Multidimensional Data Analysis for Drilling Process in Underground Mines

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ABSTRACT

In many underground mines the excavated ore is produced during the blasting process. Drilling machines that are used to drill the blastholes, where later the explosives will be mounted, are crucial for this task. In order to optimize the currently used techniques, great emphasis is placed on increasing the efficiency and safety of blasthole drilling operations. The natural consequence is the development of monitoring systems and algorithms for processing operational and historical data. In this article, we present the result of the analysis of drilling data carried out as part of the IlluMINEation project. The paper proposes an algorithm for work cycle detection for drilling machines, together with the estimation of general operating parameters and diagnosing the drilling process on the basis of long-term data. Based on the available data, selected components of the drilling cycles have been indicated. Several approaches based on the parameters of the defined cycles are proposed. These approaches can be used in the future to create a full-fledged system for examining the effectiveness and safety of mining drilling rigs.

INTRODUCTION

The ore extraction process in underground mining is divided into many stages that are interconnected and interdependent. One of the initial and thus key stages is the drilling of blast holes. Face drilling rigs are used for this purpose. These machines, apart from mines, are also used in the construction industry. Various drilling techniques (both pneumatic and electro-hydraulic) have been developed in recent years, and drilling rigs are equipped with various types of monitoring and control systems [1]. This is to improve the efficiency and accuracy of their work as well as increase safety. This is so important due to the key role of drilling rigs in the mining industry, which has a direct impact on the velocity and volume of production. Therefore, there are many variables that are important to analyze in the context of the optimization of the blast hole drilling process. In the literature, we can find many indicators that provide in-depth analysis in order to understand the course of the entire process over time, the energy required for drilling, and the relationship between operating parameters and rock mass properties [2]. There are also some guidelines for the processing of monitored parameters [3-6].

In this way, one of the basic parameters called drillability is determined [7]. This is a term used to describe the effect of various parameters on drilling speed and drill bit wear. In the classic approach, high drillability means faster drilling speed and less wear on the drill bit

[8]. In the paper [2], the relationship between the rate of penetration and the specific energy was examined, which allowed the development of indicators of drillability. In [9], the authors developed a method for predicting the drilling speed depending on the characteristics of the rock mass. Another important aspect is drill wear. This has an obvious direct impact on the production process through the occurrence of failures, causing unplanned downtime and repair costs. However, the degree of wear also affects the efficiency of the drilling process. This makes this parameter doubly important to control. In [10], a method of predicting the wear of drilling tools on the basis of geotechnical tests and an assessment of rock abrasion was presented. The key role in the development of analytical research on the drilling process is played by the so-called Measurement-While-Drilling (MWD), which has recently become more and more popular. This technology allows one to measure, process, and provide real-time data about the drilling process. The sensors used in the MWD include, among others, a displacement sensor, a tachometer, a pressure sensor, and a torque sensor. Such information is used in data analysis and engineering calculations, which then contribute to the creation of tools helpful in making decisions about further mining processes and rock mass stability [11]. In [12], the authors present an overview of MWD applications in the mining industry. An example of MWD application in an underground mine is presented in [13]. The authors propose the use of monitoring to assess the chargeability of boreholes. They determined a parameter called fracturing based on variations in penetration rates and rotational pressure. In turn, other related studies [14, 15] present the use of MWD for blast design, showing at the same time that this method can be more reliable and save time compared to traditional methods. In [16], the authors used MWD to determine the parameters of the rock mass characteristics. In [17], MWD was used to classify discrete rock classes based on the hidden Markov model. On the basis of the MWD, it is also possible to detect fractures with varying dip angles [18]. Another MWD application is the assessment of the service life of drilling tools [8].

Monitoring systems in an underground mine have recently played a key role in the development of this industry. Close to the drilling process is the problem of seismic risk caused by blasting. An interesting solution to track the seismic activity of rock masses is based on MEMS (microelectromechanical systems) [19]. In [20], seismic data was used to destress blasting efficiency.

As mentioned earlier, the durability of face drills is crucial to maintaining continuous production. For this reason, there are many studies on the reliability analysis of these machines and their components in the literature [21, 22, 23]. As already highlighted, one of the most crucial elements are the drill bits, which wear down with use. Incorrect service policies can lead to sudden failures that cause unplanned downtime and interruptions in production continuity. In addition to drills, electrical and hydraulic systems are listed as critical components in terms of repair frequency [21]. The reliability analysis of the latter was undertaken by the authors in [23]. In addition to the frequency of failures, downtime is also important. This aspect was analyzed in [22] and led the authors to the conclusion that problems with hoses and feeders are characterized by exceptionally long downtimes. Reliability analysis can help you develop a maintenance plan for machine components. On the example of drills, such a schedule was proposed in [21]. In addition to reliability analysis, a great advantage in planning repairs would be early prediction of failures using data from machine monitoring.

In this paper, we focus on the analysis of operational parameters acquired from drilling tools. Our research is carried out as part of the IlluMINEation project. One of its main goals is to develop the Predictive Maintenance IoT Tool Kit, including AI and big data algorithms [24]. The operation of the drilling rig is cyclical, including components such as positioning, drilling start, drilling, and retraction. The detection of individual cycles and their components is the basis for developing further data analysis methods. This is necessary to evaluate the efficiency of the machine and the operator. The number of cycles as well as their duration are crucial pieces of information for such an assessment. Different types of anomalies can also be found in such data, which is crucial from the drilling process diagnostics point of view. For example, it is possible to detect particularly long positioning, classify it as a process irregularity, and recognize its cause.

Excessively long retraction times can mean that the tool is jammed, which is also important for detection. On the other hand, the drilling process extending over time may mean progressive wear of the drill bit. Basically, efficiency analyses, the detection of anomalies during the operation, and determining the machine's work cycles can also play a key role in early fault detection. The identified fault patterns may occur only under specific conditions. The analysis of the entire operation of the drilling rig (including machine stops and movements) may obscure the analysis and prevent early detection of damage. For these reasons, it was decided to start the article by presenting a simple and accurate method of determining the drilling cycles and their components, and then to present selected analysis ideas based on it.

The structure of this article is as follows. At the beginning, the investigated object, i.e., the drilling machine, has been described; next, the expectation of mining operators for predictive maintenance has been discussed. Afterwards, industrial data acquired from the on-board monitoring system and historical maintenance records were shown. Then, the drilling process has been characterized, and the proposed method for detecting the drilling rig's work cycles has been shown. The developed method has been tested on real data, and examples of its application have been presented. It has also been presented how the division into cycles can affect the long-term analysis in order to detect anomalies related to damage. Final conclusions have been drawn at the end.

DRILLING MACHINES

Problem description

In the case of face drilling rigs used in underground mining, downtime caused by sudden failures is a serious issue. The main tool of the machine (i.e., the drill) is particularly critical, but our operational experience and literature review show that hydraulic systems, including hoses, electrical systems, and feeders, are also problematic in terms of frequency and downtime [21, 22]. The development of a predictive maintenance toolkit can be a real solution to preventing sudden failures. It consists of the estimation and forecasting of machine health conditions and taking action at the right moment before a failure occurs. Planning such maintenance or repairs requires access to data and algorithms that automatically process this data in order to analyze the machine's workflow according to its operational conditions (contexts). For this purpose, a reliability analysis is also recommended, especially KPIs indicating the estimated residual lifetime of the machine or the period of safe operation of individual components. Another method is to continuously evaluate the efficiency of the machine. For example, a decrease in the efficiency of the drill over time may mean it is worn out and needs to be replaced. Indispensable in predictive maintenance is the premature detection of damage based on the analysis of signals measured by the monitoring system on the machine (in this case, in particular, the analysis of pressure data). Effective early malfunction detection gives the opportunity to carry out appropriate actions in advance. As a consequence, it is possible to avoid sudden failures that can be dangerous for employees, stop production, and increase repair costs.

Industrial data

In this article, data from three machines of two types was analyzed: two machines of the first type (machines A1 and A2) and one machine of the second type (machine B3). All of these machines are equipped with an on-board monitoring system that continuously harvests the operational parameters from many different sensors embedded in the machines (rotation, speed, pressure, and temperature).

The loggers divide the gathered data into three groups. Two are related to the booms on the machine (one group for each boom). The third group describes variables related to the general operation of the machine, such as machine speed or fuel level. This adds up to over 90 different variables for the type A machines and over 40 variables for the type B machines. All variables are recorded with a sampling rate of 12.5 Hz. The data contain both variables from which information about the activities performed by the machine can be extracted as well as variables from which it is possible to draw conclusions about its technical condition (variables mainly relate to pressure measurements). Data from all three machines covering a period of three months was used to develop a method for detecting machine cycles, its tests, and long-term analyses.

Accurate records of machine maintenance for selected machines were also available. The repair of each machine is cataloged with information such as date, fault description, downtime, problem, cause, and type of work. In addition, a list of materials used for each repair is recorded. Combining historical repair data with appropriate signal analysis can identify dependencies and patterns that enable early prediction of specific types of damage. If a given type of failure or repair has been noticed several times in the period under review, it is possible to compare the values of various parameters before the occurrence of the event. Such a long-term analysis can show the occurrence of certain recurring patterns and allow one to learn to recognize them.

METHODOLOGY

In the first step, to analyze the data in terms of quality and repair, we decided to develop algorithms that divide the signal into work cycles. A typical cycle of the drilling process consists of the following operations:

1. Positioning of the drill frame – it is necessary that the drill frame be firmly pressed against the mining face surface in order to prevent undesirable changes in its position during drilling.

2. Start of drilling – the process starts with reduced feed and impact pressures as well as the water washer turned on. Once the tool has penetrated sufficiently into the rock material, the parameters are kept within the nominal range.
3. Drilling – depending on the type of rock in which the hole is performed, the operator is obliged to adjust the feed pressure and impacts of the drill.
4. Retraction of the tool from the hole – when the expected depth of the hole is reached, the direction of feed of the drill is switched to the opposite one, with the revolutions and impact constantly switched on.

Typically, about 30 holes are drilled in a single rock wall. Each hole requires new positioning and drilling. The entire process of drilling one hole takes an average of 2 minutes. However, in the presence of a large variety of lithological structures in the rock mass, the progress of the drilling process may vary. This is also due to the fact that some boreholes are drilled at an angle. Then they can intersect a heterogeneous rock mass. The decisive factor here is rock strength, which has different ranges for different rock types. This may result in drilling stoppages or, in some cases, jamming of the drilling tool. There are also empty spaces, which are also unfavorable from the point of view of the reliability of the drilling tool.

Drilling cycle detection

To determine the cycles, the available signals associated with the rig (the element of the machine that is used to drill the holes) have been reviewed. The algorithm for drilling cycle detection has been based on variables related to drilling tool feed. Depending on the machine type, the list of available variables was different, namely:

1. FeedPressure: feed pressure indicating feed force during drilling operations – availability: both machine types
2. FeedForward: direction of movement of the drill (forward or backward) – availability: only type A machines
3. FeedSpeed: the speed of the drilling process – availability: type B machine.

Basically, FeedForward and FeedSpeed have similar behavior. Their relationship with FeedPressure can be seen in Figure 1.

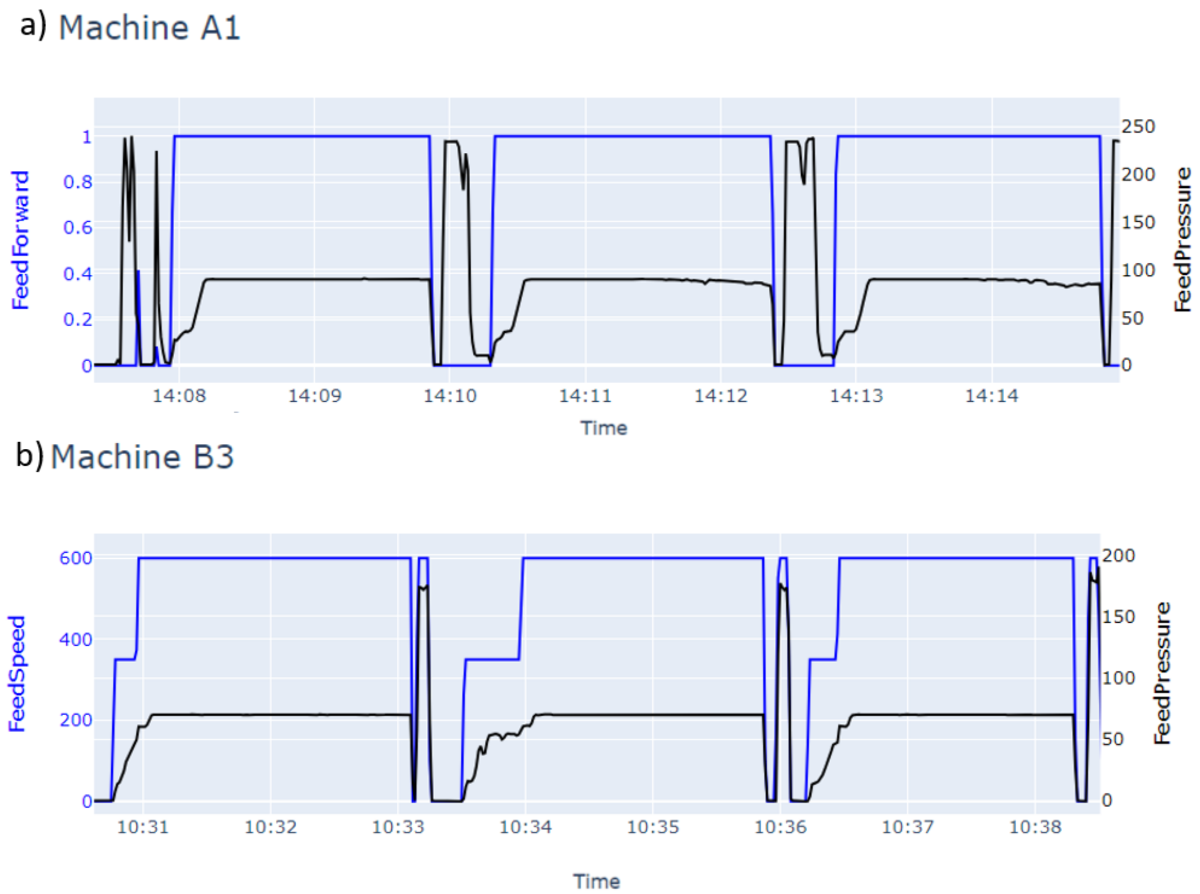

Figure 1. Examples of the variables used to determine the cycles for a) type A machines b) type B machine

As can be seen, the cycle begins and ends with a pressure peak. The drilling process can be distinguished by the FeedForward and FeedSpeed variables, which are greater than zero in this period. Thus, the algorithm that identifies the cycles can be divided into two main parts. The first one is responsible for detecting the cycle as a whole, and the second one determines the individual components:

1. The beginnings and ends of the cycles were determined by finding peaks in the pressure signal (black color on Figure 1). As mentioned above, the cycle begins and ends with a pressure peak. In the context of the used function, a peak or local maximum is defined as any sample whose two direct neighbors have a smaller amplitude. In addition, to ensure that the selected peaks are correct, a condition for the minimum distance between peaks has been added. Distance is equal to half the average expected cycle length (1 minute).
2. Once the boundaries of the cycles have been determined, we can start dividing them into individual parts. The FeedForward and FeedSpeed variables tell us which part of the cycle includes drilling (blue color on Figure 1). When drilling occurs, the feed is moved forward, which is equal to value 1 in the FeedForward variable, and for the type B machine, the speed value is greater than zero. The moment of increasing pressure at the beginning corresponds to the start of drilling. Knowing the moments associated with the beginning and end of drilling, we can divide the cycle into

individual operations. In order to be able to determine the moment when the pressure stabilizes during the drilling period, the derivative of the pressure signal was calculated. After obtaining the last point (the start of the drilling), we can divide the cycles into parts. The whole process is shown in Figure 2. Results are shown in Figure 3.

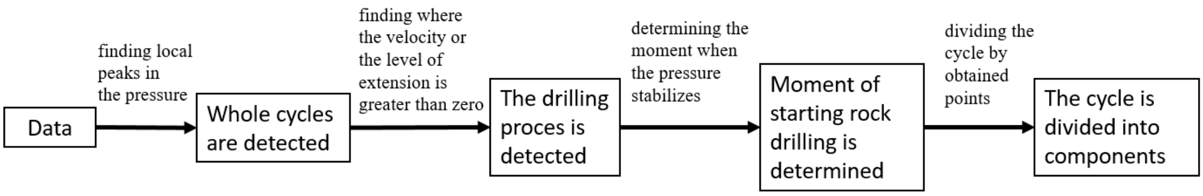

Figure 2. The process of determining the cycles and their components

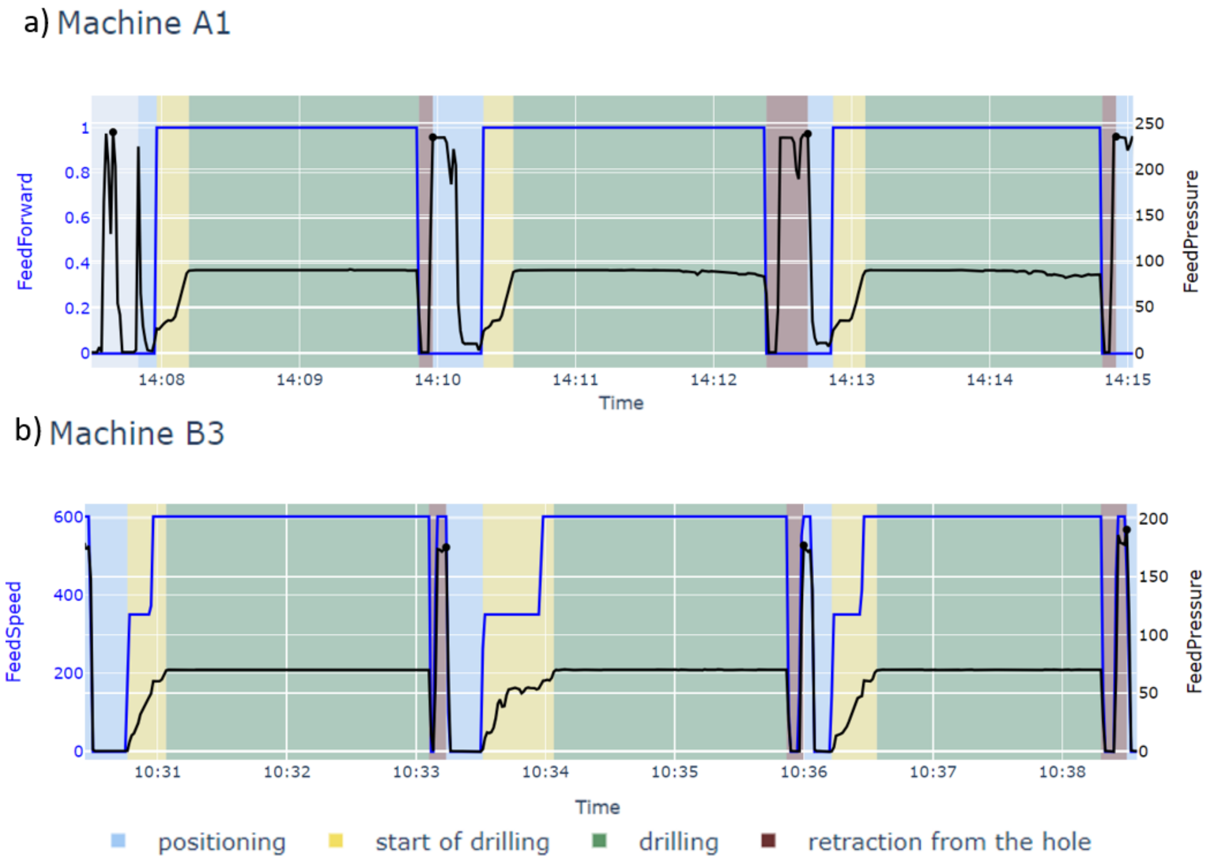

Figure 3. Chart of selected signals with determined cycles and their components

RESULTS

The algorithm was applied on the days when the signals were registered. The cycles have been determined and assigned to the signals. The next section analyzes the available data in the context of drilling cycle parameters. One focuses on the analysis of the cycles themselves (their characteristics and changes in time), and the other on their connection with the registered signals and available maintenance records.

Parametrization and visualization (key statistics and anomalies)

The developed cycle detection algorithm was tested on real data. For each of the machines, a set of data from three months in 2022 was prepared. Then, for each individual day, the algorithm checked whether data of sufficient quality was recorded and, if so, determined cycles over time. It was not possible to determine the cycles on each day due to the lack of boreholes on a given day or poor quality of data. The detection of work cycles enables a statistical comparison of the work efficiency of individual machines. Figure 4 shows boxplots of the number of cycles performed by both booms versus the average cycle duration. In this example, it can be seen that the ratio between the cycle duration and the number of cycles is not settled. The machine A1 had the highest efficiency in this period; it performed the most cycles with the shortest duration. Comparing the results of both booms, it can be seen that the values are almost the same.

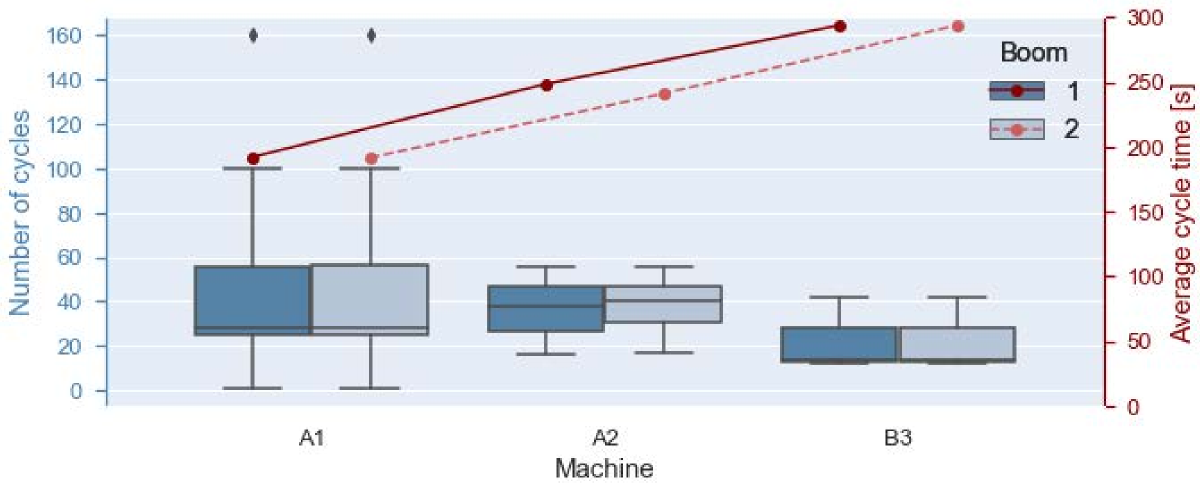

Figure 4. Comparison of the average number of cycles (box plots) with the average cycle duration (points) between investigated machines

The duration of the individual components of the cycle may also be important. A comparison of three machines covering the entire analyzed period is shown in Figure 5. It can be seen that drilling is characterized by the longest duration, which also has the greatest variability; in turn, retractions are the shortest. The proportion between component durations for each machine appears to be very similar. However, it can be seen that machine B3 differs from the other two in the longer duration of all components. It can be noticed that there are a large number of outliers that may indicate anomalies or problems. Most of them are for positioning, which may indicate breaks or changes in the mining face.

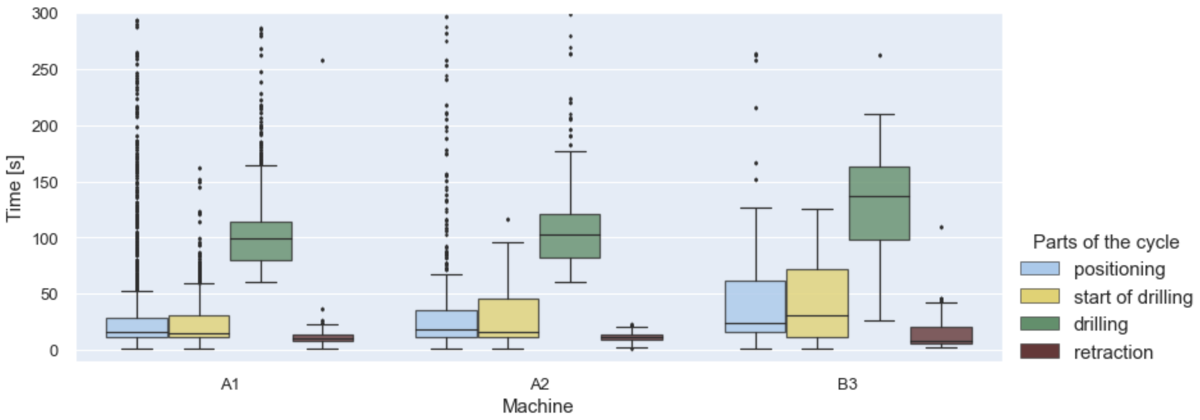

Figure 5. Comparison of the duration of the component operation of cycles for three machines

Going a step further towards detailed results, one can compare the cycles on individual days. This gives information about disproportions and anomalies in each cycle. An example of such an analysis is shown in Figure 6, where the proportions between the duration of the components in individual cycles for the selected day for the machine B3 are shown. It can be seen that in three cycles (15, 40, 41) there was a longer retraction from the hole, which may indicate some problems with jamming. In a few cases, longer positioning is also visible (cycles 4, 9, 10, and 21). Longer positioning can mean more difficult conditions, requiring the operator more time to properly prepare for drilling. However, it may also be related to the necessary movement of the machine or a stop caused by a break. The analyzed data did not allow for a distinction between these situations. In other cases, the proportion of the duration of the components of the cycle seems to be relatively constant.

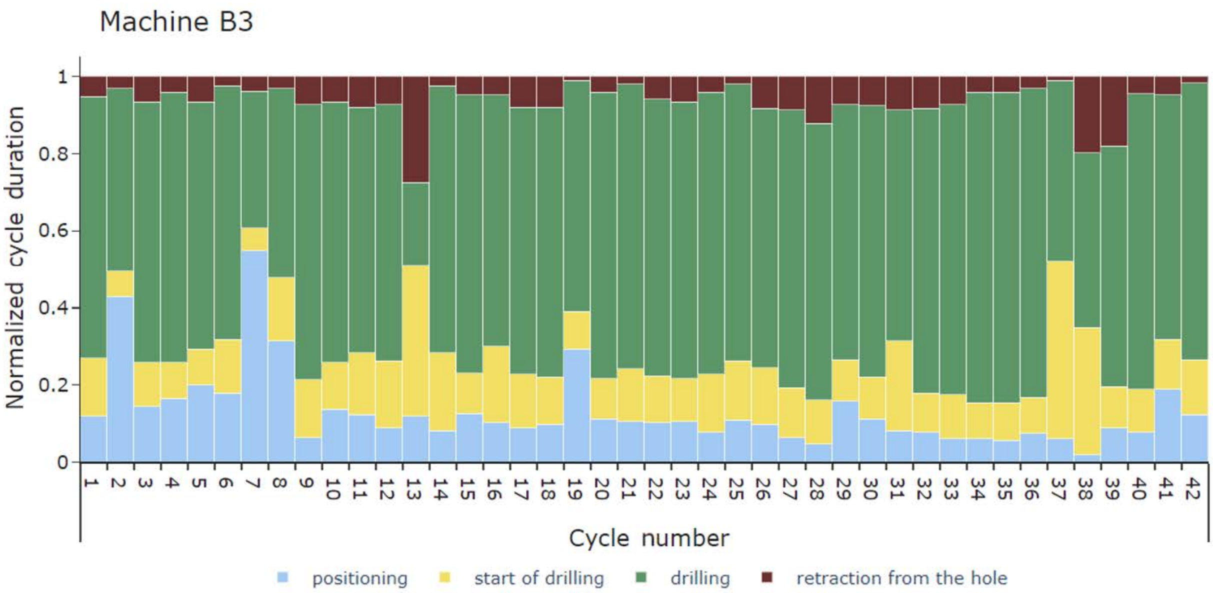

Figure 6. Normalized duration of the components of individual cycles in one day for machine B3

Long term analysis

The determined cycles can also be used to analyze changes in signals over time. Characterization of different signals for parts of the drilling process combined with failure data can help extract patterns hidden in signals that indicate specific anomalous behavior. To do this, we need continuous information about the cycles covering the whole period. The graph of the data held over time is presented in Figure 7.

As can be seen, only Machine A2 can be used for the current analysis. With the help of the experts, out of all of the signals, the most significant variables have been selected. The analysis was narrowed down to the following signals:

- Air Pressure on Compressor
- Hydraulic Pump Pressure
- Hydraulic Oil Temperature
- Feed Pressure
- Rotation Pressure
- Percussion Pressure
- Damper Pressure
- Water Pressure
- Rock Drill Return
- Lubrication Air Pressure
- Lubrication Oil Pressure
- Water Pressure

The signal from each variable was divided into parts of the cycle, and the quantiles (0.25, 0.5, 0.75, 0.95 and 0.99) were calculated from them. In Figure 8 the comparison of the 0.99 quantile for return pressure of rock drill (for all data and only for the drilling process) can be seen. Rock drills are used to drill through rock. Hydraulic pressure generates the force that drives an impact piston. Lower pressures can indicate problems, such as potential leaks, kinked hoses, or filter problems. As can be seen in the drilling data graph, there are 3 situations where the pressure was low and remained low for several cycles. Failures related to loose caps and bends in the hose were found and matched to the presented anomalies. In the last case, the situation persists for a longer period of time and there was a major failure that stopped the operation of the machine. In the graph of all data, these anomalies are invisible, even when outliers are omitted. On the other hand, after selecting data only for the drilling stage, evident lower pressure platoes are observed in the data, which can be potentially used for building of early failure detection or predictive maintenance algorithms.

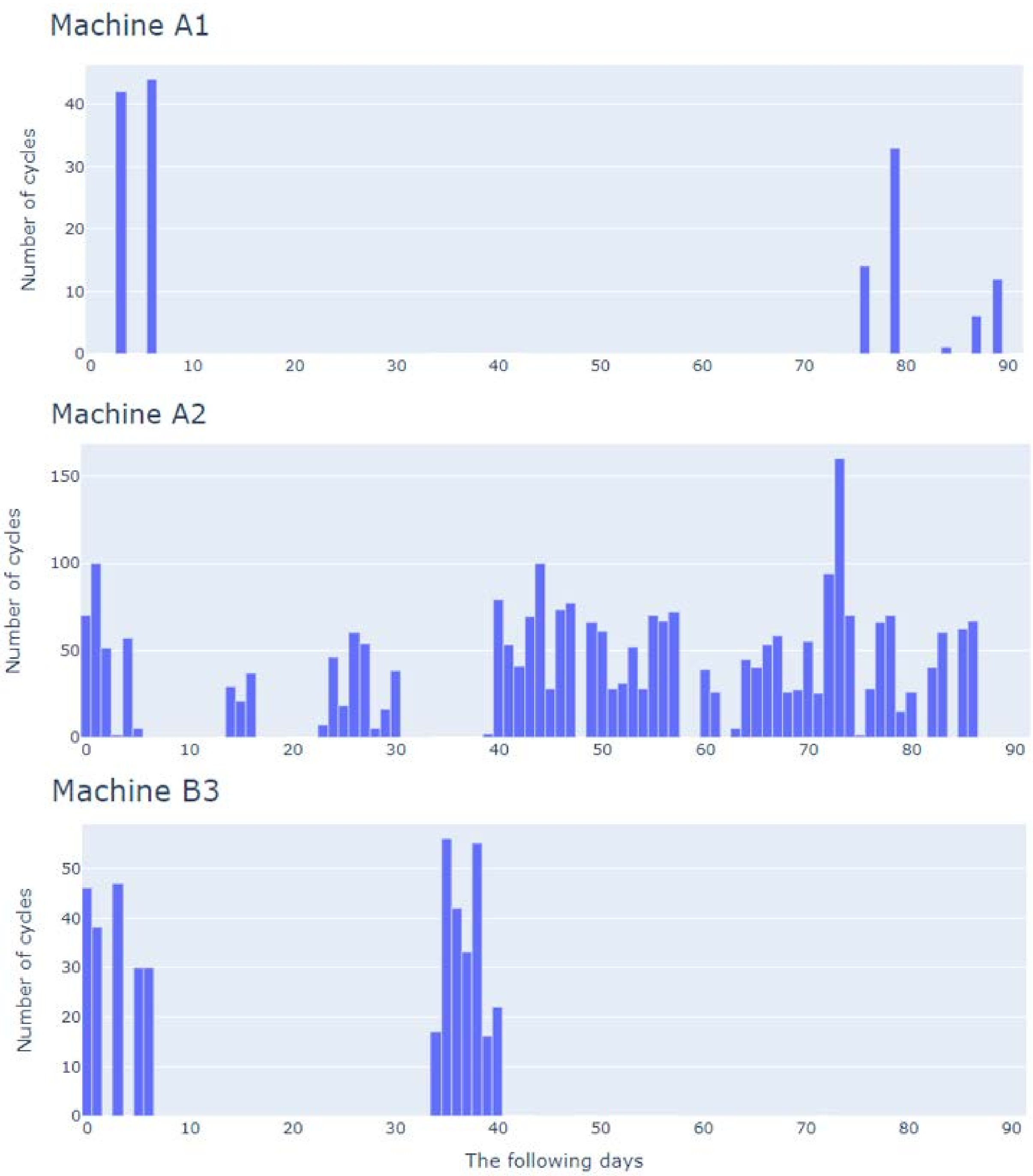

Figure 7. Distribution of cycle data over the available period

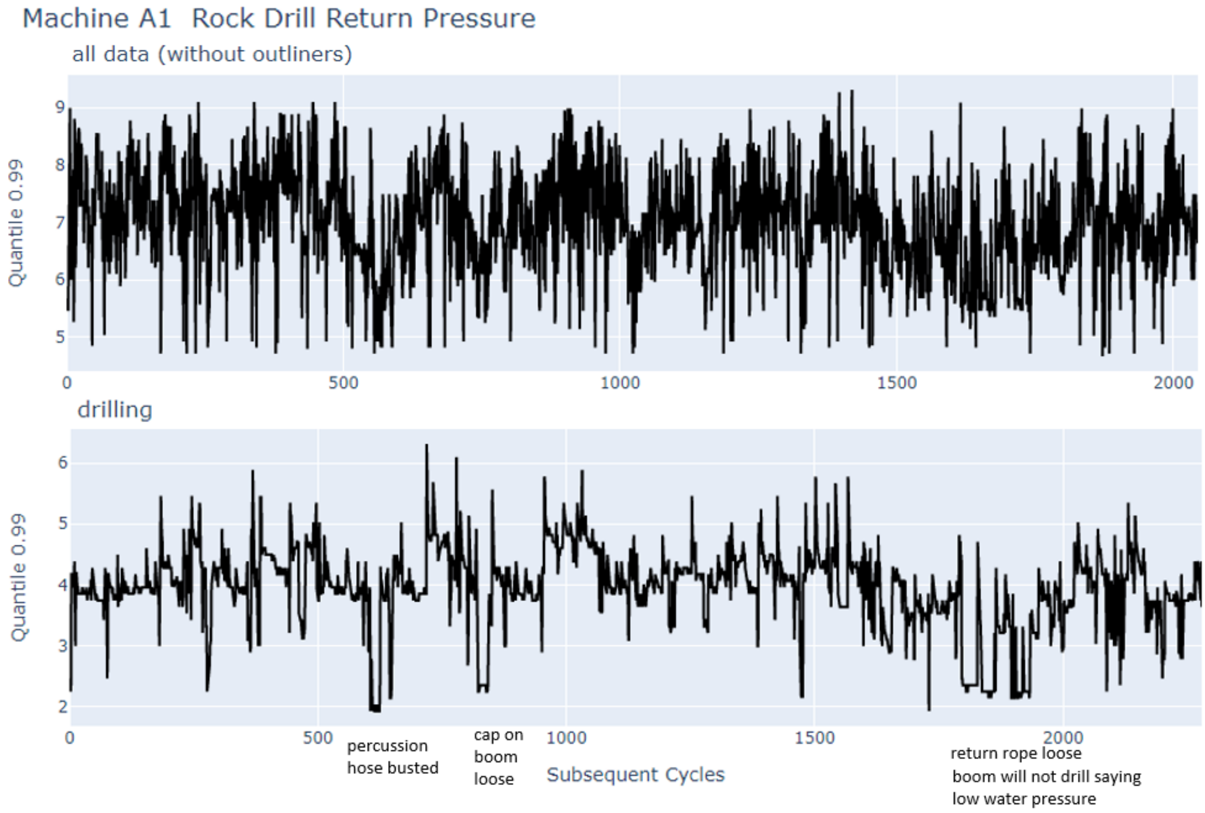

Figure 8. Rock drill return pressure quantile for all data and for drilling part of cycle

The next example of using the cycle detection method for predictive maintenance is analyzing the duration of sequential cycles and processes over consecutive days. The analysis of drilling time can be particularly important. The drilling of blast holes in a rock causes progressive wear on a drill bit. In turn, the more worn the tool is, the longer the drilling process takes. It means that an investigation of drilling duration has the possibility of finding out about the level of drill bit wear. Of course, the drilling duration does not depend only on the drill condition. The main factor is the type of stone, which changes along with the work place. It is also necessary to know which drill was used at what time and when these tools were replaced with new ones. Assuming the immutability of these conditions for a short time when the machine works every day, the hypothesis of an increase in drilling duration in relation to time was tested. Figure 9 presents an example of this relationship. It shows the duration of drilling for sequential cycles over 6 days for machine B3. The fitted line of linear regression shows an increasing trend despite fluctuating values. A gradual increase in value occurs already within one day. There are no sudden jumps in values that could indicate a change in the drilling location, so it can be assumed that the visible trend is caused by the wear of the drill. Connecting such an analysis with information about stone and drill bit type and the time of changing a tool can predict when the drill is no longer usable due to wear.

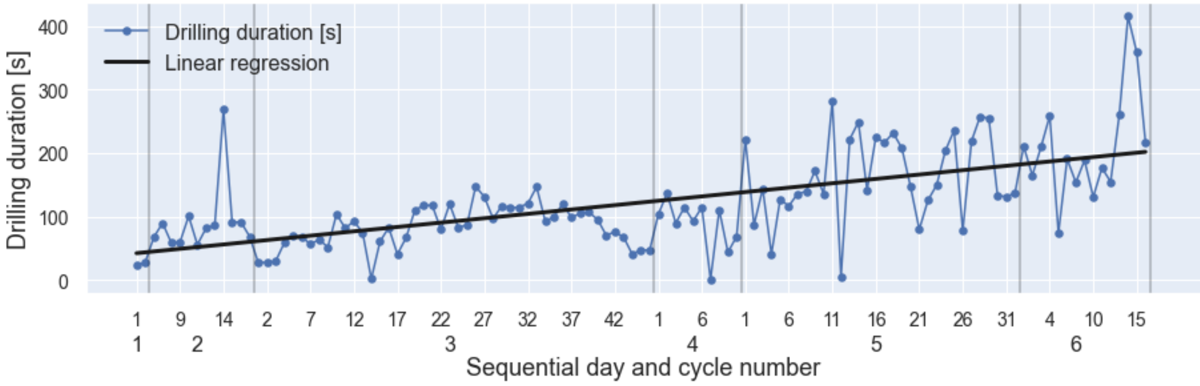

Figure 9. Drilling duration for sequential cycles in 6 chosen days (machine B3, boom 2)

CONCLUSIONS

The current challenge of the underground mining of non-ferrous materials is the constantly deteriorating geological and mining conditions. This state of affairs is related to the need to conduct exploitation in the deeper and deeper layers of the deposit. Conclusions drawn based on trials carried out so far related to the testing of various systems of mechanical mining of the deposit assumed the optimization of the currently used blasting technique. For this reason, great emphasis is placed on increasing the efficiency and safety of blasthole drilling operations. The development of monitoring systems and algorithms for processing operational and historical data is a natural consequence. In this article, we present the results of a study carried out as part of the IlluMINEation project aimed at developing drilling cycle detection methods and procedures for diagnosing the drilling process based on long-term data. The tests were carried out on three different drilling machines. Differences noted among different types of machines are presented. Selected examples show various anomalous behaviors of signals along with the interpretation of factors. It is shown that the application of cycle detection algorithms may allow for the detection of long-term anomalies in the data that are not visible in the raw signals. It means that accurate drilling cycle detection algorithms are crucial for the development of predictive maintenance algorithms. In the near future, it is planned to cover a larger population of machines and start building an expert system.

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