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Review

Prospects of Applying MWD Technology for Quality Management of Drilling and Blasting Operations at Mining Enterprises

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Abstract: This paper presents a review of measurement while drilling (MWD) technology as applied to the mining industry, describes its development path, provides a global review of literature on this topic, and outlines further trends of development for research on MWD application in drilling and blasting (D&B) operations at mining enterprises. The current review serves as a starting point for anyone interested in the research or application of MWD technology in Mining and Construction. In the paper, the authors examine major works of researchers in this area, describe current state of the art, and propose a way to improve MWD for drilling equipments. The paper contains examples of technology application in various processes, associated with drilling and mining operations, describes approaches and problems of MWD system utilization, revealed in the course of data collection and analysis of drilling processes. The study also presents a summary of existing approaches in the area of data validation and verification, applied up to the present day to cope with the problems of global MWD use in Mining and Construction. The authors outline future areas of study which are of interest and deserve the attention of the scientific community and researchers working on the development of MWD technology.

Keywords: measurement while drilling; MWD; drilling monitoring; drilling parameters; rock properties; blasting

1. Introduction

Measurement while drilling (MWD) is a state-of the-art technology that allows to measure and obtain various types of real-time data on the rock mass in the process of hole drilling. Such information has great value both in data analysis and its use in engineering calculations and timely decision making on further processes of rock excavation and assessment of its stability [1]. Presently, there are numerous projects and cases, where collection of drilling data was successfully organized, e.g., in tunneling: construction of water treatment facilities in Bekkelaget, Oslo (Norway) [2], construction of a road tunnel in Sorkjosen (Norway) [3], and a high-speed railway tunnel El Espiño (Spain) [3]; in quarry mining: excavation in a lime quarry El Aljibe (Spain) [4], in an open-pit copper mine Highland Valley (Canada) [5], in Tugnuisky coal mine (Russia) [6], among others; in underground mining: in Malmberget mine (Sweden) [7].

At the core of the technology lies a system of monitoring, composed of a drilling unit, various sensors (tachometer, torque sensor, displacement sensor, pressure sensor, among others), a block of incoming signal processing, a communication channel, and a device for storage and processing of incoming data [8]. Due to the development of hardware and software, one can encounter several variations of the conventional MWD technology ("KOBUS" [9],"VG Drill" [10],"Exp. Manager" [11], and "I-SURE" [12]. They differ in arrangement and support equipment, which allows to increase the accuracy and quality of measurement, eliminate errors, and at the same time verify obtained data.

In the process of drill monitoring, depending on the type of drilling unit, the following parameters are being measured: thrust, air pressure, feed pressure, percussion pressure, rotation speed, drilling (penetration) rate, torque, flushing pressure, flushing flow, drilling depth and time, among others [8,13]. The obtained values of parameters are subsequently presented as time or drilling depth dependencies. Data obtained while drilling become pivotal for the subsequent description of rock mass characteristics.

The main advantage of this technology, as compared to existing methods of geological, physical, and mechanical data assessment, such as core drilling [14] or geophysical logging [15], is its immediacy and relative cheapness of data acquisition [16]. It allows to make agile and efficient design decisions based on real-time data, as well as to respond quickly to the changes in the rock mass.

Companies such as Sandvik (Sweden) [12], Epiroc (Sweden) [11], Bever Control (Norway) [17], Zyfra mining (Russia) [18], Blast maker (Kyrgyzstan) [9], Peck Tech Consulting (Canada) [19], among others, actively invest in scientific research and projects associated with the development of MWD technology in the mining industry.

Presently, there are projects that have made a significant contribution to MWD development and improvement of drilling data interpretation (TUÑEL project [20], SLIM project [21], SIP-STRIM project [22], BeFo project 344 [23], among others). These projects have been supported by grants from scientific organizations and companies, such as Stiftelsen Bergteknisk Forskning ("BeFo", Rock Engineering Research Foundation) [24], Swedish Blasting Research Centre (Swebrec) [25], MAXAM [26], among others).

Leading researchers and research groups from universities such as the University of Western Australia [27], Norwegian University of Science and Technology [28], Luleå University of Technology [29], University of British Columbia [1], Technical University of Madrid [30], and Saint-Petersburg Mining University [31] actively work or have worked in the past on the development of this subject field.

Analysis of scientometric databases (Figure 1) for the last 20 years demonstrates significant growth of direct references and implicitly related literature on MWD development, which indicates a keen interest among the scientific society and mining engineers.

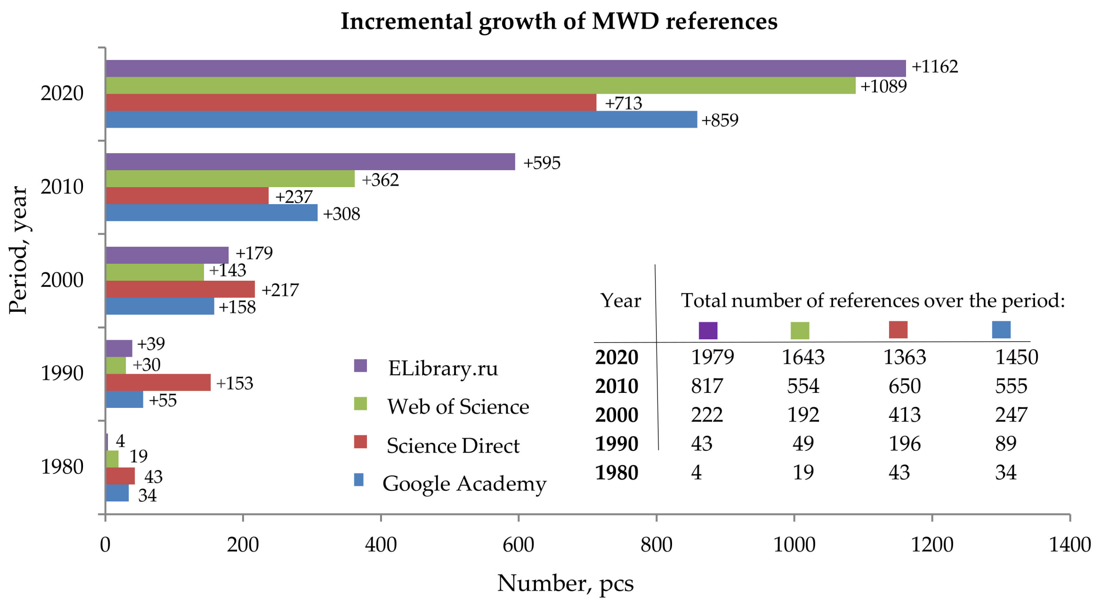

Figure 1. Analysis of scientometric databases in response to a query 'MWD'.

Detailed information on strength and structural specifics of the rocks to be blasted can be obtained while drilling blastholes with the help of an MWD system [32]. A more accurate definition of data while drilling, including information on rock properties, structural faults, and fractures and voids, allows to adjust drilling and blasting (D&B) parameters for better control of the blast energy. Research groups place an ever greater emphasis on the solution of problems associated with the correct interpretation of acquired data and correlation between MWD and D&B processes ([4,7,16,30,33–35], among others). However, up to this day, there are unresolved issues that hinder mass implementation of this technology. In this paper, the authors touch upon certain aspects of MWD application, explain cases of MWD adoption, and identify bottlenecks and future prospects of technology development in the context of D&B operations.

2. Literature Overview and State of the Art in MWD Field

For the first time, MWD technology was used in the oil extracting industry in 1911; nevertheless, the first attempts to apply and adopt this technology to the mining industry date back only to the 1970s [17].

Presently, one of the main indicators of drilling efficiency is mechanical specific energy (MSE). The concept of MSE was introduced by Teale [36] as the work required to drill a unit volume of rock. For rotary drilling, the work is performed by both bit thrust and torque. R. Teale had derived an equation for MSE, which was subsequently used by many researchers in their works [1,33,36–40].

For rotary drilling, the specific energy can be described by the Equation (1):

$$e = \frac{F}{S} + \frac{2NT}{SV} \tag{1}$$

For hydraulically driven drilling rigs, the expression is transformed into Equation (2):

$$e = \frac{F}{S} + \frac{2kPT}{SV} \tag{2}$$

For electric rotary driven drilling rigs, the expression for the specific drilling energy will be as follows (Equation (3)):

$$e = \frac{F}{S} + \frac{UI}{SV} \tag{3}$$

where: e is specific drilling energy, kJ/m^3; F is load on the drilling bit, kN; S is borehole cross section, m^2; N is drilling bit rotation speed, r/s; T is bit torque, kN·m; V is drilling rate, m/s; P is rotator inlet pressure, kN/m^2; k is structural parameter of the drilling rig rotator, m^3; U is bit rotator motor operating voltage, kW; and I is bit rotator motor operating current, A.

Based on the use of parameters such as power demand of rotary engine and drilling rate, Tangaev proposed a classification of rocks according to their drillability [41]. Multiple field-test experiments measured the input power consumed by the engine of drill rig rotator, excluding the power spent on no-load rotation. As a result, Tangaev took the measuring scale from "Unified Classification of Rocks According to Their Drillability" as a base mark [42] and enhanced it with the values of MSE consumption for various rock types. A comparison of Tangaev classification and "Unified Classification of Rocks According to Their Drillability" is presented in Table 1.

Kosolapov in his work derived a correlation between MSE, Protodyakonov strength index, and specific explosive energy for rotary, hydraulic, and electric drill rigs (Table 2) [37], thus making a transition from strength index to specific energy parameters of drilling and blasting. The advantage of this approach is that it is possible to measure MSE right in the process of blasthole drilling and use it to derive rock strength index and specific explosive energy.

Table 1. Comparison of drillability scales [41,42].

Category of Rocks According to a "Unified Classification"	Specific Energy Consumption of Rotary Drilling (Tangaev)		Typical Examples of Rocks
	E, MJ/m	MJ/m^3	
IV	-	-	Heavy clay. Loam with crushed stone and gravel. Very soft coals
V	-	-	Clay siltstones. Weak mudstones. Clay marl. Soft coals
VI	2, 16	48	Dolomites affected by weathering. Carbonaceous shales. Medium coals
VII	2, 88	64	Dense siltstones. Unchanged dolomites. Soft limestones. Highly weathered shales. Coals above medium strength
VIII	3, 60	80	Anthracites. Soft iron ores. Shales. Weathered tuffs
IX	4, 22	96	Completely weathered granites, granodiorites. Weathered sandstones, limestones
X	5, 04	112	Apatite ore. Strongly weathered granites, dunites. Serpentines. peridotites
XI	5, 94	132	Destroyed gneisses. Coarse-grained, marbled, dolomitized limestones. Slates. Pyrite and manganese ores
XII	6, 06	148	Apatite-nepheline ore. Anhydrites. Weathered: gabbros, gneisses, granites, diabases. Copper-pyrite ores
XIII	8, 28	184	Weakly weathered: granites, diabases. Coarse magnetite iron ores.
XIV	9, 52	216	Medium-grained weathered andesites. Gabbro modified. Coarse-grained: gneisses, granites, granodiorites.
XV	11, 52	256	Medium-grained granites, granodiorites, diabases. Silicated dolomites. Marbles.
XVI	13, 50	300	Medium-grained gabbros, gneisses, dunites, peridotites, porphyrites. Highly silicified limestones
XVII	16, 56	370	Medium-grained basalts. Fine-grained: gabbro, granite, granodiorite, diabase. Siliceous limestones and sandstones.
XVIII	19, 52	440	Dense andesites. Fine-grained basalts, diorites, skarns. Fine -grained titanium-magnetite ores
XIX	24, 84	550	Very dense: andesites, basalts, diabases, diorites. Microgranites, microquartzites. Dense hematite ores.
XX	26, 64	600	Unchanged drain: andesite, jaspilite, basalt, iron ore. Drain quartz. Microgranites

Zharikov [33] developed a framework for constructing a digital model of Protodyakonov strength scale based on the dynamics of drilling parameters. Strength of the rocks was estimated using their drillability index, derived from measured penetration rate, thrust, and rotation speed. Based on these results, a method to estimate powder factor from test-well drilling data was developed. It allowed to model rock strength dependency from cutting depth, estimate a balance between power characteristics of roller-bit drilling and blasting fragmentation of the rock mass, as well as to specify the mass of explosive charge for each blasthole.

Table 2. Correlation between hardness coefficient, specific drilling energy, and specific blasting energy [37].

No.	Hardness Coefficient According to M. M. Protodyakonov	Minimum Specific Drilling Energy, MJ/m^3	Maximum Specific Drilling Energy, MJ/m^3	Specific Blasting Energy, MJ/m^3
1	6	30.48	42.68	2.62
2	7	42.68	54.87	2.89
3	8	54.87	67.06	3.16
4	9	67.06	79.26	3.38
5	10	79.26	91.45	3.59
6	11	91.45	109.74	3.80
7	12	109.74	128.03	3.98
8	13	128.03	152.42	4.11
9	14	152.42	176.8	4.23
10	15	176.80	213.38	4.36
11	16	213.38	256.06	4.52
12	17	256.06	304.83	4.67
13	18	304.83	359.7	4.80
14	19	359.7	420.67	5.00
15	20	420.67	493.83	5.09

Regotunov and Sukhov [38] presented results of their research on strength properties of the rock mass in the process of roller-bit drilling using their hardware and software package. Their paper describes an algorithm that specifies strength parameters of the local rock mass to be blasted. The main parameter used to specify strength and technological properties of the rocks was power consumption (specific energy) of drilling. The calculations were already adjusted for drilling tool wear and well clean-up. From that, Rzhevsky defined a drilling work index and built a model of rock mass strength, with the help of which it was possible to regulate the explosive loading in each blasthole, taking into account local rock strength.

Brown and Barr (1978) conducted early research on dependency between drilling parameters and various geomechanical characteristics. They came to a conclusion that only continuous recording of operating parameters made while drilling could provide information on mechanical properties of the rocks [43]. Based on the analysis of rotary percussive drilling, they divided all the parameters into two groups: dependent and independent ones (Figure 2). Independent parameters were influenced only by drill rig capacity, drilling technique, and monitoring system, but not the properties of the rock mass. Dependent parameters were influenced by how the drilling system reacted to the varying characteristics of the rock mass.

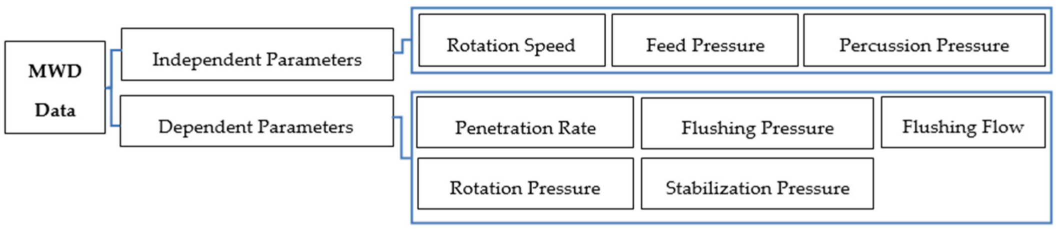

Figure 2. Ranking of dependent and independent measurement while drilling (MWD) parameters according to Brown and Barr [43].

Already in 1984, Brown et al. [39], in their paper, practically confirmed the applicability of MWD technology in the mining industry, making a conclusion that the system could estimate physical and mechanical properties of the rocks based on MSE, compressive strength of the rocks, and their geological properties. This method also allowed to identify fractures (both open and closed) and cavities within the rock mass.

At the same time, Leighton (1982) [34] used this approach to identify optimal D&B parameters, which allowed to minimize damage beyond the intended excavation perimeter while performing contour blasting at an open-pit copper mine. Based on the survey data obtained from large-hole drilling with roller bits, Leighton was the first to demonstrate optimization of D&B operations using analysis of drilling parameters to estimate rock quality index (RQI) [34]. In his study, the author used linear regression to derive a connection between powder factor and RQI of the drilling equipment.

Leighton observed that the main problem associated with this approach was that RQI values did not provide comprehensive information on the state of the rock mass, as the index took into account only two drilling parameters—penetration rate and thrust; moreover, the approach was only tested on one drilling technique [34].

Lopez (1995) combined penetration rate, thrust, bit rotation speed, and drilling diameter to overcome the limitations of RQI and introduced a rock characterization index (Ip), dependent from these parameters. He noticed that since penetration rate depended on geomechanical properties of the rock mass, Ip was closely related to rock strength. As a result, based on the analysis of data from numerous mines, Lopez derived a more accurate dependency between powder factor and Ip index [44].

Lilly (1986) introduced a blastability index (BI) based on rock mass description (RMD). He found that four key parameters significantly influenced the efficiency of blasting operations: block structure of the rock mass (joint plane spacing (JPS) and joint plane orientation (JPO)), specific gravity of rocks (specific gravity influence (SGI)), and uniaxial compression strength (hardness (HD)). As a result, an equation was derived to calculate BI using the above mentioned parameters [45].

$$BI = 0.5\ (RMD + JPS + JPO + SGI + HD) \tag{4}$$

Yin and Liu (2001) also utilized data obtained from drill logs to assess the blastability of the rock mass. They introduced an improved RQI as a measure of rock blastability and defined it as the amount of force required per unit of penetration rate. Using dimensional analysis and identifying two groups of non-dimensional parameters, including penetration rate, thrust, torque, and rotation speed, they proposed a new RQI equation, which involved two invariables that could be calculated using a set of limiting assumptions rather than a strict mathematical approach [46].

Scoble and Peck (1987) noted that monitoring and interpretation of drilling performance data allowed to estimate not only strength, but also structure of the rock mass. They discovered a correlation between operating parameters of drilling equipment and changes in strength, lithology, and fracture density of intact rocks. Essentially, they verified MWD data by locating fractures using drill bit penetration rate in the process of small diameter holes rotary percussive drilling in a limestone quarry in Montreal, Canada, and compared these data to downhole camera video records and core tests. They showed that 90% of fractures detected by the downhole camera coincided with the fractures located in the proximity of certain peaks on the graph of penetration rate against blasthole depth [47].

In 1989 [48], a research was conducted on the correlation between drilling parameters and geophysical logging in the process of large-hole rotary drilling; however, due to the difficulty of data interpretation from electric drill rigs, the correlation between the two sets of data was not too high. Scoble and Peck, just as Brown and Barr before them, came to a conclusion that parameters measured while rotary drilling could be divided into two groups: independent parameters, which were controlled by a drilling operator, such as rotation speed and bit weight, and dependent parameters, such as penetration rate, torque, and air pressure, which were associated with varying rock properties and could be influenced by changes in other drilling parameters [48].

Later ideas of these researchers were developed in the study by Khorzoughi [1] from the University of British Columbia (Canada), who investigated MWD application in large-hole rotary drilling in an open-pit copper mine in Highland Valley (Canada), with the purpose of quantitative assessment of fracture density in the rock mass. The author based his research on the existing alpha-algorithm for compensated blastability index (CBI) estimation, in turn based on the calculation of fracture reduction factor (FRF) [40]. This algorithm compensated the standard blastability index (BI) [45] derived from MSE calculation and adjusted it for the presence of fractures (see Figure 3).

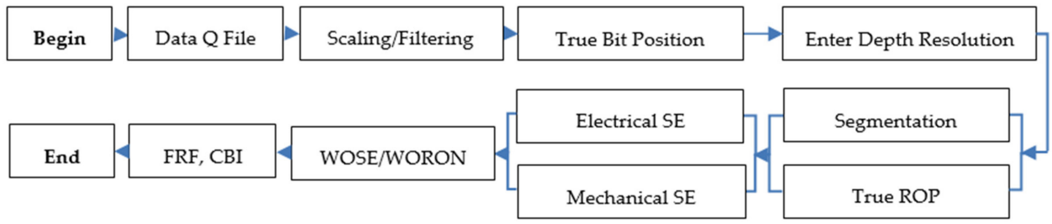

Figure 3. Flowchart of compensated blastability index (CBI) calculation algorithm [1], where: Q file—Recorded Log data parameters; ROP—Rate of penetration; SE—Specific Energy; WORON—is the monitored weight on the bit over penetration rate per revolution (WOB / [ROP / RS]); WOB—weight on the bit; RS—Rotary Speed; WOSE—examines the ratio between WORON and SE (WORON / SE × D); and D—bit diameter.

Khorzoughi interpreted and processed continuously recorded electric signals from the MWD system into physical units for subsequent data handling. Apart from measurements made by the MWD system, geophysical logging of the drilled blastholes was conducted in order to compare its results to the ones obtained using an algorithm and to confirm or refute its efficiency. Research demonstrated that the alpha-algorithm could not reliably predict fractures in the rock mass. In order to improve the existing algorithm, the author introduced an adjusting fracture reduction factor [40], calculated using a moving average method and taking into account direct interdependence between MWD parameters and the presence of open and closed fractures, detected in the logs. An improved algorithm demonstrated good results and correlation with the logs data. However, the study also confirmed that the algorithm could not detect fractures with dip angle exceeding 60 degrees [1].

In the 1990s, Schunnesson [49] conducted fundamental research on the monitoring of parameters in rotary percussive drilling and came to the conclusion that even a single parameter (e.g., penetration rate) could be used to assess the quality of drilled rocks, provided that rock properties differed significantly between geologic zones (e.g., between solid and fractured rocks in open-pit mining). However, if differences in properties between rock types were minor, the use of a single drilling parameter became unfeasible. In such cases, it was necessary to consider several drilling parameters and their interaction [49].

In 1996, Schunnesson [50] carried out research on preliminary estimation of rock quality designation (RQD) [51] depending on MWD parameters. He analyzed how drilling parameters, such as rotation pressure (torque), penetration rate, and revolutions per minute (RPM) responded to structural faults in the rock mass. Results of this research demonstrated that, in most cases, deviations of penetration rate and rotation pressure were directly proportional to the intensity of rock fracturing. However, the author pointed out that intense fracturing could lead to a decrease in penetration rate and RPM with a simultaneous increase in torque. Such situation can be explained by jamming or sticking of the drill bit. For preliminary RQD assessment, the author used the principal component analysis (PCA) [52] and partial least squares (PLS) method [53]. The correlation between calculated RQD parameters and the ones measured while drilling was strong despite the fact that the former were affected by the previous blast, whereas MWD parameters captured a certain volume of intact rock around the blasthole [50].

In another paper [54], Schunnesson proposed a method of data analysis based on a step-by-step normalization with the aim of separating interdependent drilling parameters from each other. The first step was to eliminate the impact of blasthole length on thrust, penetration rate, and rotation pressure. The second step removed thrust dependent variations of penetration rate and rotation pressure. The final step involved normalization of rotation pressure and penetration rate, as well as elimination of their interdependence. As a result of this step-by-step normalization, the only data left were those directly dependent on variation of rock properties, which later could be used for a more accurate description of rock indices [55]. The method was successfully tested in several mining projects, where the author applied PCA on parameters as normalized penetration rate, rotation pressure, and their variations (deviations) [56].

Later, Ghosh developed ideas of his Swedish colleague in his doctoral thesis [35]. This research was dedicated to qualitative assessment of rock mass composition and its impact on charging drill fans to blast iron ore in the underground mine of Malmberget (Sweden). The author collected monitoring data from a drill rig with Wassara water-hydraulic in the hole (ITH) hammer [57] and subsequently verified them using down-the-hole video shooting. For this drilling technique, pressured water (instead of pressured air used in pneumatic ITH drilling) is used to force the piston to impact the shank and the bit, thus the classical percussive pressure is represented as water pressure. The author introduced a combined fracturing parameter, based on variations (deviations) of penetration rate and rotation pressure, scaled using mean square error of the parameters recorded. Variation of this parameter implied that the blasthole entered a zone of solid rock, fractures, cave-ins or cavities [35].

Ghosh et al. applied an extended the PCA procedure [52], which included more measured and calculated variables than its predecessor's and also filtered the normalized parameters, eliminating their depth-dependent variations. From a separate analysis of all geotechnical zones, they constructed a geomechanical model for charging blastholes from the probability density functions of the first principal components of four geotechnical zones. Judging from their shapes and interrelations, the authors identified five different classes. The model was validated on actual field data, obtained in the process of charging drill fans, and demonstrated high compatibility of results [7]. Figure 4 shows a scheme of the method.

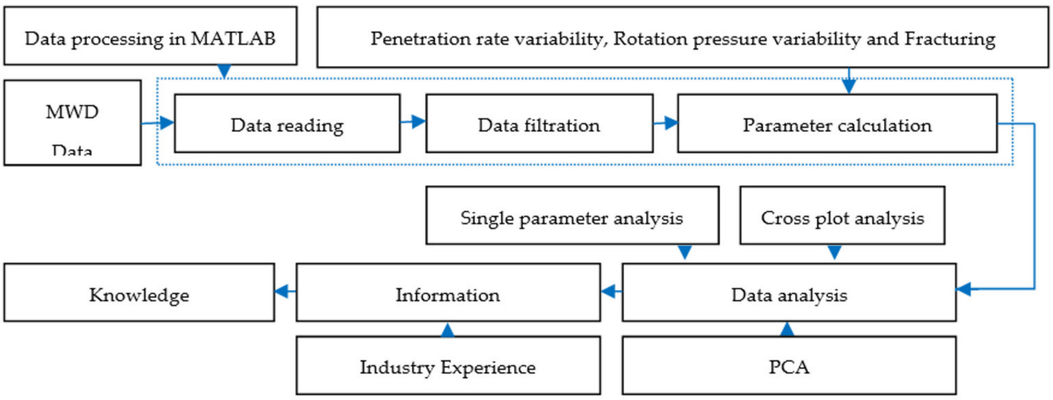

Figure 4. Methodology of data processing and interpretation [57].

In 2018, a research group from the Technical University of Madrid (Spain) carried out a comprehensive study [2–4,30,58,59] dedicated to MWD application for rock mass characterization and blast damage assessment. Their research included assessment of MWD application in mining excavation, underground blasting, and open-pit mining. Authors collected and analyzed vast amounts of data obtained from various mining enterprises and construction sites in such countries as Spain [4], Norway [58] and Sweden [59].

An assessment of correlation between MWD parameters from three tunnel construction sites was carried out in order to identify parameters that exert significant influence on the drilling process. This allowed to limit the number of variables used to characterize the rock mass. Previous research demonstrated that there were certain contradictions in the description of drilling system characteristics, in a sense of how MWD parameters were interrelated and which ones had priority over the others. To resolve this issue, authors applied statistical analysis of mutual correlation between all measured parameters. As a result, they obtained a cross-correlation matrix, which revealed a strong interrelation between 5 parameters out of 8. Of all the operating conditions, dependent on drill rig work mode, rock mass properties, and measurement intervals, only feed pressure led to variation of all remaining parameters. Rotation speed, flushing pressure, and flushing flow correlated with other parameters very weakly, which implied their dependency on variations in the rock mass and meant that they could be used to assess its properties [3].

On the next stage, an assessment of blasthole deviations was performed using data measured with an MWD system and actual measurement of blasthole trajectory with a micro probe Mk3 [58]. In some cases, comparison of these results revealed a significant deviation of the actual hole position from the one measured by the system. This happened because measuring sensors (clinometers–accelerometers) were located on the top hammer and the measurement took place outside the drilled blasthole. Peaks and valleys, discovered in the variations of rotation pressure and signals of feed and percussion pressure, were to a great extent associated with the changes in the blasthole trajectory, which, in its own turn, was influenced by fractured zones in the rock mass. Besides that, variations of rotation, percussion, and feed pressure altered the pressure of drill string on the rock mass, which could increase the probability of deviations in the process of drilling [58].

Based on the research conducted by Ghosh (2018) [7,35], authors [59] constructed a full-scale 3D block model of rock mass state and a model to predict the risk of borehole collapse in the process of drill fan blasting in the underground mine of Malmberget. The study was built on the developed geomechanical model of blasthole chargeability using PCA [35]. As the existing model was quite difficult for interpretation and included a great number of various rock classes on small intervals, the first component used in the model [35] was divided between different zones according to a sharp variation of its mean value. Adjusted like that, the model simplified quantitative assessment and automatic recognition of variations in the state of the rock mass. In order to construct a full-scale 3D block model of ore body state, the authors used a large number of fans, drilled from different mining tunnels, taking into account coordinates of drilled blastholes and the drill rig with respect to coordinate system of the ore mine. Moreover, authors constructed a full-scale model to predict the risk of borehole collapse in a drill fan, basing on a block model of rock mass state, which allowed to attribute a borehole to one of the three risk categories. Verification of the model, performed in accordance with the monitoring of charging 11 drill fans, confirmed its efficiency [59].

Within the framework of the EU SLIM project [21], a local MWD system was developed as a cheaper alternative to already existing modern systems. It was designed to monitor and record drilling data from drill rigs at small quarries. One of the quarries where the system was tested was El Aljibe (Spain), where analysis and processing of MWD monitoring data were performed for the variations (deviations) of feed, percussive, and rotation pressure. Based on acquired data, the authors carried out estimations of a rock fracturing index [4]. As opposed to the introduced earlier fracturing parameter [35], in the new index, variation of each drilling parameter was scaled from its mean value in order to minimize the differences between the values of percussive, feed, and rotation pressure. The index obtained [4] showed peaks and deviations, as the drill bit was passing through various faults in the rock mass. Qualitative validation of the index was performed using photographic records of blasthole walls, obtained with an optical televiewer [60]. Geotechnical analysis of these data allowed to identify five different types of rock faults. The authors observed that the greater the area and the complexity of the fault zone, the wider the variation of fracturing index, which explained why it was hard to assign a certain index to a certain type of rock fault. Nevertheless, research results demonstrated a strong visual correlation with the faults detected in the rock mass [4].

In 2020, van Eldert et al. [61] presented results of their research on the improved filtering algorithm of MWD data normalization. After analyzing parameters from 951 grout holes and 12, 702 blastholes under similar mining and geological conditions at the Stockholm (Sweden) bypass project, in the area between Skärholmen and Sätra, the authors refined the existing procedure of MWD data processing [55] (see Figure 5).

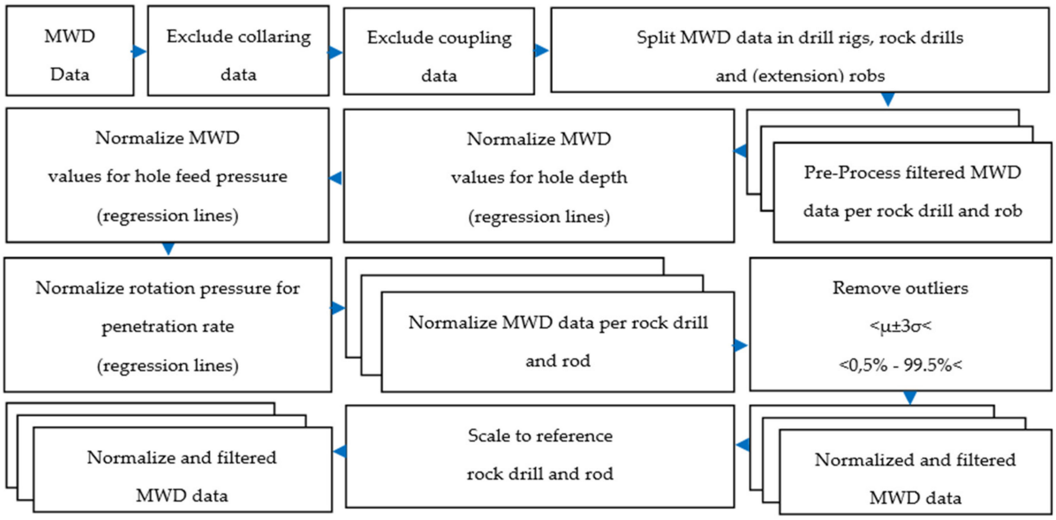

Figure 5. Process of filtration and normalization of MWD data [61].

A new algorithm included the following procedures: elimination of hole collaring data; removal of data on new extension rod attachment; separation of data according to drill rigs, rock drills and rods; data normalization for feed pressure; normalization of rotation pressure for penetration rate, and elimination of outliers and data scaling using mean values [61]. This new method demonstrated better normalization results for longer holes, where attachment of new extension rods took place. For blastholes with only one rod, the results were practically identical.

Manzoor et al. [29] established a relation between bench structure in open pit mining, obtained with digital photogrammetry, and MWD data. Having performed structural analysis of the developed model and identified various rock faults, such as fractures, cavities, interlayers, among others, authors compared deviations and peaks of pre-processed drilling parameters to those faults, in accordance with blasthole positions in the model. Dependency between the structure of bench rocks and MWD data was tested for two types of excavation blocks: hard rocks blasted after pre-splitting and soft banded rocks. The results demonstrated that in both cases feed and percussive pressure gave almost no response to the changes in bench structure. On the other hand, for a hard rock bench, penetration rate and rotation pressure increased, as the blasthole passed large fractures or cavities; notably, peaks on MWD plot were clearly visible for separate open fractures and dispersed for cavities. For banded benches composed of soft rocks, MWD data in general demonstrated an increase in average penetration rate due to lower rock strength, but neither the banded structure, nor the presence of inter layers caused deviation of penetration rate and rotation pressure, and peaks on MWD plots appeared only when the blasthole passed through an open fracture [29].

Judging from this analysis, presently, the most serious problems and obstacles of MWD technology are the accuracy of acquired data and reliability of derived dependencies between rock properties and drilling data.

The studies analyzed above demonstrate a growing interest of the scientific community in the use of MWD data to optimize mining processes from a detailed examination of rock properties in the process of drilling. However, as shown by the above review, despite the results achieved in MWD application, there are multiple obstacles and uncertainties that to a greater or lesser extent hinder the use of this technology.

3. Application of Machine Learning to MWD Data in the Mining Industry

All the activities related to the investigation, utilization, and assessment of data on geological objects are characterized by a high degree of uncertainty regarding the properties, quality, and structure of the rock mass. To overcome the difficulties associated with this, it is becoming increasingly common for the mining industry to apply methods of artificial intelligence, machine learning, neural networks [62], and fuzzy logic [63,64]. Many researchers use this approach to various aspects of the mining industry: choice of mining equipment [65], assessment of geomechanical and geological properties of the rock mass [66], rock classification, determination of D&B parameters [67], safety estimation of blasting operations [68,69], among others. A detailed review of machine learning techniques, used in various aspects of the mining business, is presented in a study [70].

There is a great variation of machine learning methods and tools that perform different tasks given input data of varying complexity. The main methods are presented in Figure 6, but, in real life, the methods and their combinations are much more numerous. They are widely used in analysis, prediction, and estimation of physical and mechanical parameters of the rocks, their classification, estimation, and prediction of D&B parameters and indices. However, in most cases, the input data are represented as simple sets of parameters, including various measured (directly and indirectly) and estimated values. The review in Section 2 demonstrates that a set of drilling data, collected using MWD technology, has greater volume and a more complex correlation of its parameters as compared, e.g., to identical geological characteristics, obtained with alternative methods. Hence, the functioning of machine learning algorithms on these data becomes more complicated, as a great number of factors need to be considered. This paper presents a review of different studies applying machine learning methods to mining and blasting operations using MWD data.

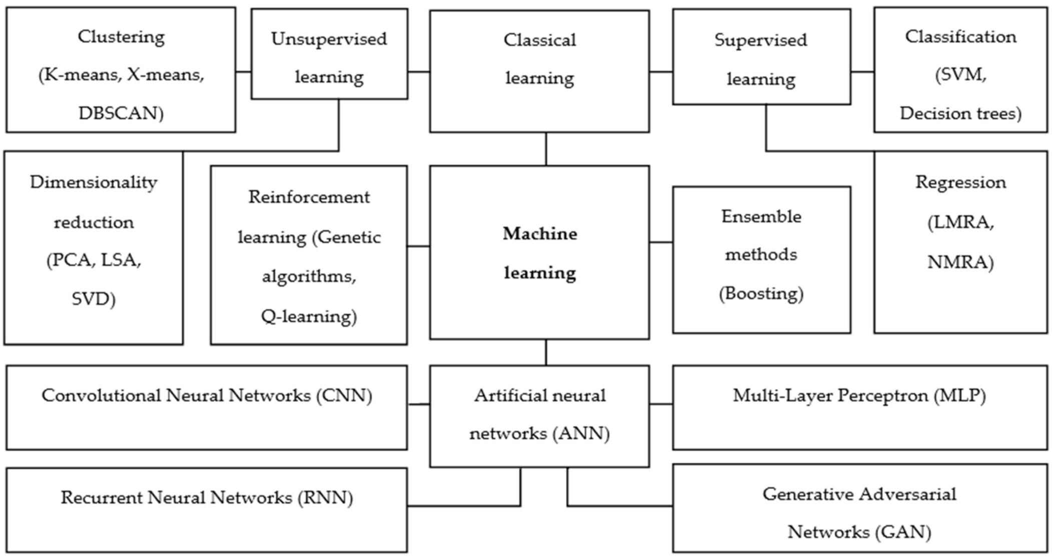

Figure 6. Classification of machine learning methods, where: DBSCAN—Density-based spatial clustering of applications with noise; SVM—support vector machine; PCA—principal component analysis; LMRA—Linear multiple regression analysis; NMRA—Nonlinear multiple regression analysis; LSA—Latent semantic analysis; and SVD—Singular value decomposition).

In 2019, a group of Russian scientists presented a research on the identification of rock type in the process of drilling, using machine learning methods applied to data collected by MWD [71]. The applied technology of logging while drilling (LWD) had one significant drawback—the information recorded lagged behind the actual position of the drill bit, because geophysical sensors were located 15–40 m from the hole bottom, which could lead to incorrect specification of well trajectory. In their research, MWD data arrived in an online mode, but it was problematic to identify the rock type from those, as opposed to LWD data. The aim of the research was to develop a prediction and classification model consisting of two classes, which would identify whether the drill bit entered a shale band (first class) or not (second class). As a result, authors compared three classification algorithms: logistic regression, gradient boosting on decision trees, and two classes of neural networks (feed forward and long short-term memory). All three classification algorithms demonstrated an increase in the accuracy of rock type identification, but the methods with the highest precision were gradient boosting and neural networks.

In 2018, a group of Spanish scientists conducted research on the assessment of rock characteristics using Bieniawski rock mass rating (RMR) classification [72] in the process of mining tunnel excavation by blasting, applying methods of machine learning, and fuzzy logic to MWD data [73]. The authors proposed a methodology, which included the following stages: unsupervised selection of variables based on PCA and factor analysis, blasthole clusterization with regard to selected MWD variables, excavation front characterization by classes of blastholes, and prediction of RMR values based on two fuzzy logic systems (linguistic L-IRL and scattered S-IRL). Decision making analysis on each stage was performed using aggregation operator ordered weighted averaging (OWA). Before entering the algorithm, data was filtered and normalized. As a result, at the stage of variable selection based on OWA ranking only three drilling parameters were selected, as a great number of parameters complicated subsequent procedures. Blasthole clusterization was carried out using several algorithms in order to compare the results and select the best algorithm. The number of clusters was different for different algorithms and was estimated with OWA. Prediction of RMR values was made with two fuzzy logic systems using three linguistic terms (low RMR, medium RMR, and high RMR) for two cases: in the first case, the prediction took into account existing geological data and MWD parameters (RMR_{basic}), in the second case only MWD parameters were considered (RMR). An algorithm based on the percentage of blasthole clusters at the hole bottom and RMR value in the previous cycle of excavation predicted RMR value for the next blast, allowing to adjust necessary D&B parameters. As a result, the most accurate combination of algorithms was selected: X-means clusterization (based on Bayesian information criterion, the algorithm determined that the optimal number of clusters equaled two) and linguistic fuzzy logic system—they predicted RMR values with the least error. Comparison of RMR_{basic} and RMR prediction algorithms demonstrated a slight scatter of results, which led the authors to a conclusion that, in the absence of input geological data, the proposed methodology allowed to predict RMR values using only MWD data.

In 2017, a group of Australian scientists conducted research on the application of adaptive fuzzy inference system (ANFIS) to predict RQD index from MWD drilling parameters [27]. Judging from previous experience and statistical analysis of correlation between drilling parameters and RQD, three parameters were selected for modeling: penetration rate, thrust, and bit rotation speed. To each input parameter, researchers assigned two linguistic terms (low and high) to relate input and output data through an "if-then" fuzzy rule (in total, 8 rules were used). Three datasets were used for modelling: training, validation and overall sets, and the quality of the model was assessed for each one using mean square error. A strong correlation between MWD parameters and predicted RQD value was obtained.

Kadkhodaie-Ilkhchi et al. [74] presented a comparative study of three machine learning techniques to identify rock type from MWD data. In their research, they applied a boosting method, fuzzy logic, and neural networks to the drilling data from blastholes of an iron ore mine in Australia. These methods were analyzed from the point of view of accuracy, ease of implementation, and calculation time. For a training dataset, the authors used a geological model, obtained as a result of geophysical logging and sampling of cores and chips in the area under study. All the methods allowed to classify each rock type with an accuracy above 80% with minor differences in precision. However, the boosting algorithm proposed by the authors, was the easiest in terms of implementation and had the highest computational efficiency. The authors concluded that the use of MWD data provided a good estimation of actual physical parameters and could significantly simplify the assessment of rock mass characteristics. The main requirement towards the use of this method is high-quality training datasets. Moreover, the method has to take into account the application of various drill rigs and variation of geological conditions.

4. Challenges and Obstacles

Present day studies [27,71–74] devoted to the use of MWD data for optimization of mining processes applying machine learning methods demonstrate that this issue is an actual scientific and industrial problem. The main problems that researchers face during processing, analysis, and utilization of MWD data are the following:

1. Cross-correlation of recorded drilling parameters does not stay constant and varies depending on specific geological conditions and utilized drilling equipment;
2. Difficulty of identifying drilling parameters, independent from other drilling indicators and monitoring system, accounting for mineral and geological factors that influence their variation, eliminating errors and factors irrelevant to the rock mass properties. Among existing studies, there are contradictions regarding the question of which parameters should be used to describe rock properties under different conditions;
3. Verification of parameters, measured by the MWD system, in many cases confirms data reliability. It should be mentioned, that in order to be able to use MWD data under new geological conditions or in new site, periodic laboratory core studies or geophysical logging are necessary to clearly indicate the type of rock, since, for example, the penetration rate can be the same for different types of rock However, despite the diversity and high precision of MWD data verification tools, including optical [4], mechanical [75], and geophysical [1] methods, there are problems of comparison between thus obtained data and information collected by a MWD system; e.g., in case of detected structural irregularities and faults in the rock mass, the parameters recorded by the system can be distorted due to jamming of the drill tool in highly fractured zones, idle rotation in the cavities, and rod deviation in the process of drilling [54];
4. All the practical applications of MWD systems refer to the qualitative and quantitative characterization of the rock mass before blasting. From the data obtained and the strength characteristics and structural features of the rock mass, it is possible to adjust the design parameters of D&B operations in order to improve their efficiency. However, direct estimation of dependency between results of D&B operations and measured MWD parameters is also necessary for prediction purposes as, besides geometric characteristics of the site, rock strength parameters and their structural features, D&B parameters themselves (type of explosive, powder factor, charge design, among others) affect the results;
5. Machine learning methods applied to MWD data limit the number of input parameters to simplify the final algorithm and reduce calculation and training time. Selection of input parameters from the scope of available data is a difficult task, especially because it may vary from drill rig and drilling technique.

5. Discussion About Future Directions of MWD Research

1. Existing methods of MWD data processing and analysis mostly use statistical analysis tools, which rule out automatic processing of data in case of changing mining, geological, and engineering conditions. It means that when an actual change takes place, e.g., change of drill rig mode, even on the same site, it is necessary to process the data all over again, i.e., define dependent and independent parameters, identify the most significant parameters dependent on rock properties, among others. Hence, a relevant task of applied research is to develop a learning algorithm, which would use machine learning methods and based on available input data, associated with specific conditions, would be able to correlate, process, and select parameters coming from the drill rig and utilize them for subsequent estimation of rock characteristics, and prediction of

optimal D&B parameters and blasting results. In the meantime, the production of a training dataset, collected in the process of algorithm operation, could simplify data collection for future applications under similar conditions.

2. Prediction of fragment size distribution in the blasted rock mass based on MWD data is a relevant production problem. Modern methods of fragment size prediction, based on theoretical and empirical models [76,77] and even machine learning methods [78,79], use only D&B parameters and existing classifications of rock strength and structural irregularities, which sometimes fail to take into account the entire unique structure and heterogeneity of the rock mass to be blasted. However, if prediction of fragment size distribution in the muck pile utilized MWD data collected from each blasthole, and then combined them into a block model, taking into account rock strength variable characteristics and structural irregularities, it might be able to provide a better estimation of the blast results. Extensive assessment of MWD data cleaning algorithms and interpretation into mechanical and structural rock characteristics, development of machine learning algorithms incorporating explosives characteristics, and verification with fragmentation data are topics where research efforts would certainly offer a high return.

6. Conclusions

This paper offers a review of MWD, a technology actively developed and utilized in the mining industry all across the globe. It contains a global literature review of the scientific research associated with collection, processing, analysis, and utilization of MWD parameters to characterize the rock mass, estimate drilling deviations, construct models of blasthole chargeability, define blastability zones, among others. The most important shortcomings are connected with the choice of the method to filter, normalize, and correlate data under specific conditions, and the machine and site-specific nature of the measured values. The paper also presents a review of machine learning methods that utilize MWD data to solve different problems.

Modern research demonstrates that machine learning methods, applied to predict various aspects of blasting operations, have an advantage over conventional mathematical and statistical prediction methods, not only in terms of accuracy, but also in terms of their speed. Incorporation of these tools to real-time MWD data analysis should allow to reduce the costs of detailed rock mass characterization, hence increasing the efficiency of drilling and blasting, and improving the quality of the overall mining operation.

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