

Review

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Review

A Review of Orebody Knowledge Enhancement Using Machine Learning on Open Pit Mine Measure-While-Drilling Data

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Abstract: Measure While Drilling (MWD) refers to a comprehensive array of sensors employed to gather performance data throughout the process of rock drilling in mining blast holes. Multiple MWD metrics are collected by researchers depending on the setup of MWD sensors. Trends in MWD data can be correlated with pre-excitation subsurface conditions. The low-cost, extensive MWD data acquisition resolution of blast holes compared to expensive and sparsely collected exploration drill holes make the former one a desirable method for characterizing pre-excitation subsurface conditions. Nevertheless, the application of MWD technology in open pit mining is constrained by a substantial amount of data that requiring manual analysis within a short time. To address this limitation, computerized data acquisition and interpretation of MWD variables has been used to broadly determine open pit mining lithological boundaries. The results of artificial intelligence algorithms, such as Neural Networks, and Gaussian Processes, to recognize subsurface conditions, such as rock type, from MWD data have consistently returned >90% prediction accuracy. However, methods of evaluating the importance of each MWD feature, such as Principal Component Analysis, has not been optimally used. This review focuses on the progression of intelligent MWD analysis using Machine Learning methods in open-pit mining, to determine the geotechnical, geological, and geochemical subsurface characteristics before open-pit mining excavation.

Keywords: Measure While Drilling (MWD); open-pit mining; subsurface characterization; Machine Learning (ML); data acquisition; rock properties; geochemical analysis; Artificial Intelligence (AI); predictive modeling; feature importance

1. Introduction

Measure While Drilling (MWD) originated from Schlumberger's downhole electrical logging system in 1911, which was exclusively successful within the oil industry [1]. They described MWD as a system of sensors collecting performance data during rock drilling of open-pit mining production blast holes that can be correlated with pre-excitation subsurface conditions. Using MWD as a characterization system is desirable due to the low-cost and high resolution of blast holes. On the other hand, exploration drill holes are expensive and sparsely collected in comparison.

While MWD was introduced to the open-pit mining environment in the 1970's, its use to characterize the subsurface was limited due to the high volume of analogue data to manually analyze. To address this limitation, computerized data acquisition of MWD variables to broadly determine open-pit mining lithological boundaries was introduced around the 1980's [2–7]. Evolving from this initial use of computerized MWD rock recognition, this literature review focuses on the progression of advancing analytics, including Machine Learning (ML) algorithms, on MWD data to determine the geotechnical, geological, and geochemical subsurface characteristics before open-pit mining.

To perform the above correlations, multiple MWD metrics are collected by researchers. Depending on the manufacturer system setup, MWD datapoints are generated as time-series or depth series in blast holes ranging from 10 meters deep in surface iron ore mines to over 60 meters in open-pit coal mines [8]. The most common variables acquired in open-pit mining MWD systems are time,

depth, rate of penetration (rop), torque or rotational pressure (tor), bit air pressure (bap; also called flushing air pressure), weight on bit (wob; also called weight on rods, thrust or feed pressure) and rotary speed or revolutions per minute (rpm) [9]. Other less commonly collected variables are the drilling acoustic changes and vibrations of the drill rods [10].

Due to the continuous nature of drill and blast cycles for excavation in open-pit operations, enormous quantities of MWD datapoints are collected. Due to this sheer volume of data to analyze, researchers have recently begun applying artificial intelligence on MWD datasets to understand nonlinear trends between drill responses and subsurface composition. For instance, a single productive rig at an open-pit iron ore mine may drill around one hundred 10-12 metre blast holes per day, generating a minimum of 10,000 MWD observations with several responses per observation, including rop, tor, wob, bap, and rpm [11]. Many major iron-ore mines employ around a dozen simultaneously operating blast drills. Despite the abundance of data as shown in Section 1.2, most studies have focused on broad classification of rock types or hardness using rop to denote lithological boundaries rather than detailed characterisation of each rock type. In industry, mine technical services professionals are not necessarily appropriately skilled to analyse large volumes of data in the brief time-period between drilling blast holes and loading of explosives.

The objective of this study is to present a systematic and thorough examination of the existing body of research pertaining to the utilisation of ML algorithms in the analyses of MWD data for the purpose of characterising rock in mining operations. Furthermore, this study incorporates a comprehensive analysis of algorithms employed for assessing the significance of each metric related to the MWD technique, in relation to variations in the subsurface, such as rock strength, fracture frequency, elemental composition and density. Additionally, it explores the potential of ML algorithms and their prospective utilisation in forthcoming applications. Figure 1 presents a flowchart that describes the research framework of this study. Section 2 presents a concise summary of the dissemination of scholarly literature through journals and the prevailing patterns in publications. In Section 3, this study presents the pragmatic implementations of data analysis derived from MWD techniques in the domains of geology identification using density, gamma, magnetic susceptibility and resistivity responses, assessment of rock mass characteristics including rock strength, fracture frequency and rock mass classification scores, and geochemical composition, such as iron percentage as well as primary and secondary contaminants. These applications are expounded upon in subsections 3.1, 3.2, and 3.3, respectively. Section 4 presents an exposition on the challenges and potential associated with the application of ML techniques for rock characterisation utilising MWD data. Lastly, the concluding remarks are presented in Section 5.

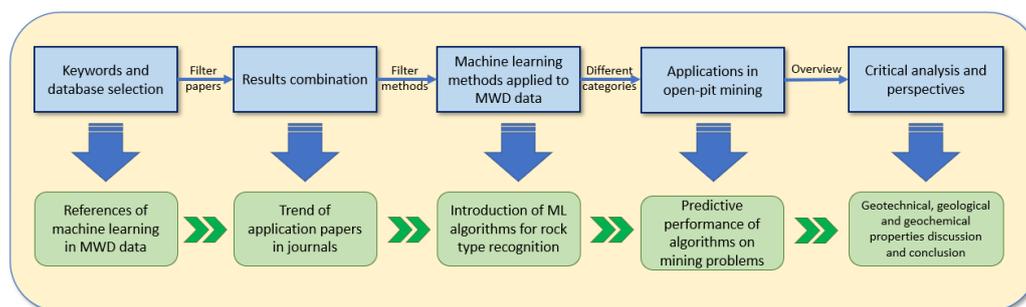


Figure 1. Research frame of machine learning (ML) review of mining MWD data.

2. Literature Sources and Dissemination

As indicated by the literature review process, the publication of papers on this topic spans around thirty years. There have been 537 research articles mentioning "Measure-While-Drilling" that have been indexed in Google Scholar (GS) since the late 1980s and up to the date, as shown in Figure 2's yellow bars. Nonetheless, when the search results are filtered to studies employing MWD to strictly characterise the rock being drilled, there are just 129 publications. The 129 articles are

organised according to the year of publication, as shown in Figure 2's green bars. Indeed, the use of MWD data for rock characterisation is limited in the first decade of the twenty-first century, whereas the number of papers has expanded dramatically in the last decade, with twenty-six publications expected in 2022. When the search parameters are restricted to using MWD to strictly characterise the rock being drilled using ML approaches, there are just 32 publications with a rapid employment of ML algorithms since 2016, as show in Figure 2's blue bars.

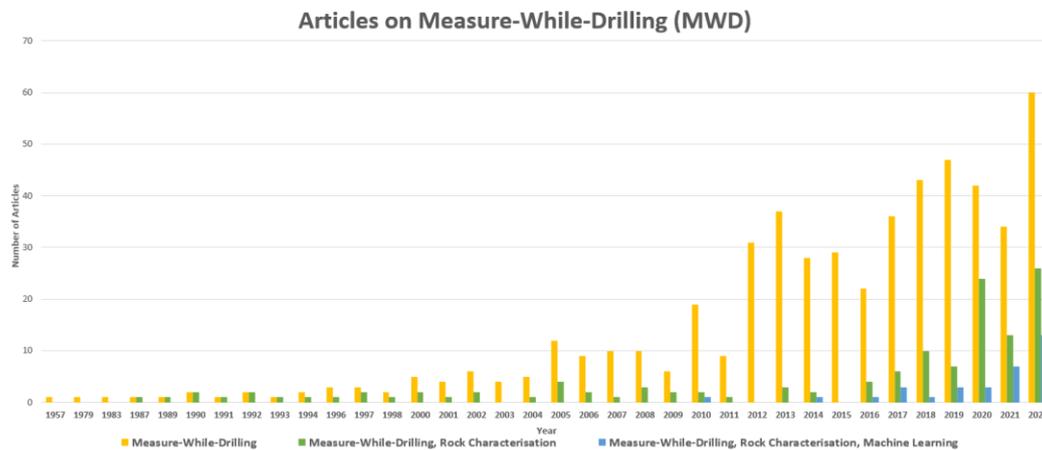


Figure 2. Annual distribution of published journal papers mentioning MWD for rock characterisation in all excavation types using ML from 1997 to 2022.

To address readers' academic interests in characterising rock types using ML techniques on MWD data in open pit mining, more journal articles than conference papers have been published. While master's and doctorate dissertations were not featured on GS, a few of them have been published [12–17]. The leading journals are *Mathematical Geosciences* and *Minerals*, which have published over 22% of discoveries concentrating on the use of ML on MWD data for open pit mining rock characterisation. Each of the remaining journals has published one paper.

Several ML techniques were applied to characterise rock conditions using MWD data in the reports identified with the GS search parameters. There are generally two types of ML techniques used in those findings: Neural Networks (NN) [12,16,18–20] and Gaussian Process (GP) [8,11,21]. Other approaches, including as Support Vector Machines (SVM), Random Forests (RF), Boosting, Self-Organising Maps (SOM), and Fuzzy Logic, have been compared to NN in various studies [19,20]). There is great potential to further investigate several supervised ML approaches, as some, such as RF, that are easier to understand than the 'black-box' inner-workings of NN and less computationally costly than GP, allowing for faster results. Moreover, Deep Learning techniques, including Convolutional Neural Networks, are adept with unstructured data and may be applicable to MWD data analysis with appropriate inputs, such as time-series or images,

3. Development of Machine Learning Models from MWD Data

The development of machine learning models comprises multiple discrete stages, depicted in Figure 3. The process begins with data in its unrefined state, a phase commonly known as data preprocessing (Figure 3A). Here, the focus is on improving the consistency and integrity of the data. In the case of sequential data, such as time-series data, it is often necessary to adjust or eliminate identifiable patterns and trends. Furthermore, to provide a cohesive basis for the following stages, any discrepancies resulting from different intervals of data recording are reconciled.

Feature engineering is the segment that follows preprocessing. In this phase, data is transformed into a form that computer algorithms can easily understand (Figure 3B). When confronted with complex data types, such as images or sound signals, it is necessary to perform transformations to convert them into a structured format. Depending on the ML model, a crucial aspect of this stage could entail reducing redundancy by replacing groups of interconnected variables with a more

succinct set that encompasses most of the initial information. After suitably structuring the data, it is segregated into distinct subsets known as training, validation, and test datasets (Figure 3C). The training data functions as the fundamental dataset upon which the model is initially constructed. The utilisation of a validation set facilitates the process of refining the model, whilst the test set is specifically put aside to act as a benchmark for assessing the model's performance in real-world situations.

After data partitioning, the focus shifts to the training of the model itself (Figure 3D). There is a wide array of models available for this purpose, encompassing neural networks, decision trees, and support vector machines. The selection of a model is primarily contingent upon the characteristics of the data and the goals of the research. In situations where it is necessary to explain the reasoning behind a model's decisions, particularly in diagnostic contexts, an additional explanatory model can be developed (Figure 3E). Nevertheless, if the decisions made by the primary model possess intrinsic transparency, this step may be deemed unnecessary. If the proposed model's performance is not acceptable, then the model's hyperparameters can be tuned, then trained, validated, and tested (Figure 3C) before acceptable predictions can be made (Figure 3F)

Ultimately, when novel datasets are introduced, they undergo identical preliminary phases of preprocessing and feature engineering as the initial training data (Figure 3G). An essential component of this phase involves determining the statistical similarity between the newly acquired data and the first training dataset (Figure 3H), although this is not necessarily always done in practice. Several analytical techniques, such as principal component analysis and t-stochastic neighbour approaches, offer valuable insights into this congruence. If a noticeable discrepancy exists between the datasets, it may be necessary to recalibrate the model.

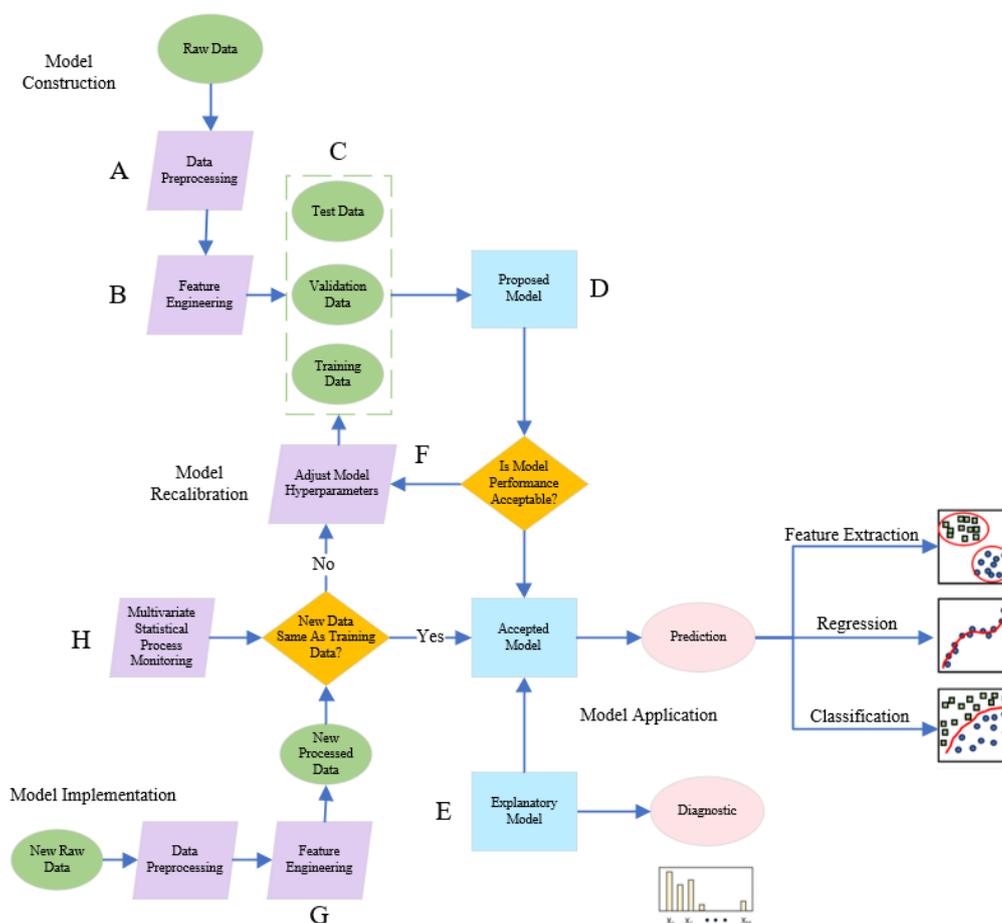


Figure 3. A general methodology for the building of ML models for the interpretation of data.

Table 1. Summary of ML applications on MWD data for open-pit mining rock characterisation.

Approach	Application	Model*	Commodity	Holes	Target	Comment**	References	
Supervised	Classification	HOP	Coal	35	Rock Type	Input of full-waveform sonic velocity	[22]	
		LB	Iron Ore	28	Rock Type	2D analysis; drill data averaged per hole	[20]	
		FIS	Iron Ore	28	Rock Type	2D analysis; drill data averaged per hole	[20]	
		GP	Iron Ore	31	Rock Type	Labels exclusive of 1m from contact	[8]	
			Iron Ore	N/A	Rock Type	BIF and shale in Brockman Formation	[11]	
			Iron Ore	N/A	Rock Type	CWT preprocessing of MWD data	[8]	
		LoR	Marble	204	Grade	6 classes of marble quality tested	[23]	
		NN	Coal	17	Rock Type	Backpropagation	[16]	
			Iron Ore	33	Rock Type	Feedforward and Backpropagation	[12]	
			Iron Ore	28	Rock Type	2D analysis; drill data averaged per hole	[20]	
		RF	Coal	35	Rock Type	ANN compares thresholding of SEM	[18]	
			Marble	204	Grade	6 classes of marble quality tested	[23]	
Regression	GP		Iron Ore	7000	Grade	Iron percentage, Phosphorous, Sulphur, Aluminium Oxide, Silicon Dioxide	[24]	
Unsupervised	Feature Importance	PCA	Coal	17	Rock Type	Used as validation of 3 input features	[16]	
			Iron Ore	33	Rock Type	To investigate Specific Fracture Energy	[12]	
			Iron ore	302	Rock Type	Used for individual index calculation	[25]	
	Change Detection	PCA	Marble	4	Rock Type	Intrusion detection of marble	[26]	
			AS	Coal	35	Rock Type	Seam roof detection to cease drilling	[27]
	Classification	KMC	Coal	17	Rock Type	4 class clusters identified	[16]	
			GP	Iron Ore	138	Rock Type	2D analysis; drill data averaged per hole	[21]
			Iron Ore	14340	Grade	Gaussian Kernel	[28]	
			HMM	Marble	3	Rock Type	Sudden material type transition	[29]
			NN	Iron Ore	33	Rock Type	Simple Competitive Learning	[12]
			SOM	Coal	17	Rock Type	3, 4 and 5 class maps for rock types	[16]
			Iron Ore	33	Rock Type	3 class maps for 3 major rock types	[12]	
SVM	Iron Ore	14340	Grade	2D analysis; drill data averaged per hole	[28]			

*HOP: Higher Order Polynomial, LB: LogitBoost, FIS: Fuzzy Inference System, GP: Gaussian Process, LoR: Logistic Regression, NN: Neural Network, RF: Random Forest, SVM: Support Vector Machines, PCA: Principal Component Analysis, AS: Adaptive Sampling, KMC: K-Means Clustering, HMM: Hidden Markov Model and SOM: Self-Organising Maps **BIF: Banded Iron Formation and CWT: Continuous Wavelet Transformation.

4. Practical Applications

4.1. Geology Recognition from MWD

This part pertains to the utilisation of ML techniques on MWD data to understand the intricate relationships between drilling metrics and forecast subsurface geological conditions before commencing mining operations. For example, a Banded Iron Formation (BIF) deposit might have classification zones of shale and BIF. These broad categorisation of geological zones from MWD data are useful for identifying the contacts between highly contrasting material types to update a deposit-scale model and increase its accuracy within localised areas [8]. This increased accuracy leads to improved blasting outcomes, in terms of achieving fragmentation around geological boundaries. However, these nongranular assortments do not provide resolution within each lithological unit that are required to optimise mining operations downstream of the drill and blast process, including excavation, haulage, and beneficiation.

First, an overview of the various types of geological deposits in which MWD data has been used to identify geology in open-pit mining operations is presented. The next section critically reviews the types of analysis performed by researchers to understand which MWD metrics are important to describe changing subsurface conditions from a data science perspective, including lithology, density, rock strength and weathering or fracture intensity. Principal Component Analysis (PCA) has been employed as a method for interpreting feature importance. However, it is worth noting that PCA is not a suitable approach for rating the significance of input variables. The final section details the application of ML to categorise rock types from MWD data. The classification methods employed by previous studies can be improved upon gaining a granular comprehension of the changing subsurface geological conditions.

4.1.1. Mined Commodities

Most researchers delineating lithologies from MWD data in open-pit mining have focused on sedimentary commodities, predominantly iron-ore and coal. In these deposits, the resource geology has been reasonably defined by exploration drilling at hole spacings of 50-meter grids in iron-ore and 100–200-meter grids in coal. The use of MWD data attempts to add local accuracies in between the exploration drillholes through blast-holes located at approximately 5-meters burden and spacing. Most of the research to recognise subsurface geology from drilling metrics has taken place in Canada [7,12,16] and Australia [8,11,18,20–22,27]. These countries have had strong research collaboration between the mining industry and universities.

The initial findings to link 6 open-pit blast hole drilling responses with the subsurface geology via the use of downhole geophysical responses was the basis for later work [7]. Nearly 20 years later, postgraduate research applied NN for open-pit geological classification from MWD datasets in coal and iron-ore mining blast holes [12,16]. Since these earlier Canadian-based studies, research on open-pit classification of geology has been entirely within Australian coal and iron-ore deposits. The research in coal geology recognition aimed to accurately predict coal roof locations to prevent blast damage in open pit mining with several reports presenting the results of various ML classification methods on the same MWD dataset from 35 blast holes in the Australian Hunter Valley coal region [18,22,27]. A few years later, coal seams in 6 gas wells were identified with 96% accuracy from the Surat Basin using five categorisation algorithms [19]. In the iron-ore industry, various classification methods in datasets of 28 holes and approximately 120 holes were utilised [20,21]. Both studies successfully distinguished BIF rock from shale in the Pilbara region to improve fragmentation by tailoring explosives loading for each rock unit. Nearly a decade later, multiple findings from the University of Sydney presented successful classification of BIF and shale units from a significantly larger dataset of several thousand blast holes [8,11].

While the majority of rock type recognition has occurred in open-pit mining in Canada and Australia, examples from civil, tunnelling, oil and gas and other mining industries have also been investigated. MWD data was used to distinguish geological zones in an urban construction project from Hong Kong. In the tunnelling industry, MWD data was also used to predict geology ahead of

blasting in the Norwegian Loren, Swedish Stockholm Bypass and the Chinese Jiudingshan projects [30–32]. The use of MWD data within the oil and gas sector has demonstrated its efficacy in the classification of lithology within narrow targets [33–36]. This classification aids to attain precise directional drilling, hence optimising the selection of well locations. In the underground coal mining industry, linear correlation and ML algorithms were applied on MWD data from roof support drills to determine geological zones and adjust locations and spacings of rock bolts and cable bolts to improve ground support [37–40]. In the open-pit quarry industry, successful use of MWD metrics to observe sill and marble boundaries was reported in 4 blast holes and alter explosives loading practices to achieve optimal fragmentation, which prevent unnecessary rock breaking of boulders from under-blasting [29]. More recently, six classes of marble qualities were predicted using Logistical Regression and RF [23]. All the above examples establish the wider applicability of determining geology from MWD data outside of open-pit mining of sedimentary deposits.

4.1.2. Mined Commodities

MWD metrics (rop, tor, fob, wob, rpm, etc.) have varying levels of feature importance in order to identify their correlations with subsurface geological conditions [41]. Feature importance refers to methods that calculate a score for each of the MWD metrics in a particular model. The resulting scores represent the contribution of each feature in the prediction of the target variable. A high score indicates that the characteristic will have a greater influence on the model used to forecast a particular subsurface geological variable. Initial manual attempts to interpret feature importance of open-pit mining MWD variables with wireline gamma responses identified local minimum and maximum variations; the changes in rop, tor, wob and SED parameters were associated with different lithological [7]. They also reported that rpm did not significantly correlate with any rock type, due to being controlled by the operator at a relatively constant rate. However, these univariate experiments each focused on an isolated, individual drilling parameter. Indeed, all other drilling metrics were required to be maintained near constant in these studies, which is unrealistic for common production blast hole drilling. An example of a surface blast hole drill rig is presented in Figure 4.

The early attempts to manually interpret the feature importance for each MWD input metric on rock type recognition models have given way to more advanced analytical methods, primarily Principal Component Analysis (PCA). PCA aims to show patterns in multivariate data by reducing the dimensionality of these datasets and creating new variables, called principal components [42]. The principal components are a set of orthogonal vectors that are linear combinations of the input variables and best describe which of these inputs represent the most variation to the data. The rop and tor were identified as the MWD metrics that were most closely linked with subsurface geological conditions, while rpm was the least significant [12,16]. Both researchers identified feature importance by using the loading plots that detailed the most variation (the first and second principal components), although this may not necessarily account for most of the variation in the target variable. PCA has also been applied to determine coal vs non-coal rock types by including gamma response and hole diameter as inputs along with the MWD metrics of rop, wob and tor [19]. This work also applied a fit-for-purpose feature importance algorithm based on random forests and determined the rate of penetration was the single most important MWD metric to classify coal vs non-coal rock types in the investigated holes. The wob, tor and rpm were presented as relatively insignificant compared to rop [19].

Several studies introduced derived drilling metrics calculated from the collected MWD variables to determine if derived features were more important than the raw drilling metrics. The Modulated Specific Energy (SEM) takes advantage of the variations in the ratio of tor to wob to identify rock type in coal blast holes [18]. SEM is calculated by modifying the Specific Energy of Drilling (SED) with a rotational work fraction, that is determined by dividing the tor by the sum of the tor and the wob. They reported SEM as an important feature from the drilling metrics to detect boundaries of multiple coal seams amongst predominantly sandstone units. A second novel drilling parameter called Adjusted Penetrate Rate (APR) was developed to account for variations between drilling operators in manually operated rigs as well as between manual and autonomous drilling rigs in iron-ore blast

holes [21]. APR is calculated by dividing the rop by the product of the wob the square root of tor. Their finding reported APR was a more important feature than SED for the categorisation of iron-ore rock types of BIF waste, mineralised BIF and shale. rule-based labelling of geology from multiple drilling metrics outperformed the univariate APR method of rock type recognition [8]. However, not all variables are consistently collected in open pit iron-ore production drilling conditions due to sensor faults or breakdowns [8]. As a result, the missing data has resulted in up to 90% of blast holes observations unable to be used for APR and SED.

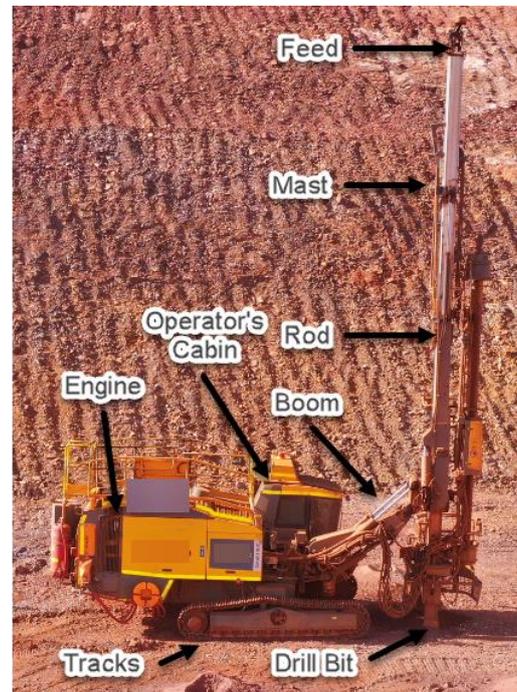


Figure 3. Typical layout of a surface mining blast drill rig (Type: Epiroc D65).

Determination of feature importance reveals which variables are essential to collect for accurate prediction of rock type. Conversely, feature importance should identify which features may be discarded during selection of variables to include for subsequent analysis using ML algorithms. As mentioned previously, the use of PCA on MWD data for the selection of features with the highest variation as the most important predictors may not be effective. In contrast, developments in interpretable and explainable AI have opened significantly more advanced approaches for this purpose. This could include Shapley value regression, permutation analysis, interpretation of model structures, kernel SHAP, LIME, etc., and in the case of deep learning models, also even direct interpretation of image or signal data, where applicable [43–45].

4.1.3. Machine Learning Classification

Classification of geology using ML methods on open pit blast hole MWD data has been demonstrated on mostly small datasets of a few dozen holes. Feature engineering has consistently been applied to clean noisy MWD data, including filtering, smoothing, normalising, and removing outliers to prepare the raw data for ML analysis. Although a range of different ML models have been used, multilayer perceptrons and Gaussian process regression have featured prominently in recent studies, as discussed in section 2.

NN algorithms have demonstrated the probability of a geological recognition in both iron-ore and coal deposits. Classification accuracy for five rock types achieved 95% using Back Propagation Neural Network (BPNN) algorithms on 17 blast holes from a Canadian coal mine [16]. Classification accuracy for three rock types in an iron-ore deposit averaged 57% based on 33 blast holes in the

United States [12]. One study used NN as an assessment tool to determine if the SEM metric was superior to APR to identify lithologies, while another study demonstrated a prediction accuracy of 96% using NN to classify coal and non-coal rock types [18,19]. A multilayer perceptron NN algorithm classified four BIF rock types at 78% accuracy [20].

GP have been exclusively used at Pilbara BIF iron-ore mines to classify geology. GP clustering of hardness values (approximated by regression modelling of APR) was used to categorise three types of iron-ore units (waste BIF mineralised ore and shale) [21]. The figures presented are in two-dimensions, indicating the researchers used an average MWD value for each hole to classify geology. This two-dimensional method provides a singular rock type and thus, a limited perspective for mine planning. In a novel three-dimensional method, MWD datapoints were labelled with categorised units from downhole gamma responses [11]. The GP-approximations resulted in a thresholding strategy that classified two BIF units in the Dales Gorge Member in 3 blast patterns at 87%, 84% and 81% accuracy, respectively. GP-derived results were reported as only 62% accurate to classify two rock types (unmineralized shale and mineralised iron-ore) [8]. They attributed this poor performance to noisy data requiring further data cleaning.

The use of NN and GP algorithms on MWD metrics has been largely successful to classify rock types. Several findings reported other ML algorithms, including Fuzzy Inference Systems (FIS), SVM, Random Forest (RF) and Boosting to compare results with NN but none demonstrated significantly superior performance to NN [19,20]. Despite ML classification accuracy greater than 90%, the prediction of a handful of broad geological categories does not adequately capture subtle differences within each geological unit. An increased resolution of rock type (including subcategories, such as massive, fractured or deformed rock) is required for informed and effective mine planning.

4.2. Rock Mass Properties from MWD

Rock mass quality has been correlated with drilling response data [41]. As with determining geological zones, the geotechnical properties are categorised rather than predicted from discrete values using ML analytical techniques. The main rock mass properties under investigation are rock strength, discontinuities or fractures, and rock mass categorisation scores, such as, Rock Mass Rating (RMR), Geological Strength Index (GSI), Q-system and Rock Quality Designation (RQD) [46–49]. These geotechnical conditions are traditionally determined by logging and laboratory testing of diamond drill core from holes that are spaced hundreds of metres apart without any regular pattern. Rock mass characterisation data collection from exploration drilling is sparse due to the expense of drilling. This low-resolution data capture requires interpolation and broad geotechnical domaining to classify a rock mass with significant uncertainty between holes. Surface mine ML applications on MWD data were generally focused on geotechnical characterisation to improve fragmentation, or rock breakage from blasting [1,6,25,50]. The focus of understanding rock mass properties from MWD data in underground mining and tunnelling based research is to reduce strata failure by adjusting spacing and locations of ground support equipment [13,51–59].

First, an overview of the various environments and mined commodities in which MWD data has been used to identify rock mass properties is presented. Next, the types of feature importance analysis conducted by researchers to understand which MWD metrics are useful to describe changing geotechnical conditions, such as strength and fracture state, are critically reviewed from a data science perspective. Finally, the application of ML to characterise rock mass zones from MWD data is surveyed. As with the geology-based findings in the previous section, these broad rock mass zone classifications are useful but do not accurately predict the complex fabric of a rock mass.

4.2.1. Commodities

As discussed in Section 1.2, there are considerably fewer studies on the ML classification of MWD data for rock mass characteristics in open pit mining than for geological types. However, the use of ML algorithms on MWD data to characterise a rock mass has been demonstrated in other industries. These include tunnelling [51,53,54] and underground mining [52,57–60], which employ

drilling prior to excavation. Exploration and laboratory-based activities [61–63] have also correlated rock mass properties with drilling metrics

In a series of classic studies, Schunnesson (1990, 1996, 1997, 1998) drill monitoring was used in underground Scandinavian iron-ore and copper mines to distinguish changing conditions in each investigated rock mass [57–60]. More than two decades later, potential blasting issues in the underground Swedish Malmberget iron-ore mine were predicted by assessing trends in MWD data [52]. In the tunnelling space, rock mass classification zones, including RMR and Rock Mass Quality, were predicted from intelligent MWD data analysis to improve ground support patterns [51,53,54].

Exploration drilling, and laboratory experiments also support the use of ML methods to predict geotechnical properties from drilling metrics. Rock strength could be predicted from an exploration drill rig's MWD data in 7 holes of diamond core in Turkey [61]. In laboratory experiments drilling through prepared samples, it was demonstrated that rock properties, including density, porosity, P-wave velocity, Schmidt hardness, UCS, tensile strength and Elasticity Modulus, could be successfully predicted from acoustics produced during drilling of laboratory samples [62]. On the other hand in the tunnelling space, simulated fractures were detected in the rock mass from MWD data trends during the excavation of a 20 metre wide tunnel [53]. More recently, several Chinese tunnel excavations have used regression and classification-based methods to determine rock properties from MWD data. NNs were used to predict rock strength values, including UCS, Elasticity Modulus and Poisson Ratio, from MWD data [64]. In terms of a classification approach, Bi-Directional Long Short-Term Memory NN was used to predict trimodal rock mass classes [65].

However, few studies have attempted to characterise rock mass conditions from MWD data in the open pit mining environment utilising thresholding or simple correlation. It was observed that high and low rop correlated with weak and strong rock strength zones in 1267 blast holes from the Aitik copper mine in Sweden [66]. To determine fracture locations from MWD data, downhole geophysical televiewer logs were interpreted to correlate fracture locations in 8 blast holes from the Canadian Highland Valley copper mine [50]. Also using televiewer logs to calibrate their findings, two novel rock description indexes were developed based exclusively on MWD data from 302 production blast holes at the Erzberg mine [25]. These systems categorised rock mass zones for structural condition and strength properties and were corroborated by highwall mapping via photogrammetrically generated models. However, no studies were identified that used ML analytical methods on MWD data to characterise subsurface geotechnical properties in open pit operations.

4.2.2. Feature Importance

As with the determination of geological zones from MWD data, research has attempted to identify the feature importance that each MWD metric has in predicting subsurface geotechnical conditions. Determination of feature importance using advanced analytical methods has almost entirely taken place within underground mining and tunnelling operations [51,52,57]. Multiple studies utilised manual correlation in open-pit mining to identify feature importance on drillability or blastability. These are outside the scope of this review due to their focus on other aspects that are not directly related to subsurface geotechnical conditions [1,6,14,55,66–68] (Ghosh et al., 2014; Khorzoughi, 2011; Liu and Yin, 2001; Manzoor et al., 2019; Navarro et al., 2018; Scoble and Peck 1987; Segui and Higgins, 2001). PCA has only been used on open-pit mining MWD data to determine feature importance for a novel MWD-based rock mass classification system (Drilling Rock Factor – DRF) [25].

PCA has been used to determine feature importance of MWD metrics for geotechnical properties in underground mining and tunnelling projects. Specifically, the features ranking highly on the first principal component have generally been interpreted to be the most important. As discussed, the variables with the most variation are not necessarily the most important (section 1.1.2). Schunnesson determined the rop was most important from PCA loading plots showing rop as low in higher rock strength zones and conversely, the rop was observed to be higher in weaker rock strength zones [57]. A later study focusing on the link between rock mass conditions and chargeability issues in underground blast holes employed PCA to identify ropS, torS, rop, and tor highly on the first

principal component, accounting for 62% of data variability [52]. Using a combination of PCA and Ordered Weighted Average (OWA), Galende-Hernández et al. determined the top three features to select for predictive analysis were wob, damper pressure and tor [51]. The inconsistent feature importance results between these two findings may be attributed to discrepancies with data collection, data cleaning equipment or geological settings. It is also likely that the results do not support one another because PCA is not a statistically appropriate method of feature selection.

PCA has also been used on an open-pit mining MWD dataset from 286 blast holes at the Erzberg Mine in central Europe to interpret feature importance of drilling metrics for input to their DRF [25]. The DRF rock mass classification system is comprised of a structural and strength-grade factors. The structural factor consists of huge, fractured, and extensively fractured zones, while the strength-grade factor has soft-waste, hard-waste, transition zone, and hard-ore categories. Navarro et al. reported that the metrics rop, ropS and torS ranked highly on PC1, the first principal component, for the structural factor evaluation, while tor dominated the positive side of PC2, the second principal component [25]. The first two main components of the structural factor explain a combined 66.02% of the entire variation, with PC1 contributing 47.47% and PC2 contributing 18.55%. In contrast, for the strength-grade factor, rop and wob dominated the positive sides of PC1 and PC2, respectively. The results of the study demonstrate that the strength-grade PC1 outcomes can differentiate between two distinct regions characterised by varying rock strength. Specifically, the schisted sandstone exhibits a Uniaxial Compressive Strength (UCS) value of 30 MPa, while the limestone displays a UCS value of 125 MPa [25]. These results correlate well with digital photogrammetry reconstructions of the pit walls after blasting and excavation [25]. However, the DRF results are heavily dependent on calibration with manually interpreted televiewer logs. In addition, since the Rock Factor zones are also based on the local iron-ore geology of the Erzberg Mine adapting DRF to different mineral deposits would require intensive re-calibration. A deposit-agnostic approach without manual calibration would be more readily adopted to determine geotechnical properties from open-pit mining MWD data.

4.2.3. Machine Learning Classification

Classification of rock mass properties using ML methods on open pit blast hole MWD data has not been demonstrated, despite an exhaustive search. It was discovered that while many reports claim to characterise rock mass conditions using ML on MWD data, what was reported was often rock type, with an assumption of strong vs weak UCS values for contrasting rock types. The results of these are discussed in Section 1.2.3. No studies were found that attempted to predict geotechnical properties using ML methods in the open-pit mining, underground mining, or construction industries.

4.3. Geochemical Properties from MWD

Very few studies attempt to predict geochemical properties from MWD data [24,25,57]. Commonly reported ore geochemical properties included aluminium oxide (Al_2O_3), calcium oxide (CaO), iron (Fe), total loss of ignition (LOI), magnesium oxide (MgO), manganese (Mn), phosphorus (P), sulphur (S), silica oxide (SiO_2) and titanium oxide (TiO_2). All findings reporting geochemical properties from mining MWD data were located within an iron-ore deposit and listed grade or iron-ore percentage.

Fe was reported as the only ore quality investigated [25,57]. Partial Least Squares (PLS) was applied on MWD data from an underground mine and closely predicted iron-content against assays of drill cuttings in areas of high and low phosphorus geology [57]. The ore grade prediction of Navarro et al. was split into two simple categories of 1) waste consisting of less than 20% iron and 2) ore consisting of greater than 20% ore [25]. These waste and ore class results appear equivalent to the DRF results. However, there is no explicit mention of the ore-grade prediction accuracy which suggests it is probable that no validation of results was conducted against laboratory assays.

Only one study reported the use of ML classification for geochemical properties from MWD and drill cutting assay data from two Australian iron-ore mines [24]. Unlike previous studies that only reported the investigated ore properties were Al_2O_3 , CaO, Fe, LOI, MgO, Mn, P, S, SiO_2 and TiO_2 . Fe was predicted with acceptable R^2 values of 0.79, 0.79 and 0.78 in the first mine and 0.64, 0.64 and 0.63 in the second mine for GP, SVM and RF algorithms, respectively. The datasets were combined to predict P and S. Acceptable R^2 values for P were 0.79, 0.78 and 0.81, and S were 0.91, 0.90 and 0.92 for GP, SVM and RF algorithms, respectively. The report also identified that several of the geochemical properties correlated with each other. Based on this, cross-assay predictive models showed improved results for the remaining ore properties. For example, the R^2 value for Al_2O_3 of 0.65 on MWD data alone in a RF model was improved to 0.90 and 0.85 when adding the cross-assay results for Fe and SiO_2 , respectively. The primary benefit of this result is that if one assay can be directly measured with a sensor or strongly predicted from a model, these measurements can be utilised to enhance estimates for other geochemical properties.

5. Discussion

5.1. Current Challenges

This summary makes it clear that the motivation behind these findings is to circumvent the limitations of conventional subsurface characterisation prior to excavation. NN and GPs are the two primary categories of ML algorithms utilised with MWD data for rock categorization. While some artificial intelligence algorithms have been applied to the same datasets, different ML architectures produced distinct outcomes [18,22,27]. Thus, no model has been proposed as optimal for characterising geological, geotechnical, and geochemical features from MWD data, as model selection depends on underlying aims, scientific objectives, and model restrictions. Notably, some ML approaches are more attractive (NN and RF) than others (GP) due to their computational efficiency [19]. In addition to there being no accepted, optimal ML modelling algorithm to characterise subsurface conditions from MWD data, there is no consistent approach to MWD data collection and processing.

There are still some challenges in data collection and processing that must be overcome. First, most of the investigated projects featured limited amounts of data from blast holes, making it difficult to extensively analyse and interpret the subsurface. Second, the quality of the output is dependent not just on the model but also on the condition of the gathered data. Quality Assurance and Quality Controls processes are not commonplace with open pit MWD data acquisition. During the development of predictive models, the robustness of the model may be affected due to the existence of missing values or outliers within the dataset. In addition, the feature importance among MWD variables may also affect the modelling robustness. Existing studies [16,25,52] disagree as to which metrics should be utilised to characterise rock properties under different environmental situations, as they vary based on deposit-specific conditions. To identify feature importance of drilling variables, PCA has been used to choose input variables from the MWD data. A statistically suitable strategy for determining feature relevance should enhance feature selection to improve computational precision and speed. In conclusion, the subsurface characterisation applications of ML techniques applied to MWD data are in an escalating stage of development.

5.2. Future Potential

Even though non-traditional approaches to comprehend mining subsurface conditions require further development, they are gaining popularity in research. ML technologies can be utilised as a supplement to conventional theory [8,25]. They have the potential to extract insights about a vast array of spatial data, which can then be narrowed to investigate areas of interest in greater detail. However, despite the widespread use of ML classification algorithms for categorising geology in MWD data, ML analytical methods have seldom been applied. A common assumption has been that it is far more crucial to understand the boundaries between dissimilar rock types than the variation within each rock type [11,18,25]. As a result, the categorisation of 'strong' and 'weak' rock types, such as BIF and shale, respectively, has dominated projects by investigating univariate relationships, mainly ρ_p and τ [69]. In contrast, existing multivariate ML regression algorithms have significant prospects for solving the complicated challenge of variance within each rock type.

To interpret subsurface properties using MWD data, supervised [8,18,22,25] and unsupervised learning [12,16] techniques have been implemented. Supervised learning can use all available information to make predictions and classifications, while unsupervised learning may identify potential relationships and extract features from a substantial volume of unlabelled data. In the context of both supervised and unsupervised learning applications, it is essential to employ suitable data pre-processing approaches. These techniques encompass the removal of noise, outliers, and false attributes. This necessity arises from the considerable geographic variability observed in measurements while considering the data related to MWD and subsurface conditions [70].

Existing techniques of MWD data processing and analysis rely heavily on manual interpretation, such as determining the most critical rock-property-dependent metrics [31]. Consequently, it is difficult to repeatedly process data from new sources and places. A pertinent aim of applied research is therefore to design an automated workflow in which ML methods and available input data, connected with specific conditions, can correlate, process, and select drilling variables for subsequent estimation of rock properties. In the interim, the gathering of a training dataset during algorithm execution could facilitate data collecting for future applications operating under comparable conditions.

The implementation of ML techniques is dependent on the training data set accurately representing the connection between the input datasets, MWD and subsurface properties, respectively. It is crucial to select attributes for the training set that accurately represent the population. As a result, ML training progress is impeded by the challenges of overfitting, extended training time, and a notable inclination to get trapped in local minima [12]. As demonstrated in the tunnelling sector, these obstacles may be overcome with optimisation algorithms, including genetic algorithm, particle swarm optimisation and imperialist competition algorithm [54]. Due to their ability to rapidly analyse massive and complex MWD datasets, ML methods provide an effective

solution to provide accurate and relevant predictions of subsurface properties in open cut mining operations.

6. Conclusions

The mining industry is increasingly using methods of artificial intelligence to overcome the uncertainty associated with data on geological objects. ML algorithms have been applied on mining MWD datasets to understand pre-excavation subsurface conditions. Numerous studies have been conducted on the collection, processing, analysis, and application of MWD variables for the characterisation of rock type, rock mass, and ore properties.

From this review of the literature, the following conclusions can be made:

- The most commonly measured MWD variables measured together with the depth of drilling in open-pit mines are rate of penetration (rop), torque or rotational pressure (tor), bit air pressure (bap), weight on bit (wob) and rotary speed or revolutions per minute (rpm).
- Several studies have analysed the relative importance of each of these variables related to the identification of rock types and characteristics with mixed results. This is an emerging area that can benefit from recent significant advances in machine learning, where models are interpreted or explained.
- Several studies have analysed the relative importance of each of these variables related to the identification of rock types and characteristics with mixed results. This is an emerging area that can benefit from recent significant advances in machine learning, where models are interpreted or explained. This would particularly be the case where other MWD variables, such as vibrational or acoustic signals are included in models.
- In most studies, ML models could successfully categorize geological zones or rock types from MWD data, but further work is required to capture more subtle differences within geological units.
- Classification of discrete rock mass properties, including rock strength and fracture count, using ML methods on open pit blast hole MWD data does not appear to have been demonstrated yet. Instead, rock type is typically identified as a proxy for rock strength based on assumptions associated with each type.
- Only one study predicted geochemical properties using ML classification on MWD and drill cutting assay datasets. ML analytical methods applied on MWD data resulting in discrete values for geotechnical, geological, and geochemical will enable a low-cost, high-resolution comprehension of subsurface conditions beyond simple rock type classification.
- Overall, these studies have not yet taken full advantage of recent developments in deep learning and as more data are collected, these ML are likely to play a more important role in MWD data analysis for enhanced comprehension of geology, rock mass characteristics, and ore attributes for enhanced sustainability, efficiency, and safety of mining operations.

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