Determination of the formation properties from Rotary Percussion Drilling data

Zijian Li, Igor Kyzym, Hongyuan Qiu, Stephen Butt
Drilling Technology Lab (DTL) of Memorial University of Newfoundland, St. John's, NL, Canada

ABSTRACT
The object of this research is to investigate the potential of determining rock formation strength and gold mineralization from rotary percussion drilling data. To achieve this objective, an electronic Logging While Drilling (LWD) system was developed to record real-time drilling parameters. For the drilling data analysis, it was determined that the damping pressure (which is related to the percussion rebound energy) was inversely proportional to the measured ROP. As well, the rotary pressure (which is related to rotary speed) was proportional to the measured ROP. Percussion Index (PI) is used in the attempt of calculating in-situ UCS of the rock. PCA (Principal Component Analysis) is introduced to build the prediction model of gold grade using the real-time LWD data. Result was obtained after the model training and cross-validation.
RÉSUMÉ
L'objet de cette recherche est d'étudier le potentiel de détermination de la résistance de la formation rocheuse et de la minéralisation en or à partir de données de forage par percussion rotative. Pour atteindre cet objectif, un système de diagraphie en cours de forage (LWD) a été développé pour enregistrer les paramètres de forage en temps réel. Pour l'analyse des données de forage, il a été déterminé que la pression d'amortissement (qui est liée à l'énergie de rebond de percussion) était inversement proportionnelle au ROP mesuré. De plus, la pression de rotation (liée à la vitesse de rotation) était proportionnelle au ROP mesuré. L'indice de percussion (IP) est utilisé pour tenter de calculer le SCU in situ de la roche. La PCA (Analyse en Composante Principale) est introduite pour construire le modèle de prévision de la teneur en or en utilisant les données en temps réel de la LWD. Le résultat a été obtenu après la formation du modèle et la validation croisée.

1 INTRODUCTION

The target of this study is to collect the blast hole drilling performance data in real time using Logging While Drilling (LWD) technique, to analyze the data and to investigate the potential to determining rock formation strength and gold mineralization from the data. Conventionally, core drilling is widely used to characterize the rock mass properties. The application of this method, however, requires a high cost and a large number of cores obtained from the field. Also, the certainty of the rock properties in the area between coring holes cannot be guaranteed, especially when the distance between the core holes is large.

Laboratory tests are one of the most accurate methods for rock characterization; despite that, it is time consuming and cost consuming. The laboratory tests, however, only gives a rough idea about the rock mass properties in the field if the rock samples are not collected from a relatively large area or too few. Hoek (1977) conducted a series of rock mechanical laboratory tests, such as uniaxial compressive strength (UCS), shear strength. The experiment result was reviewed, and empirical methods are also incorporated in rock characterization, and empirical methods are also applied in rock characterization. Previously, a series of rock characterization methods were proposed, such as Rock Quality Designation (RQD) (Deere, 1968), Rock Mass Rating (RMR) (Bieniaswki, 1973) and Q system (Barton and Lien, 1974). In these methods, indirect parameters were calculated from the rock mechanical properties and then served as the proof for rock classification. However, they are not able to present in-situ rock properties but only a general assessment of the rock properties during the whole drilling process. These methods are reviewed, revised and used by previous scholars. Their applications were proved to be reliable under certain circumstances. However, they are not able to present in-situ rock properties but only a general assessment.

To investigate the in-situ properties of rock, several borehole-based methods have been developed over time. Borehole radar and auto-scanning laser systems have been utilized to image the cavities and fractures in the intact rock (Haeni et al., 2002; Liu et al., 2008). However, existing stable holes are needed to put the measuring tools in the hole before the test, which leads to higher downtime and disturbances (Schunnesson, 1996).

Measurement While Drilling (MWD) and LWD techniques were introduced into mining engineering in open pit bench drilling in the 1970s (Segui and Higgins, 2002). Until now, it has been widely used in both petroleum engineering and mining engineering and is compatible with different drilling techniques. The MWD technique is favored for its low cost and real-time data acquisition with no downtime required. It should be noted, however, besides the formation geological properties, the operators, rig control systems, bit wear, measurement errors and other system factors also influence the data. Thus, the influence of these system factors should be removed to make the rock properties independent in the data analysis (Schunnesson, 1998). To do this, several approaches have been tested, including theoretical models for rock drilling, statistical methods, and, more recently, advanced data processing tools.

There are 5 parameters obtained from the LWD are potentially involved with the variation of the gold grade. The large number of parameters make the establishment of the gold grade prediction model complicated. Thus, PCA (Principal Component Analysis) is introduced in the model building. PCA is a widely used technique in multivariate data analysis. The advantage of PCA is to effectively reduce the number of variables while retaining valid information regarding the target parameter variation (Wold, 1987; Jolliffe, 2011). Given that there are several drilling performance parameters collected by the LWD system which are potentially related to the gold grade, PCA is favored to be used to predict the gold grade using real-time LWD data.

2 MINING SITE GEOLOGY

In this study, the rotary percussive drilling method was used in the blast hole drilling in the Pine Cove mining site. Gold mineralization is hosted by mafic volcanic and intrusive volcanic rocks in Pine Cove area. On the edge of the mining site, argillite was observed as surrounding rock. The estimated average gold grade is 2.07g/t Au at a cutoff of 0.95 g/t (Puritch, 2010).

Figure 1 Pine Cove open pit mining site

The rotary percussive drilling method was used for the blast hole drilling for the open pit mining in Pine Cove. Cores were drilled from the mining site, and a series of laboratory tests were conducted on the cores to determine the mechanical properties of the rock, for example, uniaxial compression test. The core samples are shown in Figure 2. Among all the mechanical properties of the rock, e.g., Uniaxial Compressive Strength (UCS), tensile strength and Young's modulus, UCS has the strongest relationship with the Rate of Penetration (ROP) (Bakar, 2018; Kahraman, 2003). According to the laboratory test, the average UCS of the quartz ore which contains gold is 66.5MPa while the UCS of surrounding rocks (mafic volcanic and argillite) ranges from 51MPa to 56MPa. The difference in UCS shows a potential to distinguish gold ore from waste rock by analyzing the variation of in-situ UCS value or other drilling performance parameters. If the ore and waste boundary was effectively distinguished, the dilution will be reduced, and the recovery will be obtained. Traditionally the gold grade and rock classification are conducted by cutting analysis. In practice, the cutting analysis is time-consuming and increases the production downtime, because it requires laboratory experiments. Thus, real-time MWD data analysis to predict in-situ UCS and to distinguish between ore and waste rock is of benefit for the mining industry by reducing the time and cost during the operation.

In this research, MWD data was collected in a total of 37 blast holes in two blast zones; cutting samples were collected and analyzed in the laboratory every 0.5m of bit travel for ten holes. The average depth of the holes is 7.5m.

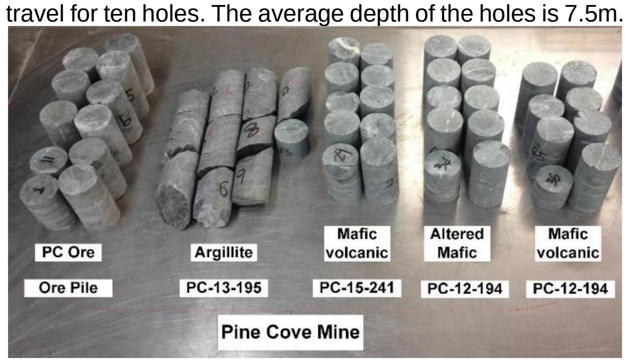

Figure 2. Core samples obtained from the Pine Cove Mine

3 LOGGING WHILE DRILLING (LWD) SYSTEM CONFIGURATION

A new LWD system was developed and installed on Atlas Copco T40 blast hole drilling rig. The Data Acquisition System (DAQ) system and the remote control for the driller are shown in Figure 3. FlexiROC T40 is a flexible and versatile top hammer drill rig. Some of the T40 parameters are shown in Table 1 (Kyzym, 2018).

Table 1. Atlas Copco T40 parameters

Parameter	Characteristics
Drilling method	Top hammer
Hole diameter	76 mm - 127 mm
Rock drill/DTH hammer size	COP 2560+
Maximum hole depth	28 m
Engine power	168 kW

Major LWD components include:
- hydraulic and pneumatic pressure transducers that measure the various drilling parameters;
- cable position sensor (string pot) that measures the travel of the hydraulic line carousel;
- DAQ to record the data from the sensors;
- electrical cables, pneumatic and hydraulic fittings to connect the sensors to the DAQ system.

The Data Acquisition System (DAQ) system and the remote control for the driller are shown in Figure 3.

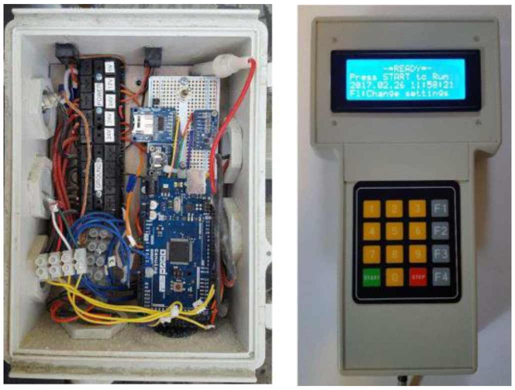

Figure 3. Data Acquisition System (DAQ) system (left) and the remote control for the driller (right)

The LWD was designed to be compatible with the T40 drill rig. The hydraulic and pneumatic pressure data was read from the rig system using pressure transducers. The hole depth was measured using an independent system by mounting a string potentiometer, on the plate on top of the mast. The recorded parameters were:

- The time during the whole drilling operation.
- Hole depth.
- Rotation pressure.
- Feed pressure.
- Percussion pressure.
- Torque pressure.
- Damping pressure.
- Flushing air pressure

Rate of Penetration (ROP) cannot be measured directly, but it was calculated by dividing the hole depth increment of each time interval by the time interval.

4 LWD DATA COMPREHENSIVE ANALYSIS

The time, hole depth, rotation pressure, feed pressure, percussion pressure, torque pressure, damping pressure, and flushing air pressure were collected in real time during the top hammer drilling by LWD system. Then the ROP is calculated using time and hole depth. A total of 37 holes are drilled, and around 25 thousand data points were generated in the drilling process. For ten holes, the gold grade for each 0.5m deep interval was obtained through laboratory cutting analysis (Kyzym, 2018).

4.1 The relationship between rotary pressure (torque) and ROP

Among all the drilling performance parameters, it was observed that the torque pressure and damping pressure have a relatively good relationship with the ROP. Rotary pressure is applied to the drilling rod by the rotary motor. After each percussion, the rotary pressure on the bit overcomes the friction with the bottomhole and makes the bit rotate.

Combining all the available LWD data, the relationship between the ROP and rotary pressure is presented in Figure 4. Before we analyze the raw data, the raw data need to be filtered to remove some data points that lay out of the reasonable range. The rotary pressure within the range of 0 bar to 200 bar are reserved for further process. Considering the physical limit of the drill rig, the data points smaller than one or larger than 200 bar are considered as error and discarded. The LWD data was collected in real time by the frequency of 10 Hz. It is observed that the data acquisition frequency is not high enough to capture the bit vibration, comparing to the bit percussion rate of 48 Hz. On the other hand, the number of data points was large. Thus, the average value of every 5 seconds time interval (50 time steps) are calculated. A new data set was generated, and the number of data points reduced by 50 time, making the data process simpler. The relationship between the ROP and rotary pressure of the new data set was presented in Figure 5.

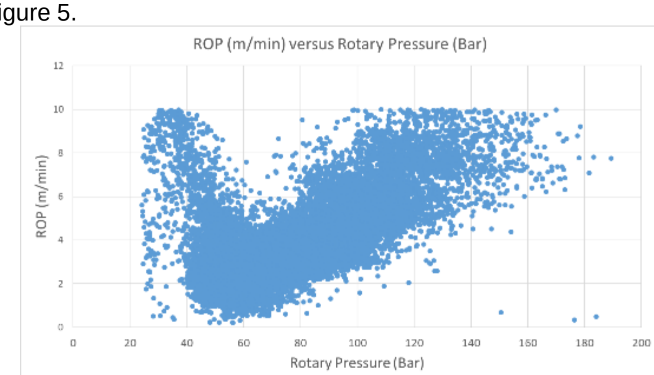

Figure 4 Relationship between ROP and Rotary Pressure

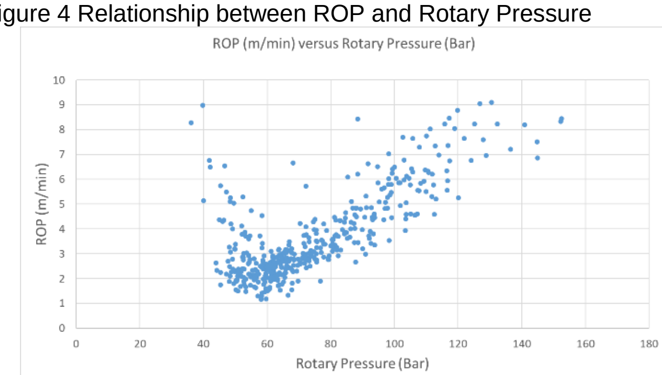

Figure 5. Relationship between ROP and Rotary Pressure using the new data set(Average value)

It is noticed that these two figures show the same trend: ROP decreases with the rotary pressure when the rotary pressure is less than 60 Bar. After that, the ROP increases with rotary pressure. After going back to check the raw data, it is found that most of the data points where the rotary pressure is lower than 60 Bar are collected when the drilling rod is tripped or when the drilling operation just start or stop. Referring to the previous study (Schunnesson, 1996), these data points are considered as error data and should be discarded. After eliminating the error data, the relationship between ROP and rotary pressure is fitted with a linear trend line, and the trend line equations are shown in Figure 6 and 7.

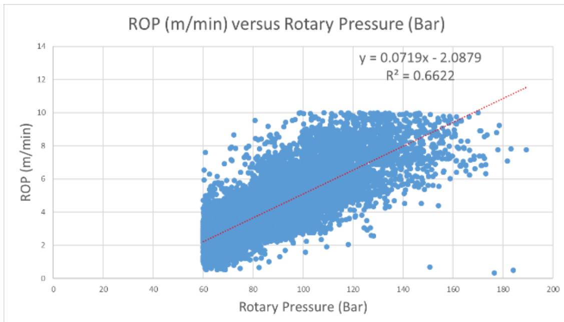

Figure 6 Relationship between ROP and Rotary Pressure after discarding error data

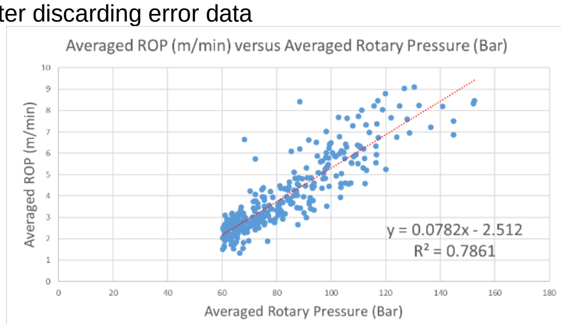

Figure 7 Relationship between ROP and Rotary Pressure (new data set) after discarding error data

Comparing these two equations, it is concluded that the fitting results of the raw data and the processed data have the same trend and the equations are similar. The processed average data, however, presents a better fitting accuracy than the raw data, in terms of the R square. The rotary pressure is proven to has a strong relation to the ROP of top hammer rotary percussion drilling.

4.2 The relationship between damping pressure and ROP

Damping pressure is the pressure of the damping system absorbing the rebound energy from the rebound piston. It directly reflects the strength of the rock to some extent. Previously, the relationship between rotation pressure (torque) and the ROP has been widely discussed. The damping pressure, however, has not been studied as much as other drilling performance parameters.

Combining all the available LWD data, the relationship between the ROP and damping pressure was presented in Figure 8.

Before we analyze the raw data, the raw data need to be filtered to remove some data points that lay out of the reasonable range. The damping pressure within the range of 0 bar to 80 bar were reserved for further process. Using the same strategy as mentioned above, a new data set was created by calculating the average value of the data points within every 5 seconds time interval. The ROP was plotted against damping pressure using the new data set in Figure 9.

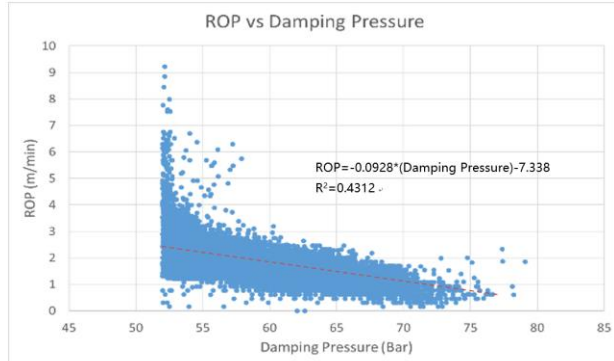

Figure 8 Relationship between ROP and Damping Pressure

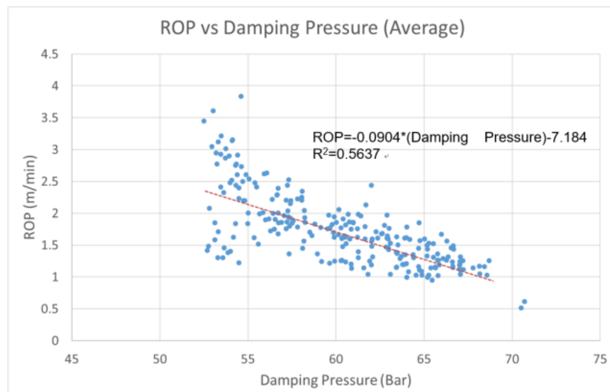

Figure 9 Relationship between averaged ROP and averaged Damping Pressure

From figure 8 and 9, it is noticed that below 52 Bar the data points suddenly disappeared. In the region between 52 Bar and 54 Bar, the ROP went up to 9 m/min. It wass assumed that this phenomenon is induced by the physical limit of the damping system of the drill rig or the limit of the damping pressure transducer. Both figures give the same trend that the ROP decreases with the damping pressure. It concurs with our general understanding of damping mechanism of the percussive drill rig. When the rock strength increases, more percussion energy was required to penetrate the rock and more energy is rebounded. The two figures were fitted by linear trend lines. The fitted equations were given in Figure 8 and 9.

From the equations, it is known that the relationship between ROP and damping pressure have the same trend and close parameters for raw data and the processed average data. In the processed average data, data points which are far from the trend line are eliminated because of the average algorithm and the accuracy is higher because its R square is higher. The damping pressure is proven to be potential in terms of predicting the ROP of top hammer rotary percussion drilling, although further study is needed.

4.3 In-situ rock UCS calculation

Calculation of in-situ rock UCS is a time and cost consuming task. The laboratory experiment is a reliable method but it requires a long time to move the cuttings to the lab and for the test, sometimes it would even lead to an increase in downtime. In this study, the parameter Percussion Index (PI) (Chitty, 2005; Xiao,2018) is used as an attempt to calculate the in-situ rock UCS using the real-time LWD data.

The Percussion Index (PI) is an empirically defined metric that could calculate the in-situ UCS of rock and identify the change in the rock mechanical properties and thus change of rock face. It requires real-time ROP, percussion frequency, impulse (momentum) in each hammer blow. The calculation of Percussion Index and the in-situ UCS is shown below:

$$\lambda_p = \frac{e^{(0.00127 I_b^2 + 0.00708 I_b)} \times \omega}{ROP} \quad [1]$$

$$UCS = 0.13 {\lambda_p}^3 \quad [2]$$

Where, λ_p is the Percussion Index; I_b is the impulse (momentum) in each hammer blow, N*s; ω is the percussion frequency, Hz; ROP is the rate of penetration in real time, mm/s. In the real-time LWD data collection, the percussion pressure is recorded. Based on the percussion pressure, the percussion power for each blow is then obtained.

$$I_b = \sqrt{2W \times m \times \beta} \quad [3]$$

Where, W is the percussion power per blow, Walt; m is the mass of the piston in the percussion drill assembly; β is the energy transfer coefficient from the hammer to the piston, dimensionless. Then the Percussion Index (PI) was calculated using the real-time LWD data.

The in-situ UCS result is calculated using Percussion Index (PI) for one hole and shown in Figure 10. It is seen that some data points are highly deviated from the trend. Thus, the in-situ UCS of each 0.5 depth interval is calculated and a new data sed is generated. In this way, the influence of the highly deviated data points is reduced. The new data set is plotted in Figure 11 ascending order.

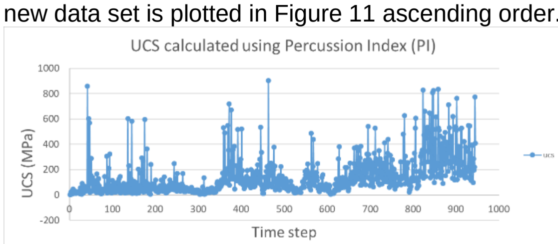

Figure 10. Real-time UCS calculated using Percussion Index (PI)

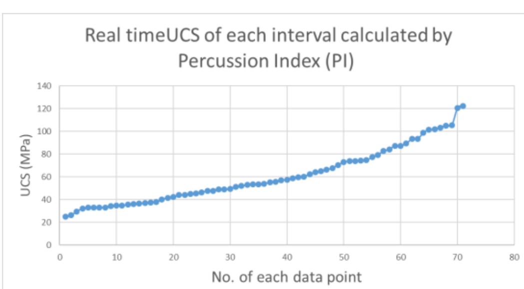

Figure 11. Real-time UCS of each interval calculated using Percussion Index (PI)

Comparing Figure 10 and 11, it is observed that the influence of the highly deviated data points is eliminated in the new data set, where the in-situ UCS of each layer is calculated. In the new data set, UCS ranges from 22 MPa to 124MPa. According to the laboratory core test of the Pine Cove rocks, the UCS of the ore and the host rock in the mining site ranges from 41MPa to 75MPa. Comparing to the core test result, the distribution of the calculated in-situ UCS is dispersed in a large range. As an empirical method for the in-situ UCS determination in rotary percussion drilling, the formation related parameters Percussion Index (PI) is first developed based on drilling in concrete. It is suggested that further study is needed to calculate in-situ UCS using Percussion Index (PI) because parameters are needed specially for the mining area.

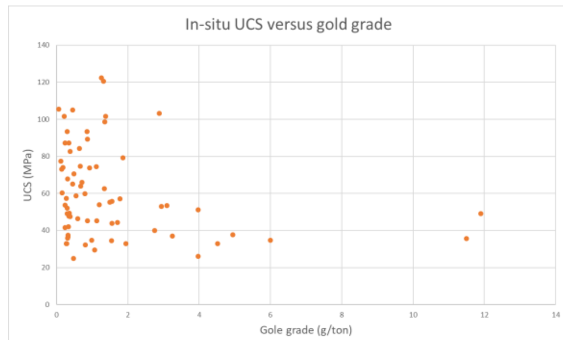

Figure 12. In-situ UCS versus gold grade

The in-situ UCS of each 0.5 depth interval is plotted against the gold grade data of each interval as shown in Figure 12. From Figure 12, it is concluded that the gold grade cannot be predicted only by the calculated in-situ UCS, although the UCS of gold ore and the surrounding rock are different. Thus, gold grade prediction model with multiple parameters is developed in following content.

4.4 Development of gold grade prediction model with multiple parameters

Among all the measured LWD parameters, ROP, feed pressure, damping pressure, percussion pressure and rotation pressure potentially influences factors of gold grade. A gold grade model is developed using multiple regression with the five independent parameters above. To decrease the number of independent parameters, PCA is used afterwards. By using this, five new independent parameters are proposed and calculated from the old parameters. The relationship between the target parameter (gold grade) and the new independent parameters are calculated. Then, the new independent parameters with the highest influence the variation of the target parameter is identified and retained, while the parameters with less influence are discarded.

Table 2. PCA components and weight

Contribution of each parameter in each Principle Component					
	PC1	PC2	PC3	PC4	PC5
ROP	0.011	-0.103	-0.108	-0.369	0.917
Damp	0.820	0.547	0.143	0.080	-0.023
Feed	-0.399	0.696	-0.527	0.2758	-0.024
Percussion	0.408	0.417	-0.8052	0.103	-0.011
Rotation	0.007	0.176	0.202	0.877	0.397
Weight	0.006	0.013	0.043	0.104	0.832

According to the table, the component 5 accounts for 83% of the variation of gold grade, and component 4 has 10.4 percent weight. By keeping these two components, more than 93% of the gold grade variation can be kept. In the meantime, there are only two parameters determining the gold grade, making the calculation simplified. Then using the correlation between the component 4,5 and the gold grade, the gold grade is predicted as shown in Figure 13. The gold grade data is assigned to a number. The rank of the number in the ascending rank of the corresponding ROP. It makes the data points distribution looks clearer by using assigned number as X-axis than the corresponding ROP value. Note that average value of the LWD parameters every 0.5m depth interval are used, the number of the data points is reduced, because the gold grade information if obtained every 0.5m depth. In Figure 13, only 10% of the data point is used in the prediction, because 90% of the data points are used for model training and cross-validation with the shown 10% data points.

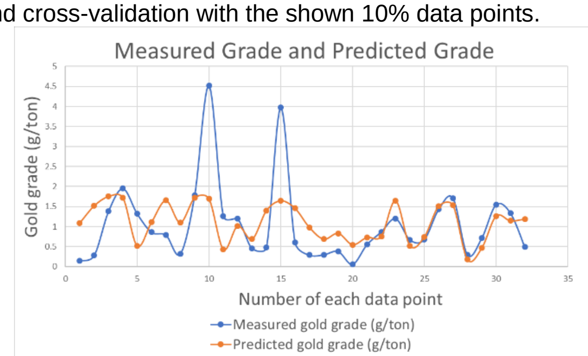

Figure 13. Comparison of measured gold grade and predicted gold grade using PCA analysis.

From the comparison result, the predicted gold grade does roughly capture the trend of the measured gold grade. For high ROP region, the prediction is more accurate. However, for some measured gold grade, especially for some extremely high gold grade, the prediction model fails to give a close answer. Although the prediction is close to some of the data points, the overall accuracy is not satisfying enough.

5 CONCLUSIONS AND RECOMMENDATIONS

In this study, the geology of the Pine Cove gold mine is studied by laboratory tests and rock face mapping before the LWD tests. The mechanism and operation of LWD are reviewed, and the LWD system is successfully used for the data collection of top hammer rotary percussive blast hole drilling for the open pit mining. The time during the whole drilling operation. Hole depth, rotation pressure, feed pressure, percussion pressure, torque pressure, damping pressure, and flushing air pressure are collected in real time during the drilling operation. Using time and hole depth, the ROP is calculated in real time rather than measured by accelerometer.

Rotary pressure and damping pressure are found to have a linear relationship with ROP. After discarding some data points which are considered as error, rotary pressure gives a good linear relationship with the ROP. The R square of the linear fitting is around 0.75. The linear fitting between damping pressure and the ROP presents a lower R square around 0.5. For both of the parameters, the average value by a certain time interval gives a better result than the real-time discrete data.

The concept of Percussion Index (PI) is used for the prediction of in-situ UCS using LWD data. The result shows that the distribution of the predicted UCS is dispersed in a larger range compared to the core test result. Some data points are highly deviated from the trend. It is suggested that further research is needed to calibrate the formation related parameter for the specific drilling site before using Percussion Index (PI) to determine the in-situ UCS using rotary percussion drilling data. It is because the formation related parameters in the Percussion Index (PI) empirical correlations are first developed based on concrete. The relationship between the predicted in-situ UCS and the gold grade is analyzed. It is suggested that the gold grade cannot be used alone to estimate the gold grade.

In order to identify the most important influence factor and to discard the influence factors with less weight, PCA is used to predict the gold grade using the LWD data. The best two principle components out of five accounts for more than 93% variation of the gold grade. Although the final prediction result is not satisfying enough, the predicted gold grade does roughly capture the trend of the measured gold grade. More data points are needed in future research to train the model and for the cross-validation. The gold grade data may need to be classified into two or three classes in further research. This will eliminate the influence and error regarding the extremely high gold grade data.

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