Extracting Knowledge about Production Process Execution through Analysis of Cutting Machine Motor Current

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Abstract

This paper presents a multi-stage study focused on analyzing current data from sensors installed in cutting machine motors. The collected data serves as a foundation for monitoring machine performance, diagnosing anomalies, determining efficiency, and identifying the machines' cutting direction. For this purpose, VBA-based applications were developed, which operate on data retrieved from a database server. Additionally, exploratory analyses were carried out in the R programming environment. The findings demonstrate that analyzing energy-related data can be a valuable source of operational knowledge and can support decision-making within the Industry 4.0 paradigm.

The results obtained have significant practical implications. Firstly, they enable real-time monitoring of machine operations and allow for rapid responses to irregularities. Secondly, historical data becomes a knowledge base for maintenance planning, work reorganization, and evaluating operator performance. Thirdly, the ability to determine the cutting direction based on motor current readings creates opportunities for developing semi-autonomous control systems for mining machines.

The study also includes an analysis aimed at extracting knowledge for automatic classification of machine operating states, which may serve as a basis for generating reports based on recorded data. This knowledge can, in turn, support the verification or correction of event logs.

Keywords: *industry 4.0, cutting machine motor*

1. Introduction

This publication presents an approach to acquiring information and knowledge about the operation of cutting machines based on the analysis of continuously recorded measurement data. The analyzed data is processed using computational environments such as VBA and R, applying data mining techniques, pattern classification, and anomaly detection. This work summarizes several years of research conducted by the authors, with earlier results published separately. The present study integrates these elements into a unified model for extracting knowledge on the operation of mining machinery, incorporating both technical and organizational aspects.

In recent years, heavy industries—including, in particular, underground mining—have shown growing interest in implementing the Industry 4.0 concept. A central idea of this paradigm is the real-time acquisition, analysis, and use of data generated by machines and technical systems. Longwall shearers, the core machines at mining fronts, are now equipped with various sensors for real-time monitoring of their performance. Current sensors measuring the load on motors—cutting, feed, and auxiliary—play a particularly important role. This parameter directly reflects the operational load of individual machine components and thus enables inference about the machine's operational state and mode of work.

Software development for such systems is usually handled by large IT teams or outsourced to external units. One of the additional aims of this article is to demonstrate that, at least in the prototyping stage, such software can be developed in-house using high-level programming languages.

The effective use of low-level data obtained from existing monitoring systems is a critical element in optimizing operational processes and enterprise management. These data, typically heterogeneous in nature, are generated by numerous sensors that monitor the performance of machines and equipment within complex technological processes. To deliver real value, such data must undergo preprocessing and be enriched with domain-specific knowledge related to the analyzed process. Of particular importance is the transformation of raw sensor data into higher-level representations such as event logs [1, 3, 4, 15].

Decision-makers in modern mining enterprises rely on data from various operational areas and multiple sources. Process-related data can originate from systems such as Enterprise Resource Planning (ERP), machine monitoring, environmental sensors, or worker localization systems. The diversity of data sources results in different levels of granularity—from general information (e.g., geometric parameters of the mining face), through machine operation states (e.g., running, alarm, downtime), to basic physical measurements (e.g., methane concentration, motor current, transformer switching) [16]. It is essential that all data is assigned to the appropriate stages of the process and analyzed in that context to enable in-depth evaluation of efficiency and safety.

Scientific literature presents a variety of approaches to analyzing data related to industrial processes and environmental conditions. Many authors employ data mining techniques for event classification [7, 8], prediction [2, 14, 17], and process description [13]. When the goal is process improvement, process-oriented methods such as Process Mining (PM) are

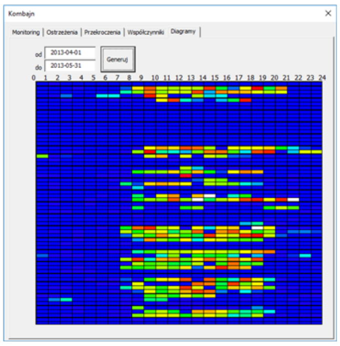

Fig. 1. Energy Consumption Diagram. Source: Author's own work
Rys. 1. Wykres zużycia energii. Źródło: Opracowanie własne autora

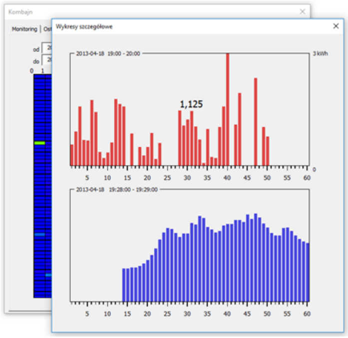

Fig. 2. Detailed Visualization of Machine Motor Load. Source: Author's own work
Rys. 2. Szczegółowa wizualizacja obciążenia silnika maszyny. Źródło: opracowanie własne autora

recommended. PM originates from workflow analysis and is widely used in business process management. It includes techniques such as process model discovery, conformance checking, model enhancement, role discovery, bottleneck analysis, and remaining time prediction [5, 6].

In real-world scenarios, complete datasets necessary to reconstruct process execution are often unavailable, hindering optimization efforts. The reasons may include incorrect sensor configuration, equipment failure, data transmission issues, or inaccurate readings. This article presents an algorithm for partial reconstruction of process data using the R programming language. The approach is based on the analysis of motor current signals to identify machine operation states, enabling the discovery of new insights, validation of existing data, and deeper process analysis.

2. Measurement System and Data

The data structure is based on triplets consisting of a motor identifier, a timestamp, and a current value. When the machine is idle and no current is flowing, no new entries are generated. This enables inference about downtime periods by analyzing the time gaps between consecutive records. After appropriate preprocessing, this type of data structure allows not only for the analysis of electrical component loads but also for examining work schedules, the occurrence of unplanned stoppages, and even changes in the organization of the mining crew's operations.

The data acquisition system used in the study includes a series of sensors installed on the motors of the cutting machine, which continuously monitor current levels. Detailed descriptions of the data structure can be found in studies [9, 10, 11, 12]. The main motors analyzed include: two haulage motors, one cutting motor, and one responsible for handling the power cable. The sensors record current values with a resolution of one second, and the data is transmitted to a central database built on Microsoft SQL Server.

To ensure efficient data storage and optimize disk space usage, a mechanism was implemented to store data only when a change in current value is detected. As a result, the database contains only observations that reflect machine activity, significantly reducing its size without compromising data quality. The software used in this research was developed based on archived data.

3. Functionality of the Developed Software

The application's performance remained high despite processing hundreds of thousands of records — thanks to the use of SQL views and query optimization, the time required to generate key indicators did not exceed two seconds. This tool served as the foundation for further exploratory analyses conducted in the R programming language.

The application, developed in the Visual Basic for Applications (VBA) environment, is a tool for real-time monitoring and analysis of data from cutting machine sensors. Integrated with a SQL Server database, it enables reading and processing of large data volumes while maintaining high efficiency and flexibility. The software includes numerous features supporting not only the visualization of motor current levels but also anomaly detection, efficiency analysis, and report generation.

Monitoring

The monitoring module includes graphical representations of current values flowing through the motors. Visualization enables real-time tracking of current levels for each motor, analyzing their variability, and identifying potential

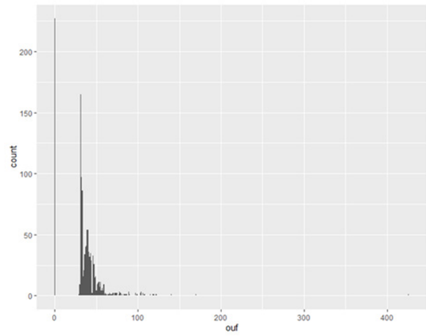

Fig. 3. Histogram Illustrating the Current Distribution of the Cutting Motor. Source: Author's own work
Rys. 3. Histogram ilustrujący rozkład prądu silnika tnącego. Źródło: Praca własna autora

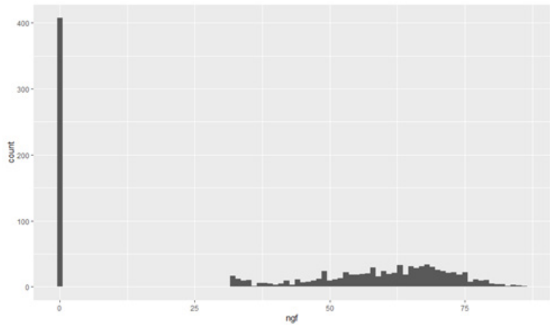

Fig. 4. Histogram Illustrating the Current Distribution of the Main Haulage Motor. Source: Author's own work
Rys. 4. Histogram ilustrujący rozkład prądu głównego silnika transportowego. Źródło: Opracowanie własne autora

overloads. Monitoring these values also allows real-time inference about the machine's current operating mode. This makes it easy to distinguish between states such as downtime, cutting, or idle movement. The detection of these machine states is described in detail in Section 4 of this article. Moreover, since the data is pulled from a database, the user can pause the visualization, scroll through historical data, and analyze the machine's operation over time.

Warnings

Another module handles warnings related to improper machine restarts after short downtimes. The application analyzes the first seconds of motor operation after startup, identifying cases in which the current exceeds a defined threshold (e.g., 400 A). If the motor is restarted under heavy load shortly after being stopped, it may cause overloads. The application recorded such events when the current surpassed the threshold within the first second after a pause shorter than five minutes. These events were flagged as critical and their frequency was analyzed in relation to machine operators and the machine's technical condition. This module also allows for the generation of histograms and lists of critical events.

Overloads

Prolonged and excessive loading of electric motors is another factor negatively affecting machine performance. Such situations are recorded by the application. Users can define current thresholds for each motor on the machine. The program detects and displays these events in a list from which records can be exported to an XML file. This data can be used for comparison with personnel assignment records to identify operators for whom such cases are more frequent.

Indicator Reporting

This application feature enables calculation of aggregated machine utilization indicators. Users can access information on energy consumption, total operating time of a specific motor, and the percentage of this time within the duration of a work shift — which is a component of the Overall Equipment Effectiveness (OEE) indicator.

Indicators calculated over successive days are compiled in a list. Selecting any given day from the list generates a chart displaying hourly energy consumption, enabling observation of machine activity patterns throughout the shift and supporting the evaluation of plan completion. It also allows the calculation of a set of indicators describing machine efficiency. The most important include: total working time, active cutting time, downtime, energy consumption, and efficiency ratio (calculated as the ratio of cutting time to total working time). Data can be exported in XML format, and summaries can be viewed by shift, day, or week.

Energy Consumption over Time

This module enables the analysis of energy consumption trends on an hourly, daily, and weekly basis. Charts and heat maps help identify shifts in machine workload intensity as well as periods of inactivity or overload. This analysis supports maintenance planning and work schedule optimization. The module enables long-term observation of machine activity. The generated diagrams (Fig. 1, Fig. 2) visualize energy consumption by the machine's motor. Each row in the diagram represents a different workday, while columns represent consecutive hours. The color of each cell reflects the machine's workload intensity based on energy drawn during that time. This makes it possible to identify operational hours, extended idle periods, and load levels.

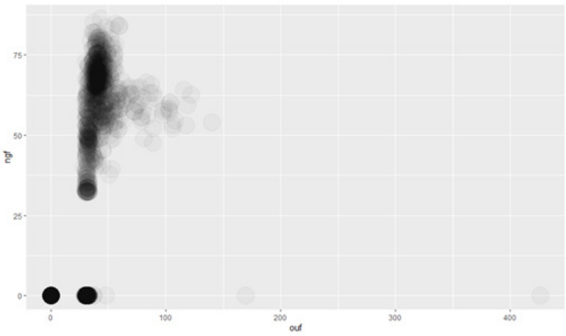

Fig. 5. Observation Density in the Current Space of Two Shearer Motors. Source: Author's own work
Rys. 5. Gęstość obserwacji w przestrzeni prądowej dwóch silników ścinających. Źródło: praca własna autora

Tab. 1. Assignment of Operating States Based on Observed Motor Current Values. Source: Author's own work
Tab. 1. Przypisanie stanów pracy na podstawie obserwowanych wartości prądu silnika. Źródło: Praca własna autora

ngf \ ouf	0	0 - 33	> 33
0	Off	Iddle	X
> 32	Maneuvering	Maneuvering	Extraction

Where:
ouf – current of the cutting motor [A],
ngf – current of the main haulage motor [A].

If the user wishes to examine the machine's operation in more detail for a selected time period, they can click on a specific hour to view its activity broken down into minute intervals (Fig. 2). If this level of detail is still insufficient, clicking on a bar representing the minute-level value will generate a chart showing the motor current with second-level resolution.

The obtained results have significant practical relevance. First, they enable real-time monitoring of machine operation and allow for rapid response to abnormal situations. Second, historical data serves as a valuable knowledge base for maintenance planning, work reorganization, and evaluating operator performance. Third, identifying the cutting direction based on current readings allows for the development of semi-autonomous control systems for the shearer.

4. Exploration of Recorded Data

The use of data mining techniques enables a deeper analysis of recorded information. The R programming language facilitates the application of advanced data mining algorithms that are currently being developed. Below, an analysis of machine states (types of activity) and an attempt to identify the direction of operation based on previously used data are presented.

To gain a more detailed understanding of the load distribution on the shearer's motors, histograms were created for the current values of the cutting motor (Fig. 3) and the main haulage motor (Fig. 4)

where:
ouf – current of the cutting motor [A],
ngf – current of the main haulage motor [A],
count – frequency.

In Figure 3, a high number of zero current values can be observed, corresponding to periods when the machine was idle. Additionally, there is a significant number of observations around 30 [A], which represent the operation of the cutting motor without active cutting load. Higher current values are observed during actual cutting activity.

Interpreting the current distribution shown in Figure 4 reveals, similarly, a large number of zero values. However, in this case, it is more difficult to clearly distinguish the current values associated with haulage motion of the shearer without engagement of the cutting unit.

A more comprehensive understanding of the shearer's operating states can be obtained by overlaying the above histograms. Figure 5 presents a chart created by plotting the observations in a two-dimensional space defined by the current values of the cutting motor and the haulage motor.

The number of observations corresponding to specific current values is represented by the darkness of each point in this coordinate system. This was achieved by layering highly transparent points on top of one another. In Figure 5, four distinct operating states of the machine can be identified.

The first state, where the current values of both motors are zero, represents the machine being switched off.

The second state is idling, in which the haulage motor current is zero, while the cutting motor current is approximately 30 [A].

The third state is maneuvering, where both motors draw current of around 30 [A]. This state appears in Figure 5 as a dark circle in the lower part of the point cloud.

The final state is active cutting, in which both the cutting and haulage motor currents exceed 30 [A].

Based on these threshold values, it is possible to assign recorded current readings to the identified operational states of the shearer, and subsequently calculate the percentage distribution of these states over the analyzed time period. From an economic perspective, it is expected that the cutting state will constitute the largest share of this distribution. The assignment rules for the shearer's operational states are summarized in Table 1.

The state marked with the symbol "X" in Table 3 warrants additional commentary. This is a prohibited state, in which the shearer would be cutting coal without advancing. Observations of such a state are possible, but only as a result of improper operation of the machine. One example could be activating the cutting motor while the cutting drum is embedded in the coal seam. Such action could very likely lead to machine damage.

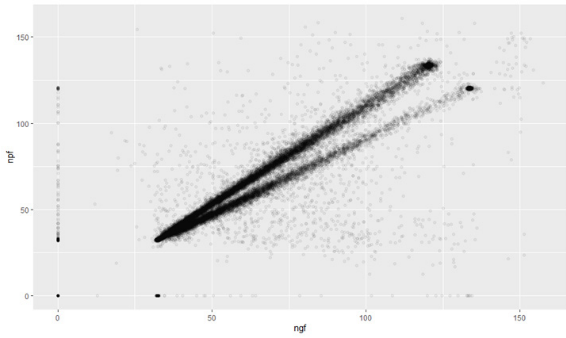

Fig. 6. Relationship Between Load Levels of Haulage Motors. Source: Author's own work. npf – current of the auxiliary haulage motor [A]; ngf – current of the main haulage motor [A]

Rys. 6. Zależność między poziomami obciążenia silników transportowych. Źródło: opracowanie własne. npf – prąd silnika pomocniczego transportowego [A]; ngf – prąd silnika głównego transportowego [A]

Tab. 2. Percentage Shares of Cases. Source: Author's own work

Tab. 2. Udziały procentowe spraw. Źródło: Opracowanie własne autora

case	share [%]
Main > Auxiliary	52
Main = Auxiliary	1
Main < Auxiliary	47

In the next stage of the study, the operation of the haulage motors (main drive ngf and auxiliary drive npf) was analyzed. The observed distributions of current values flowing through these motors, along with their trends in the plotted charts, suggested a high degree of similarity between them. To confirm this, a chart was created (Figure 6), where the axes represent the current values of both motors.

In Figure 8, it can be observed that the data points align along two distinct straight lines. The upper line represents cases where the power drawn by the main motor is greater than that drawn by the auxiliary motor, while the lower line represents the opposite scenario. It is also evident that the difference between the current values of the two motors increases proportionally with their load.

To better understand the structure of these occurrences, their percentage shares were calculated. The results are presented in Table 2. In this summary, as well as in the subsequent analysis, cases in which the haulage system was inactive have been excluded.

Since the structure of these cases turned out to be evenly distributed, the next step involved generating a histogram (Figure 9) illustrating the distribution of differences between the current values of the two motors.

Values to the right of zero represent cases where the main motor draws more power than the auxiliary motor. This histogram displays strong symmetry, which—together with the previously calculated percentage distribution—suggests that these motors frequently alternate roles in driving the shearer's haulage system.

This observation forms the basis of a hypothesis regarding the possibility of distinguishing the direction of the shearer's movement. Due to the potential inclination of the longwall face, differences in load between the motors powering the haulage system may occur. These differences could be amplified by the process of loading the mined material onto the armored face conveyor, which is carried out as the shearer moves and may vary depending on the direction of travel. Similar differences related to the direction of motion, but observed in the cutting motors, have been described in [31].

Partial confirmation of this hypothesis is provided by the chart shown in Figure 10.

Figure 10 was generated by creating an additional variable (stanyw) in the dataset, based on the intervals identified from Figure 9. This variable takes values according to Table 3.

To improve the readability of the chart, the values of this variable were smoothed by averaging within a 15-second moving window. The chart shown in Figure 10 covers a period of 5 hours and 30 minutes. The red line indicates the presumed directions of the shearer's movement (values 0.4 and 0.6), while a value of 0.5 denotes machine downtime.

5. Summary

This article presents an integrated approach to analyzing energy data from cutting machines. The data has been transformed into information and further into operational and managerial knowledge. It has been shown that the developed tools can significantly support production management in mining conditions. Future work should include integrating current analysis with visual and geolocation data, as well as developing comprehensive decision support systems.

The application of energy data analysis provides insight into machine operation, including movement direction and work modes. The combination of VBA applications and data exploration in R enables both monitoring and advanced interpretation. This work lays the foundation for the development of decision support systems in mining aligned with the Industry 4.0 concept.

The developed tools also enabled trend analysis and long-term assessments of machine performance. Weekly and monthly visualizations proved especially useful, illustrating machine workload intensity over the hours of each working day. Heat maps—with rows corresponding to days and columns to hours—used color to represent energy consumption, making it easy to identify peak hours, planned downtimes, and unplanned interruptions.

The analysis of the ΔI values over time allowed the generation of directional charts, where polarity shifts in current differences corresponded to changes in the machine's movement

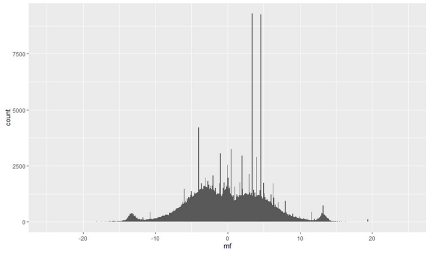

Fig. 9. Histogram of Motor Load Differences. Source: Author’s own work
Rys. 9. Histogram różnic obciążenia silnika. Źródło: Opracowanie własne autora

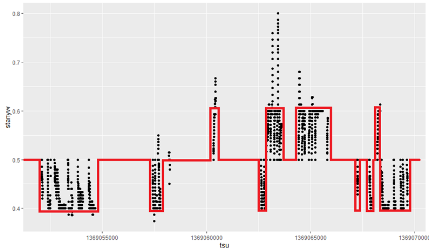

Fig. 10. Changes in Shearer Movement Direction. Source: Author’s own work
Rys. 10. Zmiany kierunku ruchu ścinacza. Źródło: Praca własna autora

Tab. 3. Values of the stanyw Variable for Defined Ranges of Haulage Motor Current Difference. Source: Author’s own work
Tab. 3. Wartości zmiennej stanyw dla zdefiniowanych zakresów różnicy prądu silnika transportowego. Źródło: Praca własna autora

range	value
(-∞, -12.5>	0.2
(-12.5, 2>	0.4
(-2, 2)	0.5
<2, 12.5)	0.6
<12.5, ∞)	0.8

direction. In practice, using this indicator could allow for automated tracking of the shearer's movement without the need for additional position monitoring. Furthermore, the differential current indicator could eventually be used as a feedback element in autonomous shearer haulage control systems.

The results obtained are of practical importance. First, they enable real-time monitoring of machine operation and rapid response to abnormal situations. Second, historical data serves as a knowledge base for maintenance planning, workflow reorganization, and evaluation of operator performance. Third, identifying the cutting direction based on current analysis facilitates the development of semi-autonomous control systems for shearer operations.

Currently, the technical capabilities provided by the electronics industry pose little limitation in the areas of data measurement and storage. However, challenges arise—especially with increasing data volume—during data processing.

Proper analysis of the production process is essential in the current economic environment. It can lead to increased equipment utilization, reduced production costs, and higher revenues through improved production rates. The use of appropriate IT tools that analyze data from databases and convert it into information is the first of two steps toward acquiring knowledge about the production process. The second step—extracting knowledge by uncovering patterns in the information—is more complex and requires a tailored approach to the specific problem being investigated.

Designing and developing data analysis applications leads to enterprise resource optimization, not only through improved work discipline and prediction of technological downtimes (e.g., for maintenance), but also by allowing insight into the conditions under which the work is being performed.

The information provided by the presented application can be cross-referenced with other data sources available to the company. For example, it should be compared with records of machine operator assignments on specific days. This would allow for conclusions about operator skill levels and support actions aimed at improving qualifications or adjusting equipment operation procedures.

Modern programming languages enable the rapid development of applications with such functionality. When these applications are connected to database servers that also collect information beyond the monitored area, more precise and broader analysis of process anomalies becomes possible.

The application of energy data analysis provides insight into machine operation, including movement direction and operational modes. The combination of VBA-based applications and data mining in R enables both monitoring and advanced interpretation.

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Wydobywanie wiedzy o realizacji procesu produkcyjnego poprzez analizę prądu silnika maszyny tnącej

W artykule przedstawiono wieloetapowe badanie skoncentrowane na analizie bieżących danych z czujników zainstalowanych w silnikach maszyn tnących. Zebrane dane stanowią podstawę do monitorowania wydajności maszyny, diagnozowania anomalii, określania wydajności i identyfikowania kierunku cięcia maszyn. W tym celu opracowano aplikacje oparte na VBA, które działają na danych pobranych z serwera bazy danych. Ponadto przeprowadzono analizy eksploracyjne w środowisku programowania R. Wyniki pokazują, że analiza danych związanych z energią może być cennym źródłem wiedzy operacyjnej i może wspierać podejmowanie decyzji w ramach paradygmatu Przemysłu 4.0.

Uzyskane wyniki mają istotne implikacje praktyczne. Po pierwsze, umożliwiają monitorowanie pracy maszyn w czasie rzeczywistym i pozwalają na szybkie reagowanie na nieprawidłowości. Po drugie, dane historyczne stają się bazą wiedzy do planowania konserwacji, reorganizacji pracy i oceny wydajności operatora. Po trzecie, możliwość określenia kierunku cięcia na podstawie odczytów prądu silnika stwarza możliwości opracowywania półautonomicznych systemów sterowania dla maszyn górniczych.

Badanie obejmuje również analizę mającą na celu pozyskanie wiedzy do automatycznej klasyfikacji stanów pracy maszyn, która może stanowić podstawę do generowania raportów na podstawie zarejestrowanych danych. Wiedza ta może z kolei wspierać weryfikację lub korektę logów zdarzeń.

Słowa kluczowe: *Przemysł 4.0, silnik maszyny urabiającej*