910	26.07930	21.015540	4.53740	320.0	60.00	0:47:21	6.623509	True
61	Austnes	5856	5856_19	23.999	-8.837270	4.238590	1.369600	16.50739	22.792530	7.12670	42.0	60.00	0:14:01	2.700000	False
62	Austnes	5856	5856_20	23.977	-6.811220	3.970610	1.450900	19.73772	15.504190	6.42530	129.0	33.00	0:15:22	6.761175	False
63	Austnes	5856	5856_22	29.484	-12.400000	4.603630	1.331110	33.80769	21.256720	8.74350	94.0	60.00	NaN	NaN	False
64	Austnes	5856	5856_23	23.978	-12.905950	4.346620	1.025430	31.80692	17.509950	4.68740	25.0	15.00	0:05:33	4.097143	False
65	Austnes	5856	5856_24	23.989	-9.204540	4.686290	1.069060	33.26406	18.423800	5.78480	270.0	64.00	0:31:11	8.589894	False
66	Austnes	5856	5856_25	29.479	-5.065310	5.545920	1.225130	29.52562	26.560010	8.43600	300.0	63.00	0:55:58	5.332641	False
67	Austnes	5856	5856_26	23.983	-10.716180	4.382390	1.085640	14.52707	15.425570	5.39600	11.0	50.00	0:03:17	4.261905	False
68	Austnes	5892	5892_1	23.505	6.507940	1.603990	1.462360	37.60539	16.800530	6.25836	3594.5	99.90	5:23:00	8.819823	True
69	Austnes	5892	5892_2	23.477	-1.344900	3.939420	1.568020	32.98139	18.859180	5.65914	1801.5	74.10	2:44:46	10.845986	False
70	Austnes	5892	5892_3	23.370	3.540490	4.690220	1.278280	35.94885	16.820690	5.19842	679.9	84.90	1:05:59	9.310930	False
71	Austnes	5892	5892_4	14.931	-0.230520	0.168590	2.214300	2.84473	3.907070	25.68012	1588.3	84.00	4:16:31	8.570575	True
72	Austnes	5892	5892_5	23.489	-2.583070	3.236990	1.207780	19.60834	17.315880	15.05720	225.2	84.40	0:56:02	7.300686	False
73	Austnes	5892	5892_6	23.485	-9.930100	1.973020	0.941310	23.28227	14.746030	12.70843	2206.1	74.90	2:32:06	8.154663	False
74	Austnes	5892	5892_7	23.475	-1.045690	4.076700	1.300730	26.16489	17.109830	6.52621	177.9	92.20	0:53:24	4.968796	False
75	Austnes	5892	5892_8	23.504	-0.503110	4.129830	0.959360	27.23633	21.956270	5.69015	2409.1	72.80	4:35:46	8.770993	False
76	Austnes	5892	5892_9	23.503	2.788690	3.239970	1.370400	32.17226	13.595350	12.47096	4935.0	61.00	5:54:13	10.562845	False
77	Austnes	5892	5892_10	23.507	23.042810	2.268840	1.801630	43.22766	14.686510	37.53916	4100.5	57.60	6:44:48	11.765398	False
78	Austnes	5892	5892_11	23.484	10.434140	2.607750	1.055300	39.02823	16.594280	3.85184	1307.3	91.80	2:32:38	9.409518	False
79	Austnes	5892	5892_12	23.493	2.585640	3.032880	1.352440	36.19185	18.205470	7.13103	1191.8	94.40	1:53:10	18.115116	False
80	Austnes	5892	5892_13	23.486	10.933960	2.872280	1.392410	40.62447	18.844250	5.82650	267.7	60.60	0:42:32	6.650423	False
81	Austnes	5892	5892_14	23.491	9.212410	3.212310	1.460460	39.45597	19.501570	10.70620	1835.6	67.70	2:17:18	17.482325	True
82	Austnes	5892	5892_15	23.478	6.225940	3.124050	1.049020	40.20195	17.349660	6.71379	52.5	67.10	0:10:25	5.073437	False
83	Austnes	5892	5892_16	23.501	7.381240	2.639120	1.180210	44.31775	33.281050	6.53095	303.6	30.90	1:24:29	5.727200	False
84	Austnes	5892	5892_17	23.493	-10.179800	2.322050	2.708080	27.53766	15.701250	25.06155	16.3	0.00	0:14:09	1.279167	False
85	Austnes	5892	5892_18	23.503	-3.099160	5.042940	2.497990	36.71686	18.368910	25.77655	610.1	42.10	1:46:48	5.690796	False
86	Austnes	5892	5892_19	23.570	-3.371350	4.227730	2.267070	35.58275	18.855100	16.46665	308.2	42.60	0:28:26	10.804070	False
87	Austnes	5892	5892_20	23.504	1.384960	4.491310	1.872200	34.34413	18.840320	13.45039	981.0	41.50	2:24:45	4.539910	False
88	Austnes	5892	5892_21	21.046	-13.017350	2.473420	2.773710	36.42496	19.487300	10.87284	218.3	63.00	0:57:03	3.842690	True
89	Austnes	5892	5892_22	23.498	-2.296440	4.467660	2.172260	32.18809	19.045560	37.80778	1058.5	91.20	1:52:42	12.031579	True

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	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
90	Austnes	5892	5892_23	23.506	-1.238370	3.717130	1.435480	25.14669	20.930790	10.23608	1402.7	68.00	2:50:48	11.819306	True
91	Austnes	5892	5892_24	23.476	-0.323260	4.024550	1.669130	34.63026	15.743520	15.16257	1297.0	60.80	1:55:47	12.860316	False
92	Austnes	5892	5892_25	23.482	0.300180	3.377400	1.245630	29.97987	19.802530	6.81665	942.1	66.20	2:28:25	6.326777	False
93	Austnes	5892	5892_26	23.498	3.794210	1.363190	0.774740	40.55666	33.346060	14.89051	2829.4	63.90	4:25:54	11.109984	True
94	Austnes	6045	6045_1	23.502	-4.024330	2.866970	1.015010	23.17708	16.069213	7.78000	1260.2	63.00	2:37:20	NaN	False
95	Austnes	6045	6045_2	23.489	-10.469200	3.402380	1.293910	24.05560	19.652280	8.49000	503.2	61.40	0:48:59	NaN	False
96	Austnes	6045	6045_3	23.501	-8.647540	2.640430	0.967110	26.17539	19.027550	5.76768	1001.2	59.00	1:26:29	NaN	False
97	Austnes	6045	6045_4	23.480	2.146170	2.197840	0.999240	26.97472	18.296250	5.10170	1813.0	59.00	2:14:56	NaN	False
98	Austnes	6045	6045_5	23.489	-15.170400	3.865140	1.519790	23.86079	19.125290	8.80384	3999.2	51.90	5:16:32	NaN	False
99	Austnes	6045	6045_6	23.493	-14.038450	2.892130	1.220170	11.39831	16.267050	7.22589	1017.7	62.00	1:21:07	NaN	False
100	Austnes	6045	6045_7	22.631	-11.405140	2.945490	1.390500	15.09373	23.007700	10.15864	1019.7	55.60	1:36:09	NaN	False
101	Austnes	6045	6045_8	23.478	-10.869090	2.497520	1.225150	33.57691	16.240570	7.48541	2702.8	61.90	3:46:51	NaN	False
102	Austnes	6045	6045_9	23.483	-10.979310	1.700000	1.186750	10.93971	14.441060	12.40248	3335.0	58.40	3:11:44	NaN	False
103	Austnes	6045	6045_10	29.490	-3.133650	3.686790	1.459190	31.36678	18.955670	10.64849	341.6	58.00	0:57:59	NaN	False
104	Austnes	6045	6045_11	23.502	-12.484780	3.967770	1.429330	36.13909	25.404120	18.00423	2056.0	58.80	2:02:03	NaN	False
105	Austnes	6045	6045_12	23.496	-5.548610	4.006230	1.297460	19.46186	17.688280	7.50915	921.6	56.40	1:47:40	NaN	False
106	Austnes	6045	6045_13	23.479	16.410510	3.244340	2.581850	136.92592	54.759200	15.11842	500.6	32.70	0:31:44	NaN	False
107	Austnes	6045	6045_14	23.506	-1.759260	5.073100	1.906720	48.14970	22.935750	13.21582	2182.3	57.10	2:30:21	NaN	False
108	Austnes	6045	6045_15	29.493	-0.639880	4.595530	1.845840	29.29396	16.771990	19.55445	1682.8	57.50	1:53:45	NaN	False
109	Austnes	6045	6045_16	23.483	-2.388330	4.815540	1.240470	56.37435	47.080500	6.39046	986.4	45.70	1:14:15	NaN	False
110	Austnes	6045	6045_17	23.506	-2.300960	4.406720	1.531620	38.83983	34.225550	25.61954	111.2	46.10	0:15:53	NaN	False
111	Austnes	6045	6045_18	23.487	4.089020	4.164240	2.249810	51.24193	20.882090	14.18217	148.8	39.80	0:21:20	NaN	False
112	Austnes	6045	6045_19	23.495	3.088490	3.354100	2.565390	30.18365	15.969540	16.19742	201.0	46.10	0:25:04	NaN	False
113	Austnes	6045	6045_20	29.497	-6.971630	4.230130	2.230910	43.51517	22.206630	16.06788	82.0	43.70	0:16:49	NaN	False
114	Austnes	6045	6045_21	23.476	6.639520	4.458990	2.013100	48.20578	25.511730	14.55968	107.2	61.40	0:32:49	NaN	False
115	Austnes	6045	6045_22	23.492	-0.848970	3.607730	1.790010	58.61753	26.141120	14.72140	60.7	62.30	0:05:49	NaN	False
116	Austnes	6045	6045_23	23.496	-1.090050	3.065290	2.051840	51.23907	30.530630	24.10306	68.1	62.10	0:12:37	NaN	False
117	Austnes	6045	6045_24	23.506	-10.199800	3.294730	1.881640	13.06025	16.540630	14.20324	877.4	56.80	1:25:44	NaN	False
118	Austnes	6045	6045_25	29.497	-7.512990	4.143450	1.175800	26.83076	18.733220	8.22345	2917.5	55.90	2:43:48	NaN	False
119	Austnes	6045	6045_26	23.486	-13.210720	5.242730	1.620530	71.52769	38.218850	14.16854	1.7	61.60	0:03:52	NaN	False
120	Austnes	6203	6203_1	23.384	-9.652980	4.821030	1.418620	63.08564	39.311560	13.90191	2000.9	27.40	3:58:32	12.168728	False
121	Austnes	6203	6203_2	23.471	-9.762070	5.310870	1.090590	50.91589	45.129420	5.20831	494.9	48.00	1:38:28	4.252656	False
122	Austnes	6203	6203_3	23.497	-3.803360	5.707530	1.255950	17.99526	15.652360	10.91141	1067.9	81.30	1:53:45	7.599682	True
123	Austnes	6203	6203_4	23.489	-17.139860	4.843090	1.219940	15.40577	21.200770	6.80610	656.1	60.30	1:18:24	4.645226	False
124	Austnes	6203	6203_5	23.497	-20.483490	4.241460	1.184900	8.78658	18.036690	6.10231	2008.1	27.50	3:03:40	29.914523	False
125	Austnes	6203	6203_6	23.500	-15.812070	4.715670	1.010590	10.62032	19.963420	6.93028	1247.3	44.90	2:39:15	7.930537	False
126	Austnes	6203	6203_7	23.498	-14.639400	4.967470	1.060650	15.46994	21.580680	4.70967	2000.1	31.70	2:46:41	13.501416	True
127	Austnes	6203	6203_8	23.485	-11.423910	4.838680	1.095730	26.00880	22.627120	7.63649	2008.8	31.60	1:47:10	18.782841	False
128	Austnes	6203	6203_9	23.498	-21.100100	4.593820	1.377440	40.23068	28.198760	17.82220	2104.9	30.00	1:55:41	18.133442	False
129	Austnes	6203	6203_10	23.487	-14.416460	5.216460	1.290880	26.68781	21.757660	8.86696	2240.1	63.00	3:07:19	18.861587	True
130	Austnes	6203	6203_11	23.481	-19.202170	4.392620	1.339090	24.50290	19.469770	9.25971	2062.3	59.90	2:08:04	16.651375	False
131	Austnes	6203	6203_12	29.499	-12.334690	4.689990	1.174400	24.28419	14.989650	6.15209	2188.0	59.50	2:23:44	-15.892030	False
132	Austnes	6203	6203_13	23.490	-10.733700	4.917140	1.262530	28.06705	15.421200	7.46496	2406.1	34.30	2:33:26	14.380039	False
133	Austnes	6203	6203_14	29.494	-10.503120	3.284180	1.135950	6.38000	11.077830	22.41394	2016.6	57.70	3:49:55	8.448052	False
134	Austnes	6203	6203_15	23.511	-4.703980	4.946630	1.119880	33.12181	19.066530	7.58365	2027.7	36.70	1:34:56	20.575872	False

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	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
135	Austnes	6203	6203_16	23.488	-4.012020	4.210920	1.121580	24.92606	15.070370	7.64399	81.7	49.20	0:28:22	2.953216	False
136	Austnes	6203	6203_17	23.503	-5.289490	4.157190	0.975260	45.53546	14.914630	5.88287	150.8	41.60	0:21:19	7.004651	False
137	Austnes	6203	6203_18	23.483	-7.543060	4.298230	1.246080	27.93332	15.984290	8.38459	914.0	44.60	3:43:53	5.102127	False
138	Austnes	6203	6203_19	23.494	-7.016110	4.580930	1.044320	23.91517	18.235500	5.12072	613.4	54.50	2:23:27	3.285897	True
139	Austnes	6203	6203_20	23.484	-1.982600	3.780690	1.203030	35.77485	15.860340	5.68934	1.8	44.30	0:59:21	4.053030	False
140	Austnes	6203	6203_21	23.596	-5.756840	3.738420	1.363080	14.17129	11.483300	4.75906	1377.0	37.70	1:47:11	12.866979	True
141	Austnes	6203	6203_22	29.480	11.464120	2.803500	0.962100	45.02155	17.414230	5.19550	1463.3	62.40	1:50:37	9.648913	False
142	Austnes	6203	6203_23	23.476	-4.510360	4.007960	1.140140	20.08059	16.576530	7.13016	483.0	63.90	0:40:38	12.648704	False
143	Austnes	6203	6203_24	23.486	-5.654060	4.530490	1.318100	44.26567	20.170580	12.63895	1421.6	62.60	2:36:45	6.618285	False
144	Austnes	6203	6203_25	29.476	-5.511590	4.529710	1.189260	85.60776	33.623750	9.10539	2476.0	52.30	3:15:47	16.503984	True
145	Austnes	6203	6203_26	23.487	-6.839770	4.812620	1.027710	28.52435	28.615610	8.74335	272.4	59.90	1:08:03	4.527532	False
146	Austnes	6203	6203_27	23.497	-17.676000	4.893270	1.240180	21.45205	20.149820	6.45596	2208.5	41.50	3:17:59	9.940787	True
147	Austnes	6203	6203_28	23.506	-12.205230	4.933210	1.398160	26.75976	26.661000	7.57368	2250.1	60.10	3:39:41	-17.523598	False
148	Austnes	6203	6203_29	23.481	-4.977480	5.107890	1.093900	30.46654	23.781820	5.09380	2132.2	30.20	3:20:31	10.609040	True
149	Austnes	6203	6203_30	23.502	-11.637380	4.938260	1.157870	18.11525	18.780750	5.19328	958.4	60.10	1:12:30	9.735152	False
150	Longva	23545	23545_1	23.681	-8.536670	10.017900	1.043400	36.82570	29.464150	5.98208	1416.7	66.70	5:22:43	4.259232	False
151	Longva	23545	23545_2	23.684	-14.160740	7.163320	1.020920	14.74458	26.659780	6.25509	2442.3	72.00	3:53:12	8.821911	False
152	Longva	23545	23545_3	23.705	-8.780510	13.732450	1.174650	27.93597	42.645600	6.70456	1092.7	59.20	2:27:02	6.392838	True
153	Longva	23545	23545_4	23.680	-8.282650	9.802130	0.976330	33.92083	32.309080	5.98969	4114.1	62.80	6:18:56	7.321801	False
154	Longva	23545	23545_5	23.685	-13.982150	8.844380	1.176130	37.18347	36.068620	6.64603	399.8	64.30	1:29:12	5.357117	False
155	Longva	23545	23545_6	23.701	-20.538660	4.685770	0.724000	36.07736	32.650090	8.22020	161.3	61.40	0:31:33	4.936649	False
156	Longva	23545	23545_7	23.547	-18.280620	5.781970	1.495600	44.94639	33.795720	18.65103	74.6	60.70	0:25:56	2.508917	False
157	Longva	23545	23545_8	23.689	-19.806980	5.960040	1.030130	6.53611	16.184340	10.87789	5722.3	68.00	6:15:00	14.882697	True
158	Longva	23545	23545_9	23.677	-20.322240	6.540040	1.878640	35.73167	48.797000	21.96358	658.6	97.30	1:19:24	9.315744	False
159	Longva	23545	23545_10	23.702	-13.861540	5.348790	0.968250	39.54653	21.007700	11.51166	528.7	62.20	1:32:49	8.031667	False
160	Longva	23545	23545_11	23.694	-15.756820	5.013870	0.876960	5.69611	14.787560	7.20594	742.7	38.50	2:06:28	9.702153	False
161	Longva	23545	23545_12	23.692	-14.965800	5.822990	1.126580	34.61111	32.913950	8.01559	266.3	61.80	1:04:02	2.944255	False
162	Longva	23545	23545_13	23.674	-13.428480	5.337840	0.670000	12.35458	23.886130	6.70808	2189.5	65.50	3:42:49	10.693892	True
163	Longva	23545	23545_14	23.689	-23.202450	5.167450	1.038030	46.94375	40.023550	6.82126	3788.9	61.20	6:45:00	11.939213	True
164	Longva	23545	23545_15	29.676	-10.935350	7.795630	1.129890	72.09778	33.000100	18.78497	1689.2	65.00	1:58:35	14.374945	False
165	Longva	23545	23545_16	23.595	-18.798260	4.378360	1.089780	11.95639	16.633650	8.05579	1722.1	61.70	4:09:34	6.848357	False
166	Longva	23545	23545_17	23.604	-18.967330	4.759580	0.954440	98.21667	68.358960	7.45577	520.4	61.50	1:44:52	4.976115	False
167	Longva	23545	23545_18	23.686	-24.105050	4.330300	0.997840	3.79416	11.353840	6.67193	2469.6	65.10	6:27:30	6.048387	False
168	Longva	23545	23545_19	23.702	-24.811930	4.521930	0.847430	12.30806	19.930760	6.21563	3.8	70.50	0:11:40	0.729167	False
169	Longva	23545	23545_20	11.955	-5.774050	8.123200	1.440710	31.81028	25.056340	6.46365	1.9	61.70	0:13:48	0.882353	False
170	Longva	23545	23545_21	23.704	-14.776010	7.461650	1.192140	25.60097	22.779340	7.12596	1.5	59.80	0:02:59	0.080000	False
171	Longva	23545	23545_22	23.705	-14.806530	7.339430	1.153910	28.49694	26.086540	6.87106	517.1	65.60	1:01:34	5.535484	False
172	Longva	23545	23545_23	29.581	-15.276950	7.442090	1.144230	24.14597	23.115030	7.84058	1364.6	67.20	2:05:52	10.467275	True
173	Longva	23545	23545_24	23.603	-11.444470	8.291170	1.127450	33.75069	28.302070	6.28043	534.7	67.50	1:22:51	7.479642	False
174	Longva	23545	23545_25	23.603	-10.117920	9.470290	1.061890	38.70056	29.426870	5.97883	1422.3	63.00	2:03:37	6.977168	False
175	Longva	23545	23545_26	23.470	-12.547750	9.733510	0.889100	7.07750	22.234300	10.25653	319.4	60.40	0:56:56	5.322112	False
176	Longva	23545	23545_27	23.589	-12.711780	9.296410	1.089600	30.78986	29.379420	9.03218	171.1	79.40	1:27:02	3.076093	False
177	Longva	23545	23545_28	23.685	-14.085500	4.434620	0.919200	62.24875	36.274970	14.24656	3962.0	63.90	8:15:54	8.971313	True
178	Longva	23528	23528_1	23.573	-9.815910	6.959400	2.153750	63.22292	60.646620	20.49989	794.5	72.30	1:15:42	10.469451	False
179	Longva	23528	23528_2	23.604	-10.595210	5.344780	1.027100	38.66667	27.274800	6.82830	2053.7	64.80	2:19:20	13.938850	False

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	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
180	Longva	23528	23528_3	23.578	-21.453680	5.208800	1.130580	10.41389	20.242150	8.90981	1983.2	62.70	3:15:40	10.533866	False
181	Longva	23528	23528_4	23.584	-20.813970	5.649810	0.736780	14.53514	16.141490	7.40450	440.1	66.80	1:31:11	5.003877	False
182	Longva	23528	23528_5	23.599	-25.532720	5.742800	0.707850	2.63444	20.491720	9.15287	73.6	63.20	0:20:43	3.417460	False
183	Longva	23528	23528_6	23.596	-24.445400	4.978400	1.047750	2.68180	13.922630	6.09289	2034.4	56.00	5:53:58	7.315081	True
184	Longva	23528	23528_7	23.580	-21.121350	5.219570	0.723230	8.94361	23.917530	8.04432	2.9	62.30	0:05:44	0.369444	False
185	Longva	23528	23528_8	23.585	-16.634720	5.146130	1.024850	12.81111	26.768690	5.78107	2954.4	65.40	6:24:18	7.610650	True
186	Longva	23528	23528_9	29.603	-16.418890	5.059970	0.911220	8.66000	17.717170	7.60150	3066.7	55.00	7:02:30	5.782987	True
187	Longva	23528	23528_10	23.597	-18.956720	4.906620	1.024490	16.86556	16.670110	7.51869	154.2	47.40	0:49:52	3.222395	False
188	Longva	23528	23528_11	23.581	-21.612160	4.766150	0.895940	10.96222	15.996020	6.17374	155.4	48.80	0:58:01	2.541989	False
189	Longva	23528	23528_12	23.578	-17.631640	4.579900	0.836820	5.58069	18.132150	9.01495	587.6	40.90	1:35:26	6.312977	False
190	Longva	23528	23528_13	23.604	-21.651070	4.839480	1.058290	7.62889	12.941940	8.55054	200.8	44.60	1:00:20	3.118277	False
191	Longva	23528	23528_14	29.602	-18.688570	4.828960	1.072070	11.78097	15.250300	7.27487	183.8	46.80	1:43:57	3.059956	False
192	Longva	23528	23528_15	23.579	-20.841740	5.097840	0.976430	7.10833	17.994600	6.15589	577.1	57.80	2:50:52	3.806113	True
193	Longva	23528	23528_16	23.595	-23.974020	5.398930	0.858850	3.13250	18.915980	6.74338	801.0	60.10	4:02:18	4.561211	False
194	Longva	23528	23528_17	23.583	-30.524230	5.046650	1.204510	2.44389	19.747650	7.95772	886.3	49.90	1:39:28	9.341551	True
195	Longva	23528	23528_18	23.600	-28.067540	5.532370	1.568540	11.60444	19.035950	8.06793	3184.7	57.50	3:55:15	14.978483	False
196	Longva	23528	23528_19	23.596	-21.536410	6.024630	1.162590	5.44278	23.073030	6.08074	4041.6	69.20	5:03:40	11.161489	True
197	Longva	23528	23528_20	29.605	-18.091920	5.215880	1.236590	20.82125	20.524220	6.33467	3106.4	63.40	8:08:39	7.644103	False
198	Longva	23528	23528_21	23.579	-20.162630	6.704590	1.401960	68.34208	50.528760	15.06599	1025.7	67.20	2:51:24	4.921902	False
199	Longva	23528	23528_22	29.578	-13.994950	5.164250	1.618250	32.18972	43.560200	18.97783	1.9	67.20	0:04:41	0.390000	False
200	Longva	23577	23577_1	23.701	-18.598865	4.234984	2.023945	49.83403	23.618480	40.87172	1246.7	78.70	4:58:04	3.875660	False
201	Longva	23577	23577_2	23.687	-17.220235	4.597757	1.008998	54.49611	22.429310	5.96726	135.7	46.93	0:26:11	5.196835	False
202	Longva	23577	23577_3	23.678	-16.749976	5.157668	1.274978	62.51389	32.761620	6.90900	2.5	59.03	0:04:38	0.262069	False
203	Longva	23577	23577_4	23.693	-16.791657	4.886485	1.430363	48.05583	24.062760	7.69016	2528.9	63.70	3:35:58	6.681766	False
204	Longva	23577	23577_5	23.685	-14.351723	6.173974	1.275234	38.56695	23.898460	16.40434	1675.3	63.03	5:11:34	4.302034	False
205	Longva	23577	23577_6	23.382	-19.305649	7.170860	1.356799	66.76667	31.964460	11.59858	2484.7	85.53	5:36:19	7.481066	True
206	Longva	23577	23577_7	14.807	-2.855181	7.985738	2.129549	72.14334	35.351160	24.03564	2349.6	35.63	4:08:18	9.804116	False
207	Longva	23577	23577_8	23.700	-18.222106	6.851452	1.052838	95.48070	34.968420	11.67425	777.9	65.43	2:40:23	7.711277	False
208	Longva	23577	23577_9	23.676	-18.171493	9.090194	1.452091	96.55347	51.344670	13.44182	144.7	62.87	0:39:11	3.514407	False
209	Longva	23577	23577_10	24.767	-6.640865	11.403110	1.366550	43.64625	44.299480	8.88298	5.6	63.73	0:09:24	0.432759	False
210	Longva	23577	23577_11	23.694	-12.776453	10.314752	1.211348	69.32805	36.253130	8.98936	659.3	46.87	1:00:03	7.909883	True
211	Longva	23577	23577_12	23.676	-7.293715	10.777862	1.305850	39.57084	35.242580	10.65086	1856.2	59.80	4:06:35	7.004298	False
212	Longva	23577	23577_13	23.693	-15.695071	7.034747	2.175067	40.09861	21.016720	17.60058	11.2	1.60	0:41:42	5.321429	False
213	Longva	23577	23577_14	29.703	-3.016862	10.506119	1.245392	63.90208	31.913250	9.31802	2014.0	41.10	6:20:12	5.771973	False
214	Longva	23577	23577_15	23.685	2.124140	8.137018	1.993168	68.38611	43.483270	11.47615	262.9	32.50	2:07:01	4.213092	False
215	Longva	23577	23577_16	23.694	2.584414	11.023107	3.716570	84.16333	46.987360	33.09741	1541.1	35.53	3:40:52	9.139046	False
216	Longva	23577	23577_17	23.697	8.535046	11.446650	2.201470	83.21069	43.401660	14.27032	1727.0	76.10	3:50:02	8.696784	True
217	Longva	23577	23577_18	23.702	7.472612	11.820684	1.769986	85.73000	48.874590	17.88178	324.3	66.03	1:09:09	4.504327	False
218	Longva	23577	23577_19	23.688	8.319242	6.697714	2.006440	62.42903	29.939310	17.68299	166.3	69.40	0:37:23	4.120889	False
219	Longva	23577	23577_20	23.685	-14.223055	7.862007	2.846925	63.05042	43.675390	16.42023	174.2	72.00	0:33:10	4.724500	False
220	Longva	23577	23577_21	23.678	-15.223432	7.078260	2.032137	74.03056	77.091090	28.45028	557.3	60.20	0:55:47	9.600298	False
221	Longva	23577	23577_22	23.685	-14.781218	5.803354	2.194861	51.09028	29.179210	12.97740	261.7	68.93	1:07:41	3.735381	False
222	Longva	23577	23577_23	23.706	-18.911619	5.154168	1.429841	36.47806	18.781900	9.19395	330.0	66.97	0:44:52	7.192593	False
223	Longva	23577	23577_24	29.699	-18.094701	5.391468	1.670123	31.35514	41.612530	22.95634	228.7	61.40	0:27:14	8.605625	False
224	Longva	23577	23577_25	23.703	-20.160506	7.404583	1.802270	50.89889	50.233080	14.61450	1551.1	73.97	2:49:12	10.203905	True

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	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
225	Longva	23577	23577_26	23.701	-24.429502	4.924856	1.360447	35.73653	20.943800	14.58837	705.8	66.20	1:03:50	10.979427	False
226	Longva	23577	23577_27	23.690	-20.980824	4.748416	1.116570	28.19069	20.544320	7.77307	269.1	63.37	2:07:36	2.978269	False
227	Longva	23577	23577_28	29.680	-17.521741	4.639645	1.334847	54.06236	25.326540	8.29999	325.7	37.10	1:52:54	1.877343	False
228	Longva	23577	23577_29	23.680	-20.811252	5.592520	1.155208	50.15333	27.328210	6.23151	11.7	60.00	0:11:24	0.835391	False
229	Longva	23577	23577_30	23.701	-25.562257	7.035185	2.122200	62.82459	93.696420	21.94902	3125.3	64.73	4:27:03	10.942311	True
230	Longva	23577	23577_31	23.699	-3.509429	15.384576	1.292914	47.00264	41.926010	7.53159	1051.1	63.83	1:46:24	9.171140	False
231	Longva	23654	23654_1	23.598	-5.377500	9.764210	1.341670	36.73820	25.809690	7.60980	150.2	66.10	0:32:00	4.435751	False
232	Longva	23654	23654_2	23.583	-11.559550	3.720070	1.277680	15.62667	17.620240	6.52654	39.7	59.50	0:15:11	3.193548	False
233	Longva	23654	23654_3	23.605	-20.320440	4.303400	1.132570	5.08028	14.509210	6.19017	0.0	73.50	0:41:51	3.301852	False
234	Longva	23654	23654_4	23.584	-22.823770	4.026610	1.097640	28.23195	24.253880	6.80613	499.2	63.50	0:59:50	8.388889	False
235	Longva	23654	23654_5	23.576	-15.154530	4.239390	1.243560	26.59514	18.218070	10.54444	851.6	63.80	0:58:05	14.526149	True
236	Longva	23654	23654_6	23.606	-22.709640	3.976670	1.089960	11.66292	12.221560	6.67741	262.2	61.90	0:42:44	6.109728	False
237	Longva	23654	23654_7	23.603	-13.614510	3.695400	1.370030	20.61056	13.776640	7.21412	216.9	60.90	0:18:32	11.960714	False
238	Longva	23654	23654_9	23.582	-7.780320	4.328770	1.142450	41.18041	17.043620	7.99914	231.0	61.60	0:30:45	7.555376	False
239	Longva	23654	23654_10	23.797	-21.738940	5.311550	1.278320	19.12639	29.319170	10.12199	2430.4	64.30	2:51:37	16.824500	True
240	Longva	23654	23654_11	23.604	-18.056880	5.436390	1.144190	37.71486	55.713450	7.76805	1612.9	64.60	2:42:45	12.675547	False
241	Longva	23654	23654_12	23.592	-10.239640	5.450030	1.272670	56.66764	33.260710	17.79872	118.7	60.60	1:31:42	7.592967	True
242	Longva	23654	23654_13	23.608	-11.861140	5.607960	1.300510	25.75292	22.968810	8.49886	901.9	65.60	1:42:53	9.249317	False
243	Longva	23654	23654_14	23.594	-7.353640	6.206120	1.625020	51.42111	58.483110	36.13855	189.3	63.00	0:14:39	12.815730	False
244	Longva	23654	23654_15	23.599	-8.327960	5.666560	1.413880	21.29917	26.104680	6.62185	672.0	60.50	1:04:50	10.984741	False
245	Longva	23654	23654_16	23.598	7.094400	12.578150	1.313500	58.75653	35.237550	11.01000	1211.2	61.70	1:47:03	11.213841	False
246	Longva	23654	23654_17	23.600	-12.081440	6.560780	2.598520	100.34722	48.852390	25.66486	2686.0	62.80	2:24:56	17.303648	False
247	Longva	23654	23654_19	23.584	-6.781780	7.031070	1.771630	85.95958	66.838540	23.45008	593.2	61.20	1:16:57	7.633117	False
248	Longva	23654	23654_21	12.504	-3.130890	7.280790	3.668570	48.86944	26.645930	23.13129	2353.9	63.40	5:35:11	8.293866	True
249	Longva	23654	23654_22	23.592	-0.249780	9.678410	2.473250	64.96528	39.519740	27.17802	117.1	61.40	0:47:14	2.395931	False
250	Longva	23654	23654_23	23.599	6.789130	14.143500	2.086600	71.23000	61.087920	21.50053	31.7	61.10	0:21:31	1.386923	False
251	Longva	23654	23654_24	23.579	3.520680	12.875460	1.546980	58.64180	58.145140	7.09880	0.9	62.30	0:07:04	0.000000	False
252	Longva	23654	23654_25	23.580	-0.891640	11.686980	1.453220	50.10014	38.215180	11.60200	1.4	61.50	0:14:17	0.172414	False
253	Longva	23654	23654_26	23.575	-4.356840	6.494160	1.682860	49.58750	22.291630	13.87884	1.4	68.70	0:09:23	0.000000	False
254	Longva	23654	23654_27	23.601	-10.955160	7.674030	1.488400	50.94375	38.845470	12.49230	3746.1	61.90	5:43:09	15.858969	True
255	Longva	23654	23654_28	23.613	-9.375130	8.001370	2.245670	138.01402	60.893880	16.77848	1130.6	63.00	1:11:45	15.746172	False
256	Longva	23654	23654_30	23.591	-5.285930	10.585380	1.510940	35.58458	34.377650	11.00769	1228.8	65.10	2:31:14	6.144329	False
257	Longva	23654	23654_31	23.581	-15.308260	10.136410	1.787220	42.26292	37.483950	15.84329	56.0	60.00	0:28:51	1.524138	False
258	Longva	23654	23654_32	23.585	-29.836980	6.245420	1.199510	42.70556	27.866280	6.86274	895.0	63.50	1:32:19	9.626173	False
259	Longva	23654	23654_33	23.602	-35.857260	5.165030	1.147730	14.62278	23.411870	6.94573	1555.6	63.60	2:53:43	6.575294	True
260	Longva	23654	23654_34	23.595	-42.161630	4.473770	1.146660	3.49195	14.837760	8.80753	481.6	59.90	1:08:31	6.876214	True
261	Longva	23654	23654_36	23.581	-13.721400	4.201580	1.110880	24.18597	14.841840	6.03554	114.8	59.80	0:19:22	3.826344	False
262	Longva	23654	23654_37	15.429	-23.869610	4.615860	2.951660	34.30361	19.421010	23.25114	41.0	64.50	0:10:12	3.957143	False
263	Longva	23654	23654_39	23.574	-43.103010	7.082310	1.288060	18.70236	28.184050	6.77657	431.9	58.20	0:43:22	9.979310	False
264	Longva	23654	23654_40	23.590	-13.316930	6.701300	1.323090	43.31639	33.057740	5.93233	2417.5	59.90	3:17:01	12.383026	False
265	Longva	23654	23654_41	21.044	-11.613540	6.728040	3.023740	58.75639	21.074660	34.30903	3189.8	61.70	2:58:32	17.467245	False
266	Longva	23654	23654_42	23.591	-6.553400	4.914360	1.530270	28.38458	14.515680	7.32549	1522.3	62.10	3:10:48	5.387081	False
267	Longva	23654	23654_43	23.592	-17.152530	4.713990	1.274480	12.72014	17.782160	6.27640	283.4	60.10	0:36:36	7.645249	False
268	Longva	23654	23654_44	23.588	-22.688660	4.737970	1.300900	-2.36709	13.842690	6.13571	133.9	59.60	0:14:51	8.806667	False
269	Longva	23498	23498_1	23.696	-13.495660	5.246390	1.453790	48.75195	31.064730	30.49937	1833.1	61.60	2:57:20	9.159182	True

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	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
270	Longva	23498	23498_2	23.684	-21.175860	4.755440	2.543230	64.51069	30.562220	26.51306	593.1	61.00	0:52:49	10.631068	False
271	Longva	23498	23498_3	23.677	-18.801330	5.097590	1.651240	42.57764	28.221710	17.47945	654.7	61.50	16:10:06	8.453137	True
272	Longva	23498	23498_5	23.673	-11.893470	4.670360	1.479660	23.52570	18.950770	28.77197	594.3	60.20	1:53:16	7.463789	True
273	Longva	23498	23498_6	23.674	-7.802690	5.924820	1.692230	49.22320	65.061170	17.20081	544.0	61.50	1:57:58	10.569090	False
274	Longva	23498	23498_7	23.680	-8.960220	5.259100	0.934400	30.02639	23.509830	8.06864	2162.1	99.60	5:50:30	6.325698	False
275	Longva	23498	23498_8	23.703	-13.425190	6.872560	1.013330	31.77056	16.704630	6.61998	9.8	60.80	0:08:48	0.924074	False
276	Longva	23498	23498_9	23.720	-5.398770	7.194110	1.103410	65.44180	31.023400	8.91488	1758.9	65.00	3:48:00	7.549598	False
277	Longva	23498	23498_10	24.028	-6.553320	7.683570	1.486200	40.99222	22.501320	18.79848	1634.7	94.40	5:42:49	4.996336	False
278	Longva	23498	23498_11	23.702	-17.841480	6.944130	1.127900	42.11389	22.052300	9.75493	536.3	99.60	2:21:53	6.457195	False
279	Longva	23498	23498_12	17.498	-13.851300	6.820270	3.474480	35.03680	19.333400	19.93071	10857.9	67.00	19:58:38	10.566391	False
280	Longva	23498	23498_13	29.393	-12.421130	8.820340	1.743440	49.68055	31.034800	14.04293	9869.0	65.50	19:43:34	7.096947	False
281	Longva	23498	23498_14	23.684	-19.166220	7.697330	2.733630	112.00409	63.328000	26.56109	2039.1	71.60	2:37:21	12.887394	True
282	Longva	23498	23498_15	23.694	-22.584230	6.953450	1.900400	57.95042	29.828960	29.62827	1971.6	72.90	3:20:37	9.879634	True
283	Longva	23498	23498_16	23.683	-21.531550	7.999980	1.477240	73.42097	42.425110	25.94655	495.1	63.10	2:22:54	3.701709	False
284	Longva	23498	23498_17	23.698	-14.852530	7.628460	1.545090	155.86778	90.194100	14.69505	109.2	58.00	0:36:29	2.758182	False
285	Longva	23498	23498_18	23.678	-28.607470	7.272020	1.474820	23.36000	32.528620	14.02043	1648.3	57.20	3:50:48	9.563233	False
286	Longva	23498	23498_19	23.676	-20.959730	6.215390	1.000970	17.19528	18.476050	6.10068	2145.2	89.30	6:27:55	4.729886	False
287	Longva	23498	23498_20	23.692	-24.075860	6.121430	1.009740	10.49653	18.080150	6.36269	152.6	61.20	1:25:20	1.838791	False
288	Longva	23498	23498_21	23.702	-28.205810	6.244990	1.094390	-1.61694	24.212070	6.22083	171.3	63.70	0:27:25	6.136145	True
289	Longva	23498	23498_22	23.675	-22.340970	5.014330	1.184540	41.70820	31.884500	6.93000	106.7	80.90	0:25:42	4.296154	False
290	Longva	23498	23498_23	23.699	-11.203930	4.475290	1.677560	30.65305	17.915720	19.61083	483.0	61.30	1:38:04	6.579908	False
291	Longva	23498	23498_24	23.699	-11.174420	5.001940	1.530460	50.02097	19.551620	26.03443	0.7	63.30	0:03:50	0.454167	False
292	Longva	23498	23498_25	23.678	-11.332420	4.941430	1.907320	61.05250	25.731560	24.87651	1.5	60.20	0:04:18	0.618519	False
293	Longva	23498	23498_26	15.155	-3.992010	6.848450	2.258380	46.03875	26.003360	26.65509	13016.9	64.50	14:45:19	NaN	False
294	Longva	23498	23498_27	23.684	-14.599790	7.187010	1.886890	30.30403	33.112180	21.49131	6829.3	61.80	8:56:22	NaN	False
295	Longva	23498	23498_28	19.986	-3.038390	7.051650	1.746660	53.06681	22.186590	38.18222	3682.1	62.70	3:14:20	NaN	False
296	Longva	23498	23498_29	23.701	-13.609280	5.670630	1.694710	55.70792	20.688230	9.67894	17.7	66.10	0:07:40	NaN	False
297	Longva	23498	23498_30	23.701	-14.994310	5.027940	1.116690	50.96875	22.646380	22.80903	428.0	56.00	0:42:24	NaN	False
298	Longva	23498	23498_31	23.413	-15.401870	6.444240	1.343680	38.13167	44.346790	12.08567	2824.0	60.00	3:40:46	NaN	False
299	Longva	23498	23498_32	19.995	-10.771750	8.770430	1.495250	105.31236	41.417360	8.58317	364.6	31.70	0:28:26	NaN	False
300	Longva	23615	23615_1	23.593	1.199060	5.265360	1.180730	54.47653	58.376600	8.62893	1576.2	68.70	3:11:08	5.916370	False
301	Longva	23615	23615_2	23.602	17.576730	2.821840	1.128190	54.71070	25.486120	10.47774	1235.4	63.00	1:36:09	13.260127	True
302	Longva	23615	23615_3	23.602	1.733100	4.990990	1.064920	33.19667	25.274210	6.63499	1224.6	64.40	1:42:22	12.575627	True
303	Longva	23615	23615_4	23.592	3.282970	5.940120	1.471320	63.18222	37.961650	13.96838	706.8	60.60	1:57:58	5.921469	False
304	Longva	23615	23615_5	23.591	-5.684540	5.180710	1.133540	35.11319	13.964860	7.11666	1458.3	63.90	3:32:08	8.309658	False
305	Longva	23615	23615_6	23.579	-4.118410	4.776980	1.175090	26.57139	17.100840	6.19806	232.5	68.50	1:04:12	5.909535	False
306	Longva	23615	23615_7	23.589	-12.910890	6.066500	0.688000	38.75055	19.180280	6.19155	1521.7	67.80	4:06:55	13.248386	False
307	Longva	23615	23615_8	23.593	-14.105590	6.180810	0.907390	48.53750	21.349730	5.85116	3508.1	64.10	4:33:02	11.533127	False
308	Longva	23615	23615_9	23.603	-4.499690	6.206390	2.086510	80.44833	20.790160	26.15937	1138.6	62.90	1:40:31	11.569559	True
309	Longva	23615	23615_10	23.592	-18.635460	6.641230	1.176300	49.23944	21.853040	13.34505	202.7	67.50	0:40:03	4.939419	False
310	Longva	23615	23615_11	23.584	-17.216700	6.301390	1.264530	56.50069	29.987510	12.69702	4.1	66.50	0:03:41	2.620000	False
311	Longva	23615	23615_12	23.609	-18.527200	6.494050	1.012170	42.54945	21.331150	7.61757	2097.7	99.60	4:11:30	8.259531	True
312	Longva	23615	23615_13	23.572	-18.175490	6.893120	0.983010	60.08333	23.448240	6.43540	108.7	64.80	0:38:20	5.741295	False
313	Longva	23615	23615_14	23.581	-9.892430	6.572910	1.057630	65.18833	32.527940	6.10089	12.7	59.70	0:10:10	1.069643	False
314	Longva	23615	23615_15	23.598	-9.706390	7.272300	1.906220	73.49097	46.580930	19.33557	2215.0	60.70	3:38:52	14.754928	True

Continued on next page

	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
315	Longva	23615	23615_16	23.594	-3.764440	7.060580	1.053630	63.97653	32.965990	10.53508	886.5	64.90	2:44:50	7.509826	False
316	Longva	23615	23615_17	21.317	-9.705820	9.393570	2.291530	80.43111	76.118590	30.44518	2.4	66.00	0:12:21	0.166667	False
317	Longva	23615	23615_18	23.587	-1.287010	10.308890	1.320090	55.64250	39.460800	31.80842	718.8	60.60	1:18:00	9.137740	False
318	Longva	23615	23615_19	23.591	1.620110	11.072370	1.679590	81.98000	48.936680	41.43594	3.5	65.00	0:10:19	0.209524	False
319	Longva	23615	23615_20	23.585	1.545600	11.099600	1.535400	57.91097	32.333870	31.85756	389.1	70.90	0:42:14	9.053543	False
320	Longva	23615	23615_21	23.586	-1.117280	11.831400	2.184460	43.18625	44.347040	36.30793	502.2	59.90	2:20:11	4.468913	False
321	Longva	23615	23615_22	23.581	6.274920	12.217420	1.355320	125.16889	82.191410	8.07866	903.9	59.80	3:16:10	6.865390	False
322	Longva	23615	23615_23	23.588	5.739180	11.915090	1.618690	61.95764	53.438810	12.29576	24.1	60.00	0:20:34	0.708000	False
323	Longva	23615	23615_24	23.583	4.810090	12.591570	1.871680	109.40056	60.498730	39.09293	558.7	59.90	0:15:28	0.095745	False
324	Longva	23615	23615_25	23.592	2.181680	11.270770	1.247690	59.81972	35.975190	11.04279	831.7	64.70	1:14:06	10.202986	False
325	Longva	23615	23615_27	23.586	-1.339780	8.335930	4.021940	45.66361	27.490800	38.65588	393.9	62.40	2:59:24	7.425150	False
326	Longva	23615	23615_28	23.590	1.217870	8.342960	2.336730	39.91167	40.383800	22.22141	1309.7	62.10	3:44:55	8.480162	True
327	Longva	23615	23615_29	23.603	-0.882610	8.181270	2.509870	66.39403	77.066600	39.35574	1876.1	67.00	3:19:50	10.352430	False
328	Longva	23615	23615_30	23.579	1.934000	10.930360	2.038350	61.16237	39.340000	34.11737	157.6	61.10	0:44:52	3.247037	False
329	Longva	23615	23615_31	23.584	-1.826790	7.784850	2.077100	68.33084	38.869440	30.76461	334.3	60.80	2:10:20	2.474544	False
330	Longva	23615	23615_32	23.594	4.070960	10.678760	1.180960	76.23930	52.291310	18.20951	1.3	63.10	0:09:33	0.494915	False
331	Longva	23615	23615_33	23.585	0.140290	10.894080	1.101460	56.66861	40.173820	14.75931	1825.8	57.80	4:50:29	10.030990	True
332	Longva	23615	23615_34	23.586	-3.255250	10.602560	1.781000	67.12556	36.367450	19.19452	788.0	62.20	2:07:38	10.443014	True
333	Longva	23615	23615_35	23.598	-3.105370	10.150750	2.536950	85.34472	32.902810	17.94224	635.0	61.20	0:53:00	11.992163	False
334	Longva	23615	23615_36	23.584	-6.145560	6.423960	2.174240	37.98972	27.623230	28.51236	1563.1	63.50	1:09:52	22.812975	False
335	Longva	23615	23615_37	23.581	-1.297430	6.704140	1.104720	42.08486	38.954070	6.32936	1076.5	63.90	1:15:01	15.335841	False
336	Longva	23615	23615_38	23.587	2.173050	7.371930	1.686100	72.94389	47.147330	20.75430	1808.2	63.60	2:15:16	13.637586	True
337	Longva	23615	23615_39	23.594	-9.574980	7.105020	1.372110	59.91334	74.249880	8.28789	590.1	73.50	1:58:00	5.449902	False
338	Longva	23615	23615_40	23.602	-2.053740	10.902160	2.625300	71.29236	82.532980	34.26441	945.9	64.10	1:29:15	10.588806	True
339	Longva	23707	23707_1	23.678	-21.763010	3.612230	1.003080	4.21778	24.800570	6.01660	826.1	63.60	0:51:39	13.917222	True
340	Longva	23707	23707_2	23.696	-31.443060	3.415610	1.060570	3.69861	17.329070	5.99834	218.9	63.90	0:22:32	9.397794	False
341	Longva	23707	23707_4	23.683	-34.224940	3.841850	1.491300	6.95958	12.560470	6.29324	196.8	64.10	0:19:32	9.688983	False
342	Longva	23707	23707_6	23.694	-35.126300	5.213330	1.138450	-1.16236	19.128220	7.58905	158.3	63.80	0:17:42	8.583333	False
343	Longva	23707	23707_7	21.026	-32.638360	5.961120	1.572720	63.14056	35.134530	24.71750	413.5	64.60	2:16:44	9.929461	False
344	Longva	23707	23707_8	23.679	-37.590720	6.241610	0.774500	9.59209	20.469140	9.22576	117.5	59.50	2:17:53	7.143299	False
345	Longva	23707	23707_9	23.686	-31.028020	6.734970	0.803060	12.68833	19.936930	8.13041	203.4	59.20	0:26:20	7.652830	False
346	Longva	23707	23707_10	23.705	-26.212230	6.534460	0.987540	60.33625	30.727940	10.67328	141.3	63.30	0:18:08	8.495960	False
347	Longva	23707	23707_12	23.703	-23.370950	6.935620	1.095640	37.53903	32.397570	7.79186	472.7	68.20	0:37:58	12.356332	False
348	Longva	23707	23707_14	23.686	-16.067640	7.184670	1.169020	50.58264	39.359960	9.75005	974.0	63.50	1:24:50	12.910573	False
349	Longva	23707	23707_16	23.702	-21.354840	7.645330	2.221530	59.17292	37.877470	23.15191	4242.2	72.50	5:42:17	15.676090	True
350	Longva	23707	23707_17	23.689	-22.716430	7.179260	2.047200	12.57667	22.595640	22.59682	10.2	63.30	0:05:03	1.946875	False
351	Longva	23707	23707_18	23.692	-14.677980	6.653210	1.289500	18.15556	21.962600	9.57363	2111.9	63.50	1:46:21	21.353235	False
352	Longva	23707	23707_19	23.675	-19.498580	6.992070	2.325930	45.03153	53.099730	22.17895	1540.2	69.70	1:48:10	13.700021	False
353	Longva	23707	23707_20	23.688	-19.743400	6.807440	1.887370	65.53042	52.849900	18.60124	505.6	62.10	8:28:18	15.598090	True
354	Longva	23707	23707_21	23.698	-16.964400	6.364160	1.598670	10.05944	25.974230	10.96714	147.7	59.80	0:22:29	6.495588	False
355	Longva	23707	23707_22	23.679	-16.776260	6.959710	1.003080	143.15556	84.562110	6.91224	559.2	61.80	1:13:52	7.578829	False
356	Longva	23707	23707_23	23.673	-23.105300	6.505230	1.203720	70.29958	44.946420	8.10586	22.1	60.50	0:20:45	0.967460	False
357	Longva	23707	23707_24	23.678	-31.782730	6.446680	1.060050	10.02806	29.043620	6.26052	176.6	60.20	0:24:01	7.236552	False
358	Longva	23707	23707_25	23.707	-31.054150	6.145660	1.495420	7.46083	23.080440	10.38883	7.6	60.40	0:05:05	1.331250	False
359	Longva	23707	23707_26	23.698	-25.963820	5.603740	1.090780	5.90139	35.896820	6.62362	685.4	59.80	1:33:22	7.246429	False

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	worksite	chainage	hole_id	hole_depth	hi_mean	fi_mean	wi_mean	hi_max	fi_max	wi_max	Gr_vol	Gr_endpres	Gr_time	Gr_meanflow	HJ_detected
360	Longva	23707	23707_27	23.695	-21.134450	5.837410	1.152230	24.85042	16.472390	8.43381	941.2	65.40	1:23:15	12.029955	False
361	Longva	23707	23707_28	23.704	-26.132750	4.984650	1.515460	37.78375	59.476090	15.91396	336.3	67.30	8:36:46	7.796386	True
362	Longva	23707	23707_29	22.525	-38.090270	5.165260	1.316550	-6.12389	17.901990	7.07957	5.5	67.60	0:16:25	1.087719	False
363	Longva	23707	23707_30	23.684	-24.887790	5.201100	1.330250	98.31014	84.249030	31.38502	5.0	63.30	0:04:07	1.519231	False
364	Longva	23707	23707_31	23.706	-21.561010	3.906540	1.007000	8.06847	16.403040	5.65921	10647.4	74.90	11:32:25	17.288527	True
365	Longva	23707	23707_32	23.692	-26.429100	4.261400	1.096470	65.71125	75.079530	6.03636	35.8	64.10	0:16:47	2.027451	False
366	Longva	23707	23707_33	23.690	-32.172010	4.320690	1.120770	0.53958	22.178090	6.17728	1458.3	63.20	2:44:42	13.068596	False
367	Longva	23707	23707_34	23.676	-33.844330	5.203970	0.779900	11.10306	17.763110	6.72929	1248.9	61.40	1:38:31	10.984451	True
368	Longva	23707	23707_35	23.693	-24.320260	5.488020	1.049510	8.77792	17.685340	8.97941	116.9	59.80	0:22:41	5.016788	False

B Python source codes

```
1 import pandas as pd
2 pd.set_option('display.float_format', lambda x: '%.5f' % x)
3
4 #Define directory to excel file with MWD data
5 xls = pd.ExcelFile(r'HoleReport_5856.xlsx')
6 xl_dict = pd.read_excel(xls, sheet_name=None, header=16, usecols='V:Y')
7
8 #Empty list to append to
9 bh_lst = []
10
11 # Iterate through sheets (borehole) in excel file
12 for hole, sheet in xl_dict.items():
13
14     # Convert each sheet to dataframe structure
15     xl_df = pd.DataFrame(xl_dict[hole])
16
17     # Produce descriptive stats of all nonzero samplings from each hole
18     # using describe() function
19     xl_stats = pd.DataFrame(xl_df.mask(xl_df == 0).describe())
20
21     # Append stats and holenr. to empty list
22     bh_lst.append([xl_stats, hole])
23
24 df_fin = pd.DataFrame(bh_lst)
25 result = df_fin
26 # read to existing blank .txt-file
27 result.to_csv(r'C:\Users\kris_\OneDrive\Documents\Master\
    Master_datagrnnlag\PEL_5506\MWD\MWD_5506.txt',
    header=True, index=False, sep='\t', mode='a')
```

Code Listing 1: Source code for .xls to .csv algorithm for MWD DPI data gathering.

```

1 import pandas as pd
2 import glob
3
4 #Define directory to LOG-files in .txt format
5 path = r"C:\Users\kris_\PycharmProjects\Fv_659\LOG_5856\*.txt"
6 files = glob.glob(path)
7
8 # define empty lists to append to and column names of final dataframe
9 lst = []
10 cols = ['Hole_nr', 'Recipe', 'Mean_flow', 'End_pressure', 'Volume', 'Time']
11 #Iterate through LOG files
12 for file in files:
13
14     #Convert to csv to able Pandas dataframe data-structure
15     rawfile = pd.read_csv(file)
16     df = pd.DataFrame(rawfile)
17
18     #Extract hole nr. and recipe
19     recipe = df.iloc[4, 0]
20     holeloc = df.iloc[1,0]
21     holeno = [int(i) for i in holeloc.split(';') if i.isdigit()]
22     holeno = int("".join(map(str, holeno)))
23
24     # Define placement of each variable column
25     df['Time'],df['Pressure'],df['Flow'],df['Volume']=df['Worksite;AUSTNES'
26 ] .str.split('; ',3) .str
27     flow_df = pd.DataFrame(data = df.loc[9:, 'Flow'])
28     volume_df = pd.DataFrame(data=df.loc[9:, 'Volume'])
29     volume_df.drop(volume_df.tail(1).index, inplace=True)
30     pressure_df = pd.DataFrame(data=df.loc[9:, 'Pressure'])
31     pressure_df.drop(pressure_df.tail(1).index, inplace=True)
32
33     # Take timestamps from LOG files and convert to appropriate format
34     time_df = pd.DataFrame(data = df.loc[9:, 'Time'])
35     time_df.drop(time_df.tail(1).index,inplace=True)
36     time_df = time_df[~time_df['Time'].str.contains("PAUSE")]
37     time_df['Time'] = pd.to_timedelta(time_df['Time'])
38
39     # Convert remaining columns to appr. format
40     flow_df['Flow'] = pd.to_numeric(flow_df['Flow'])
41     pressure_df['Pressure'] = pd.to_numeric(pressure_df['Pressure'])
42     volume_df['Volume'] = pd.to_numeric(volume_df['Volume'])
43
44     # Taking sum, max and mean of grouting variables
45     mean_flow = flow_df.loc[:, 'Flow'].mean(axis = 0, skipna = True)
46     max_pressure = pressure_df.loc[:, 'Pressure'].max(axis = 0, skipna =
47 True)
48     sum_volume = volume_df.loc[volume_df.index[-1], 'Volume']
49
50     # using timedelta to find grouting duration
51     deltat = time_df['Time'].iat[-1] - time_df['Time'].iat[0]
52     deltat = deltat - pd.to_timedelta(deltat.days, unit='d')
53
54     # append all variable incl. hole-number to empty list structure
55     lst.append([holeno, recipe, mean_flow, max_pressure, sum_volume, deltat
56 ])
57     df_fin = pd.DataFrame(lst, columns=cols)

```

```
56 # Using groupby() to group equal hole numbers together, and derive max, sum
    , mean values of all
57 groupedmax_pressure = df_fin.groupby(['Hole_nr'])['End_pressure'].max()
58 groupedsum_volume = df_fin.groupby(['Hole_nr'])['Volume'].sum()
59 groupedmean_flow = df_fin.groupby(['Hole_nr'])['Mean_flow'].mean()
60 groupedsum_time = df_fin.groupby(['Hole_nr'])['Time'].agg('sum')
61
62 # Concat variables (columns) to final dataframe: result_df, and print
    result
63 frames = [groupedsum_volume, groupedmax_pressure, groupedmean_flow,
    groupedsum_time]
64 result_df = pd.concat(frames, axis=1, join='outer')
65 print(result_df)
```

Code Listing 2: Source code for gathering grouting data from LOG-files.

```

1 import pandas as pd
2 import glob
3 import matplotlib.pyplot as plt
4 import matplotlib.dates as dates
5 import seaborn as sns
6 sns.set(rc={'figure.figsize':(11, 4)})
7
8 # Declare PF-index as function, taking two input parameters
9 def pf_index(flow, pressure):
10     q = flow
11     p = pressure
12     return (0.9*q) - (0.9*p/1) + 81
13
14 # Define directory with LOG-files
15 path = r"C:\Users\kris_\PycharmProjects\Fv_659\LOG_5506\*.txt"
16 files = glob.glob(path)
17
18 # define empty lists to append to and column names of final dataframe
19 lst = []
20 cols = ['Hole_nr', 'Recipe', 'Mean_flow', 'End pressure', 'Volume', 'Time']
21 #Iterate through LOG files
22 for file in files:
23     # read each file as .csv file and convert new dataframe
24     rawfile = pd.read_csv(file)
25     df = pd.DataFrame(rawfile)
26
27     # Extract descriptions on each hole (hole number, stage, worksite, etc
28     ..)
29     recipe = df.iloc[4, 0]
30     holeloc = df.iloc[1, 0]
31     holeno = [int(i) for i in holeloc.split(';') if i.isdigit()]
32     holeno = int("".join(map(str, holeno)))
33     stage = str(rawfile.iloc[3][0])
34     injection = str(rawfile.iloc[5][0])
35     section = str(rawfile.iloc[0][0])
36     worksite = str(rawfile.columns[0])
37
38     df['Time'], df['Pressure'], df['Flow'], df['Volume'] = df['Worksite;
39     AUSTNES'].str.split(';', 3).str
40     # Delete first unwanted rows from the LOG files
41     df = df.drop('Worksite;AUSTNES', axis=1)
42     df = df.dropna(axis=0, how='any')
43
44     # extract the data for each variables with correct formatting
45     flow_df = pd.DataFrame(data = df.loc[9:, 'Flow'])
46     flow_df['Flow'] = pd.to_numeric(flow_df['Flow'])
47     flow_df.drop(flow_df.tail(1).index, inplace=True)
48     flow_df = flow_df.reset_index(drop=True)
49
50     volume_df = pd.DataFrame(data=df.loc[9:, 'Volume'])
51     volume_df.drop(volume_df.tail(1).index, inplace=True)
52     volume_df = volume_df.reset_index(drop=True)
53
54     pressure_df = pd.DataFrame(data=df.loc[9:, 'Pressure'])
55     pressure_df['Pressure'] = pd.to_numeric(pressure_df['Pressure'])
56     pressure_df.drop(pressure_df.tail(1).index, inplace=True)
57     pressure_df = pressure_df.reset_index(drop=True)

```

```

57 time_df = pd.DataFrame(data=df.loc[9:, 'Time'])
58 time_df.drop(time_df.tail(1).index, inplace=True)
59 time_df = time_df[~time_df['Time'].str.contains("PAUSE")]
60 time_df['Time'] = pd.to_datetime(time_df['Time'])
61
62 #time_df['Time'] = pd.to_timedelta(time_df['Time'])
63 time_df = time_df.reset_index(drop= True)
64
65 # - - Filtrate the pressure series with moving avg (SMA) moving median
with span of 3
66 filt_pressure = pressure_df.rolling(window=3, min_periods=1).median()
67 filt_pressure.fillna(value=0, axis=0, inplace=True)
68
69 pf_df = flow_df.join(filt_pressure)
70 # Calling the PF index function in a lambda expression
71 pf_df['PF_index'] = pf_df.apply(lambda x: pf_index(x['Flow'], x['
Pressure'])), axis=1)
72 pf_df = pf_df.join(time_df)
73
74 # Filtrate the PF index series with double moving avg (DMA) with span
of 5
75 pf_df['PF_index'] = pf_df.PF_index.rolling(window=5,min_periods=1).mean
()
76 pf_df['PF_index'] = pf_df.PF_index.rolling(window=5,min_periods=1).mean
()#,min_periods=1
77 pf_df.PF_index.fillna(value=0, axis=0, inplace=True)
78
79 # Plot the resulting graphs for each hole
80 plt.plot_date(pf_df.Time, pf_df.PF_index, linestyle='solid',
81 marker='None', label='PF Index', c='black')
82 plt.plot_date(pf_df.Time, pf_df.Pressure, linestyle='dashed',
83 marker='None', label='Pressure', c='blue', alpha=1)
84 plt.plot_date(pf_df.Time, pf_df.Flow, linestyle='dotted',
85 marker='None', label='Flow', c='green', alpha=1)
86 plt.xlim(pf_df.Time.loc[0], pf_df.Time.iloc[-1])
87 plt.legend()
88 plt.xlabel('Elapsed time [HH:MM:SS]')
89 plt.ylabel('PF Index, Pressure [Bar], Flow [l/min]')
90 plt.title('Holenr;' + str(holeno)+' '+stage+' '+injection+' '+str
(section)+' '+str(worksite))
91 xax = plt.gca().get_xaxis()
92 xax.set_major_formatter(dates.DateFormatter('%H:%M:%S'))
93 plt.show()

```

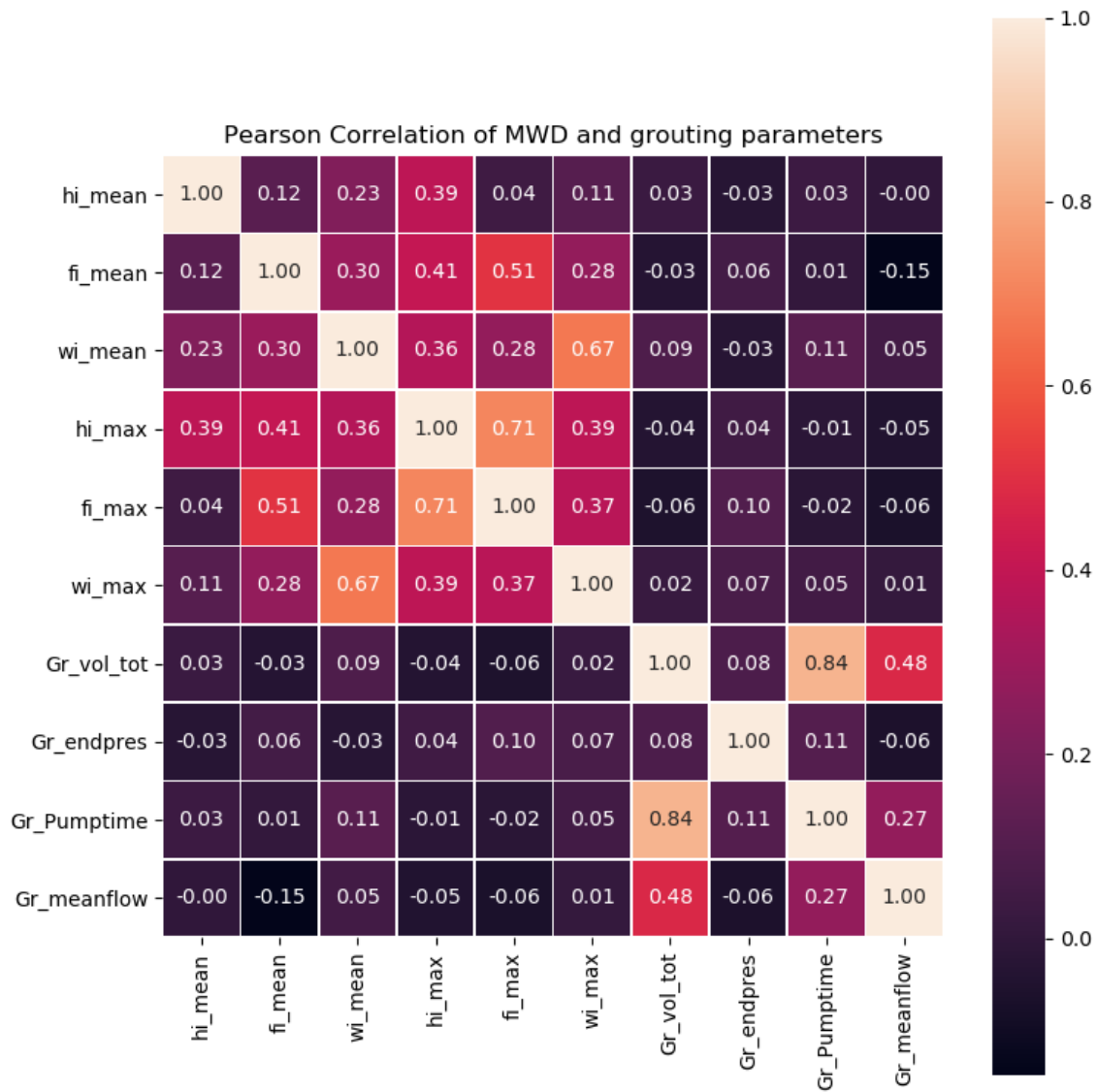
Code Listing 3: Source code for calculating and graphing PF index, flow and pressure for each grouted hole.


```
1 import pandas as pd
2 import seaborn as sns
3 from sklearn import model_selection
4 from sklearn.linear_model import LinearRegression
5 from sklearn.neural_network import MLPRegressor
6 from sklearn.ensemble import RandomForestRegressor
7 from sklearn.neighbors import KNeighborsRegressor
8 from sklearn.svm import SVR
9 from sklearn.model_selection import train_test_split
10 from sklearn.preprocessing import StandardScaler
11 import numpy as np
12 import matplotlib.pyplot as plt
13
14 #defines master dataframe
15 df = pd.read_csv(r"GroutingMWDdb_fin.csv")
16
17 # Cleaning DF by dropping empty rows and columns and adding 'worksite'
    column
18 df.drop(df.columns[range(17,26)], axis=1, inplace=True)
19 df.drop(df.index[range(369, 472)], axis=0, inplace=True)
20 df.insert(0, 'worksite', 'Austnes')
21 df.worksite.replace(df.worksite.loc[150:], 'Longva', inplace=True, regex=
    True)
22
23 # converting values to correct format
24 df.chainage = df.chainage.astype(int)
25 df.chainage = df.chainage.astype(str)
26 df.HJ_detected.fillna(value=0, inplace=True)
27 df.HJ_detected = df.HJ_detected.astype(bool)
28 df['HJ_str'] = np.where(df['HJ_detected'], 'Pot. HJ event detected', 'No HJ
    event detected')
29 df['Gr_meanflow'] = np.abs(df['Gr_meanflow'])
30
31 #declare df with no NaNs (df_dropna)
32 df_dropna = df.dropna(axis=0)
33 df_dropna.reset_index(drop=True, inplace=True)
34 # convert time from HH:MM:SS to minutes
35 df_dropna['Gr_Pumptime'].astype(str)
36 df_minutes = df_dropna['Gr_Pumptime'].str.split(':').apply(lambda x: int(x
    [0]) * 60 + int(x[1]))
37 df_dropna['Gr_Pumptime'] = df_minutes.values
38
39 #feature variables
40 features = ['hi_mean', 'fi_mean', 'wi_mean']
41
42 scaler = StandardScaler()
43 x = df_dropna.loc[:, features].to_numpy()
44 x = scaler.fit_transform(x)
45 # select target variables ('Gr_Pumptime, Gr_endpres, Gr_vol_tot)
46 y = df_dropna['Gr_meanflow'].values.reshape(-1, 1)
47 y = scaler.fit_transform(y).ravel()
48 x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.40,
    random_state=0)
49 # - - - - sklearn - - - - #
50 # prepare models in iterable list for cross validation
51 seed = 7
52 models = []
53 models.append(('LR', LinearRegression()))
```

```
54 models.append(('RFR', RandomForestRegressor()))
55 models.append(('KNN', KNeighborsRegressor()))
56 models.append(('SVR', SVR()))
57 models.append(('MLP', MLPRegressor()))
58
59 # Empty lists to append
60 results = []
61 result_print = []
62 names = []
63 # iterate evaluate each model in turn, 10 split CV
64 for name, model in models:
65     kfold = model_selection.KFold(n_splits=10, random_state=seed)
66     cv_results = model_selection.cross_val_score(model, x, y, cv=kfold,
67         scoring='r2')
68     results.append(cv_results)
69     names.append(name)
70     msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
71     result_print.append(msg)
72 print(result_print)
73 # plot boxplots of model comparison
74 fig = plt.figure()
75 ax = sns.boxplot(x=names, y=results, palette="Set3").set_title('Algorithm
76     Comparison - Target: mean flow')
77 plt.ylim([-1.5, 0.25])
78 plt.hlines(y=0, xmin=-0.5, xmax=4.5, linestyle='dashed')
79 plt.show()
```

Code Listing 4: Source code for cross validation of various ML models on the dataset.

C Figures and misc.



Heatmap depicting Pearson correlation coefficients between all involved variables (see table 7.7), color gradient ranges from light (positive linear correlation) to dark (0 to negative linear correlation).

Grouting procedure for project Fv.659 Nordøyvegen, rock cover > 20m

(Procedure can be changed according to the rock mass)

Number of holes (incl. 4 hole at tunnel face): 30

Hole spread from contour: 5-10 m

d Length of holes: 24 m

Placement of grout gasket: 2 m inside hole.

Max end pressure: 80 bar for both tunnel crown and invert holes.

Recipe 1 Portland cement

w/c = 0.9

Superplasztizer = 2%

Silicaslurry = 10%

Up to 500L grout take per hole before lowering w/c number. Where grout take is < 500L, end pressure needs to be held for 5 minutes before end of grouting.

Recipe 2 Portland cement

w/c = 0.7

Superplasztizer = 2%

Silicaslurry = 10%

Up to 500L grout take per hole before lowering w/c number. Where grout take is < 500L, end pressure needs to be held for 5 minutes before end of grouting.

Recipe 3 Portland cement

w/c = 0.5

Superplasztizer = 2%

Silicaslurry = 8%

After 1800L grout take per hole with insufficient end pressure, rest hole for 1-2 hours before resuming grouting.

Recipe 4 Micro cement

w/c = 1.0

Superplasztizer = 1%

After 300L grout take per hole with insufficient end pressure, reduce w/c to 0.8 before resuming grouting.

Recipe 5 Micro cement

w/c = 0.8

Superplasztizer = 1%

After 300L grout take per hole with insufficient end pressure, reduce w/c to 0.6 before resuming grouting.

Recipe 6 Micro cement

w/c = 0.6

Superplasztizer = 1%

After 700L grout take per hole with insufficient end pressure, proceed with use of accelerator additive.

