Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

Implementation of business intelligence system to analyze the data for mining mechanization – case study

Richard ANTAL[1], Daniela MARASOVÁ[2], Roman HÁJIČEK[3], Peter KLAPKO[4] and Vladimír MITRIK[5]*

Authors' affiliations and addresses:
[1] Technical university, Faculty BERG, Institute of Logistics and Transport, Park Komenského 14, Košice, Slovakia
e-mail: richard.antal@tuke.sk

[2] Technical university, Faculty BERG, Institute of Logistics and Transport, Park Komenského 19, Košice, Slovakia
e-mail: daniela.marasova@tuke.sk

[3] Technical university, Faculty BERG, Institute of Logistics and Transport, Park Komenského 14, Košice, Slovakia
e-mail: roman.hajiček@tuke.sk

[4] Technical university, Faculty BERG, Institute of Logistics and Transport, Park Komenského 14, Košice, Slovakia
e-mail: peter.klapko@tuke.sk

[5] Technical university, Faculty BERG, Institute of Logistics and Transport, Park Komenského 14, Košice, Slovakia
e-mail: vladimir.mitrik@tuke.sk

***Correspondence:**
Richard Antal, Technical university, Faculty BERG, Institute of Logistics and Transport, Park Komenského 14, Košice, Slovakia
tel.:+421556023125
e-mail: richard.antal@tuke.sk

Funding information:
APVV-18-0248

Acknowledgement:
This contribution was created with the support of project titled APVV-18-0248 "Smart belt conveyors ".

How to cite this article:
Antal, R., Marasová, D., Hájiček, R., Klapko, P. and Mitrik, V. Implementation of business intelligence system to analyze the data for mining mechanization – case study. *Acta Montanistica Slovaca,* Volume 27 (3), 744-753.

DOI:
https://doi.org/10.46544/AMS.v27i3.14

Abstract
In this article, we focused on the experimental implementation of the Power BI application in the field of mining mechanization. This application was created to demonstrate how an interactive data visualization tool can streamline data exploration and provide new insights that can be used to optimize selected processes. The monitored company uses a large number of reports in connection with the organization of the company. They collect many data from the attendance system and the electronic resource planning system, but also a lot of operational data related to the performance of mining mechanization. These data are evaluated in the company only at one-month intervals. Our intention was to transform the data for the year 2021 and create various visual reports through the power BI program, which, thanks to detailed analysis and evaluation, will help to improve the management of mining mechanization. The source of information in our case were tables that contained very poorly arranged data that could not be imported into the Power BI program in the given state.
After collecting the data, we had to transform them, which was a very time-consuming process. Due to limited resources, we had to adjust our original plan. From the entire portfolio of mining mechanization, which consists mainly of mining drills, loaders and trucks, we decided to only process data from mining trucks. The result will be a demonstration of the usability of the power BI system in a mining company to manage information related to mining trucks, but the same approach can be used for all types of mining mechanisms. Implementation of the power BI system was performed on data from one of the biggest underground mines in Slovakia.

Keywords
Business Intelligence, Power BI, Mining mechanization, Dashboards.

Introduction

In the logistics system of a mining company, bulk materials take the form of manipulated, transported objects, the relocation of which is ensured by active logistics elements. In the mining company, these are machinery and equipment for mining mechanization. When selecting active elements, it is necessary to consider their functional properties, expressed by technical-economic and ecological parameters. Various tools such as mathematical models (Grinčová et al., 2009 and Andrejiova et al., 2019), logistics, simulation, digitization and others can be used to assess functional properties. Simulation can also be understood as a numerical method using complex probabilistic dynamical systems through experiments performed using a computer model (Marasová, 2020). Ambriško et al. point out possible ways to improve the transport process in the extraction and processing of raw materials by applying cost-effective tools for the design of logistics systems (Ambriško et al., 2015). The research is focused on the proposal for rationalization of magnesite transport in the mining company. The inclusion of the transport process in the company's logistics model provides a comprehensive view of its operation. The application of generally applicable logistics principles can lead to an increase in the efficiency of the transport process in the mining company. The authors Šaderová and Ambriško deal with process modelling of the technological process in the quarry using simulation (Šaderova and Ambriško, 2020). Sub-solutions are good, but only digital transformation has a future. Digitization positively affects the performance, marketing effectiveness, productivity and innovation of companies (Krajčik, 2022).

All companies, including mining companies, require flexible information that allows them to make dynamic changes in processes. Business Intelligence (BI) tools address this challenge, which includes analytical models, technologies, data and information processing techniques to help us to make the best management decisions possible. Data processing produces information which is obtained from a variety of sources. Information, according to Laudon, is data that has been transformed into a form that is more meaningful and useful to humans. While the data is raw facts that represent events that occur in the organization or environment, it is processed into a form that humans can understand and use (Laudon, 2015).

Business Intelligence is the best option for meeting the company's needs. The extract-transform-load (ETL) process is supported by a set of activities known as business intelligence (Powell, 2018). It is used to analyze internal company data as well as external data from third parties in order to produce relevant information for decision-making and also analyze and prepare future strategic planning (Gowthami and Kumar, 2017). According to Akbar, business intelligence consists of four basic components that work together (Akbar et al., 2017):

- Data warehouse - is a set of data that is subject-oriented, does not change, and overlaps a long period of time to assist management in making decisions.
- Business analytics - is a set of tools for controlling, mining, and analyzing data in a data warehouse.
- Report and Queries - any type of existing query, such as drill down, multidimensional, view, grouping, and others, and any type of reporting, either statically (unchanged) or dynamically (in response to data changes).
- Data - information that has been translated into a form that is efficient for movement or processing.

Power BI is an example of a business intelligence tool. According to the Gartner Group, the two leading BI software products are Tableau and Power BI. Both software have benefits that make them popular among BI tools. In our case, we chose to use Microsoft Power BI, which we have previously used and are familiar with its functions and capabilities. Power BI provides a large number of visuals to help users fully understand the data and make better decisions. The effective use of the basic BI functionality requires the presence of structured data stored in relational databases, data warehouses or big data. The BI systems architecture allows us to connect to relational databases as well as handle large amounts of data that are not based on standard relational models. With the help of Power BI, we can provide quick coverage of the company's needs and provide information summaries online. Dashboards have the advantage of monitoring data from large volumes of data at a high level. This allows us to enter a reference depth in case of deviations from key performance indicators. Another significant advantage of BI systems is the ability to group data according to different criteria and dimensions, which transforms the report according to the needs of the company. Prior to actually implementing BI systems in organizations, it is important to establish a general vision for such systems. The systems must also be linked to the organizational objectives. This stage includes defining an organization's informational needs while also paying attention to key IT decision-makers and specialists. Ranking informational needs (on the basis of their importance) allows for the identification of important indexes, for example, when implementing business strategies (Chaudhary, 2004).

BI solutions should be tightly integrated with the company's goals. As a result, some of the most important reasons why companies use BI systems are as follows (Kalakota and Robinson, 1999; Liautaud and Hammond, 2002; Moss and Alert, 2003):

- Shifting from emotion and intuition-based decision-making to objectivism based on data.
- Adopting standards that serve as the foundation for companies' repeated, regular, and cyclical business processes.

- Integrating information transfers makes them more transparent and unifies the responsibilities of those involved in decision-making processes.
- Quick detection of information that deviates from commonly accepted standards and practices, signalling the probability of new dangers appearing
- Reducing the time required to analyze information and the number of people involved in information analysis and processing.
- Automatic and quick reporting and demand forecasting.

Observing the typical development in companies with BI projects, it is reasonable to say that the majority of BI development is driven by a top-down strategy. The information process in the mining industry is very dynamic, and the collected data are constantly updated with new variables. As a result, a large volume of data accumulates, complicating conventional analytical methods. Mining companies are currently facing an increasing number of operational and regulatory issues on a global scale. The main advantage of BI systems is that they enable fast (real-time) trend analysis, which is especially useful for strategic decisions for developing mining companies with a long return on investment (Durant-Whyte and Geraghty 2015).

Material and Methods

The scope of the study is focused on the dashboard-building process utilizing data that has gone through the ETL process. In the process of building dashboards, we will go through 4 stages:

- Data collection. During this phase, data is collected from both the system results and manually recapitulated daily data in the form of an Excel file.
- Pre-processing data. In this phase, an ETL (extract-transform-load) process is performed, which extracts the data from the collected data and then transforms them. Data errors are corrected, and unnecessary and duplicate data is removed. The data will then be sent to the data warehouse.
- Data visualization. At this point, the data has been transformed into dashboards using Microsoft Power BI capabilities.
- Data analysis. To obtain the required information, an analysis of the data supplied in graphical form is completed at this step.

The Power BI system was implemented in the mining company and specifically targeted on mining mechanization. Therefore we applied the overall equipment effectiveness (OEE) approach in a demonstrative model that we created. The performance of equipment used in mining operations significantly impacts production and costs. Modern mining mechanisms are becoming more sophisticated and capital-intensive, so it is important that they are highly efficient and perform revenue-generating tasks for as long as possible. Factors such as higher reliability, better sustainability, increased utilization and better management of mining equipment need to be monitored to achieve the goal and reduce costs. Various means and activities are available for this purpose; however, the cost-effectiveness ratio of the equipment varies significantly. As a result, it is important to assess which elements we should focus our efforts on to help improve the situation. Measuring factors affecting equipment efficiency and performing a thorough analysis of well-defined and monitored performance indicators allows us to identify opportunities, properly allocate resources, and evaluate the changes noted. With these goals in mind, we focus on various performance indicators and metrics applicable to mining equipment.

Equipment effectiveness in the mining industry is often associated with the availability and efficiency of equipment and its use. Although both of these factors are undeniably important, there are a number of others whose impact is often underestimated. The overall equipment efficiency (OEE) provides an interesting approach to the quantification of efficiency in a broader context. Koch provides a general definition for OEE in the manufacturing industry (Koch, 2003):

$$OEE = availability \times performance\ rate \times quality\ rate$$

Mobile equipment used in the mining industry is different, so the above definition needs to be adjusted. In equipment such as loaders, trucks or conveyors, the level of quality in the mining industry appears to be less important than in the equipment used in the manufacturing industry. As a result, the definition by Campbell and Jardine (Campbell and Jardine, 2001) will be more suitable for our needs:

$$OEE = availability \times ultilization\ rate \times production\ efficiency$$

Due to the simplicity of its definition and interpretation of results, availability is the most commonly used performance metric in the mining industry. Nevertheless, there is no industry-wide consensus on the interpretation of inputs. For example, the term "total hours" is unique only for those mines that operate 24 hours a day, 7 days a week. In other cases, they tend to use scheduled operating hours representing nominal working hours over a period of time (Lukacs, Z., 2001). Downtime is an even more complex concept as it is influenced by several factors and the ways of interpretation are different. Downtime is directly affected by reliability, which is determined by the average time between failures or the average time between outages. Shutdowns include all outages due to failure or scheduled maintenance, whether corrective, preventive or predictive (Campbell, 1995).

$$average\ time\ between\ outages = \frac{number\ of\ operating\ hours}{number\ of\ shutdowns}$$

The average downtime is one of the most appropriate metrics for measuring plant performance, but there are relatively few mining plants that record and evaluate this data. It is strongly recommended not only to monitor the values of the relative time between outages but also closely monitor their trends for defined time periods because they are often much more informative than just the values for a given period.

At the same time, it is worth noting that the impact of outages (downtime duration) may be less important than the frequency with which they occur. Seven one-hour outages per month, rather than one 12-hour outage, may be preferable to operators (Paraszczak, 2005).

In addition to reliability, availability also depends on sustainability and maintenance support, both of which are part of several other factors. Downtime is not limited to the so-called "active maintenance time" or the time during which the actual work (corrective or preventive maintenance) is performed on the machine, as this time is usually extended by all kinds of delays and waiting times. As a result, having accurate information on the duration of all downtime components is critical to identifying and eliminating the factors that cause the most significant time and money losses. In this context, it is suggested that the procedures for collecting performance data follow all of the guidelines listed below (Paraszczak, 2005):

- It is critical to accurately record the beginning of downtime, including the precise moment when a component of the equipment fails or is taken out of service due to upcoming maintenance. It is important to note that the start of downtime rarely coincides with the start of active maintenance, and we should avoid misrepresenting the two concepts.
- The end of the downtime should always be understood as the point at which all maintenance work (including, if necessary, final inspections and testing) is completed, and the equipment can resume normal operation. Regardless of whether the machine is used right away, it should be registered as "available" from now on. Failure to do so may cause data on reliability and maintenance to be distorted as a result of the equipment's use.
- The actual operating hours of the device are among the most important data that need to be recorded. They should be recorded by onboard instruments and sensors. Manual reports are also important and sometimes necessary but often contribute to data errors.

Assuming that we manage to take all these factors into account, we obtain accurate data that allows the calculation of useful performance indicators such as (Wiebmer and Widdifield, 1997):

- Average active maintenance time expressed in hours.
- Active maintenance + all delays.
- Proportion of different categories of delays in the total downtime.
- Ratio of planned maintenance activities to total maintenance time.

EQUIPMENT UTILIZATION

A device that is ready to use and capable of performing the function for which it was designed is rarely used for the entire time it is available. There are a number of reasons for this. Due to an operating cycle, a persistent failure, or a lack of operators, the equipment may be marked as backup, standby, or idle. (Paraszczak, 2005) Our data on the use of equipment may be distorted if the company has equipment with a capacity greater than the operating capacity of other elements that limits the deployment of all machines. The following relationship describes how equipment is used (Paraszczak, 2005) :

$$\boldsymbol{Utilization = \frac{number\ of\ operating\ hours}{uptime\ (available\ time)} \times 100\%}$$

The value of a metric, like availability, is heavily influenced by the quality of the input data. Many devices have onboard instruments that keep track of operating hours, machine usage, load, and consumption. These are devices that collect data from devices and their telematics devices via data channels. Unfortunately, many mining companies lack these systems in their equipment, leaving only approximate data available. In many cases, the lack of these technologies is due to financial constraints. The rate of utilization becomes a valuable metric in the management of mining mechanisms if we can ensure adequate quality of input data. The input data should consist of these data:

- Operating time.
- Idle - left as a standby / standby unit
- Inactivity due to the fact that the workplace for the given facility is not ready due to other ongoing work, for example - blasting.
- Idle due to lack of operators.

Analysis of availability components can help explain possible discrepancies between available time and actual operating time, allowing for the identification of areas where corrective action is required. In the case of the mining company we monitor, it is primarily a large number of trucks that exceed the loading capacity of the loaders, which are also limited by the operational capabilities of underground hauling. Due to this reason, the difference between the available time and the operating time is greater.

PRODUCTION EFFICIENCY

Referring to the manufacturing industry, Moubray states that the primary function of the machine is to be followed by the following three aspects (Moubray, 1997):

- Performs work.
- Must work at the right pace.
- Must ensure the required quality of work.

The first aspect is related to availability and utilization, but we will also discuss the other two. By Widdifield and Wiebmer, 1997, "What a machine is capable of and what it actually produces are two different things." The amount of actual work that the machine can do is greatly influenced by the operator's skills, level of training, and even attitude and motivation. On the other hand, seemingly functional pieces of equipment can have significantly lower performance even with a "perfect" operator.

$$production\ efficiency = \left(\frac{actual\ productive\ work}{(total\ hours - downtime - standby/idle) \times rated\ capacity}\right) \times 100\%$$

This value is part of the general equation for calculating the efficiency of operated equipment. However, we must also consider that operating conditions in the mining industry are often different; therefore, the application can be much more demanding than in the case of the manufacturing industry. The relevance of the concept of rated effectivity in the case of mining equipment is questionable as there are many variables in the process, and the conditions may differ.

Equipment efficiency is becoming increasingly important in terms of mining costs and profitability. It is clear that efficiency is more than availability and utilization, which are the primary performance indicators in mining companies. As already mentioned, a device's overall efficiency is a function of several, often very complex factors. At the same time, it is clear that the implementation and subsequent use of the overall equipment efficiency index (OEE) is not a universal and perfect solution to problems associated with equipment performance. OEE as a metric has its disadvantages, and it is appropriate to combine it with other metrics and information to be useful in the management of mining mechanization.

PARETO ANALYSIS

Due to the fact that we needed to identify the main causes that caused the truck to be unavailable, we used Pareto analysis. By common observation, we can state that in any system with causes and consequences, a small percentage of cases cause a significant majority of consequences. This concept, known as Pareto's principle, came into common parlance as the "80-20 rule," which states that 80 per cent of the effects stem from 20 per cent of the causes (Talib et al., 2010).

A bar graph representing the measurement of various aspects of the system is known as a Pareto analysis. The presentation of the graph is based on cumulative frequency measurements of specific metrics, which are arranged from the highest to the lowest frequency. The graph shows the areas that represent the largest percentage of the problem and the variables that play a role in these areas.

In our case, we used Pareto analysis to determine the primary causes of mining truck unavailability in the chosen mining company. Maintenance can focus its attention on the areas that are most involved in the unavailability of trucks based on the information obtained. One of the most important benefits of Pareto analysis is that it helps us identify and determine the causes of failures or problems.

Results

We gathered data from two different sources and analyzed them using Microsoft power BI . The first source is the information that is downloaded from each truck via data channels. This is the information that we obtained:

- Performance - the number of tonnes of raw ore transported.
- The number of operating hours.
- Technological downtime.
- Fuel consumption.

The second source of data is information that is recorded manually. The company operates in a two-shift mode, and at the beginning of the first and second shifts, maintenance employees record information about the condition of trucks in an excel form called an overview of the current state of the mechanisms. In the event that any fault is recorded or a fault that has occurred in the past persists, the maintenance worker will enter this information in the data for the specific vehicle. This report provides us with information about current faults or unusual behaviour of any of the truck's components. Data are recorded in a separate Excel file for each day the mine is in operation. It should be noted that these reports were poorly organized, and the data was formatted inconsistently with a number of typos. Using a power query, we combined these reports and then transformed the data and formatted it correctly. Nevertheless, it was necessary to make a lot of manual adjustments, and the goal of developing visualizations for complete mining mechanization had to be adapted only to the processing of truck data due to time constraints. In our research, we divided the recorded faults into categories according to the nature of the fault. For example, in the case that low performance is observed, this fault was classified as it is related to the engine. In the case of low braking performance or complete absence of braking of any wheel, this fault was classified into the brake system category. We used this logic for all of the reported faults. Most of the reports contained a combination of two or more failures. Some disorders, such as seat damage or a malfunctioning horn, have been categorized as others. Due to a large amount of data and the requirement to link information from two different sources, we invoked the data and combined them. Than we could use all of the functions of Microsoft Power BI software to visualize the data and further process and evaluate them. Since we could combine these data based on specific days, vehicles, and other factors, we were able to create reports in which filtering one or multiple categories resulted in changes in multiple graphs with their own source data. The layout for the first dashboard is shown in Figure 1.

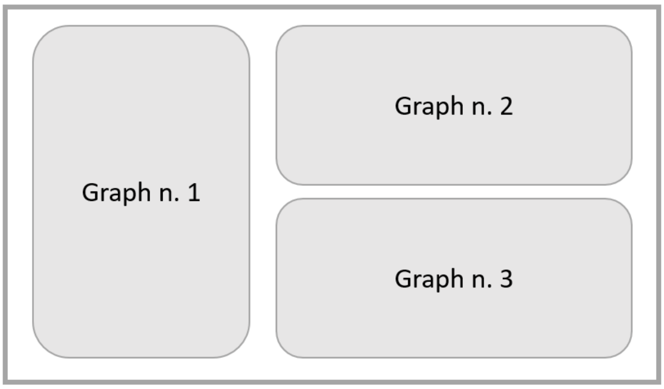

Fig. 1. Layout of the first dashboard.

The first dashboard, shown in Figure 2, allows us to track three different interdependent data. Graph number 1 displays the percentage of vehicles that were able to operate on a selected time period and also what percentage of vehicles were not available to operate due to a failure. The purpose of graph number 2 is to display the percentage of individual faults that were recorded for each category of the fault and resulted in decommissioning and classification as immovable vehicles. Graph number 3 displays the number of reported faults and the percentage of each category of the total. These faults were recorded, but nevertheless, the vehicle was registered as mobile as they were less serious. This dashboard can display any time period based on the preference of the currently analyzed problem. After selecting the time period in graph no. 1, the data in graphs no. 2 and 3 are automatically adjusted accordingly to the selected period. Through this set, we can analyze the availability of vehicles, the reason for the event that the vehicle is not able to operate and also the number of reported failures or abnormalities. All this data can also be displayed only for a specific truck, or brand or for multiple specific trucks using filtering.

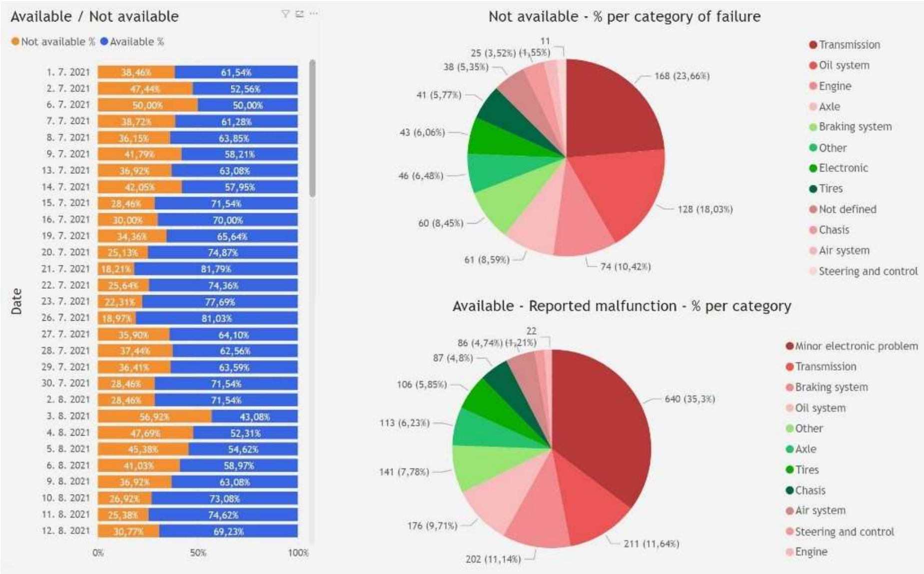

Fig. 2. First dashboard - % of availability and reported malfunctions and failures for each category.

The layout of the second dashboard is shown in Figure 3. It consists of three graphs whose data are interconnected, and the chosen selection adjusts all graphs in parallel. Graph number 4 displays working time, not available, technological downtime and also a curve showing productive working time for the selected time period, which we chose through date filters. The productive working time curve is calculated as a subtraction between working time and technological downtime. Graph number 5 displays the performance expressed in tons for a particular truck as the sum of the periods displayed (any period can be selected via filtering). The values for specific trucks are also expressed as a percentage of the total amount of raw material transported by the ones selected. Graph number 6 displays the percentage of time spent in a technological downtime out of the total operating time.

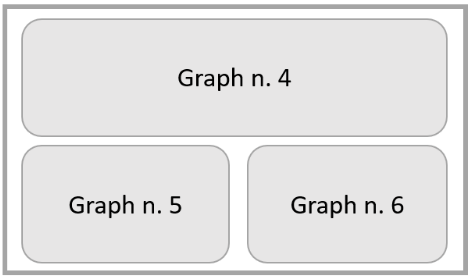

Fig. 3. Layout of the second dashboard.

The dashboard which we created is shown in Figure 4. We can easily analyze the performance dependence on technological downtime with the help of this dashboard.

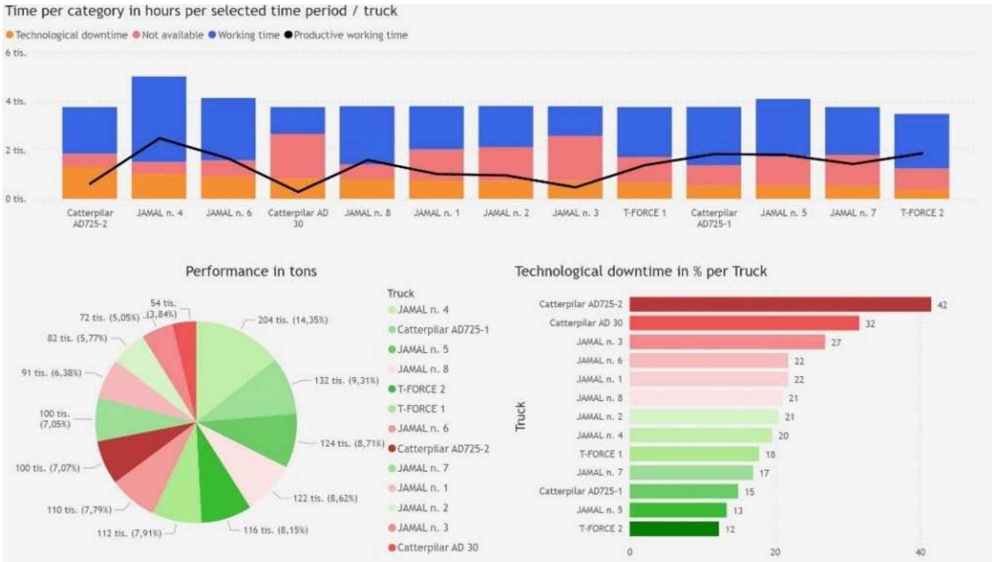

Fig. 4. Second dashboard - Utilization, performance and technological downtime

The created dashboards provide a basic overview and have a demonstrative character of how we can display data in the selected company. However, the processed data provide many options for creating graphs and dashboards according to current needs. The basic prerequisite for successfully implementing Power BI software as a tool for monitoring performance indicators is the quality of input data. The steps that would be necessary to implement the system in order to be able to include all machinery and equipment falling under the mining mechanization in the selected company are as follows:

- Standardization of machine report formatting and the creation of a template for the overview and status of mechanisms, which would be complemented by a report-filling system protocol that would be provided to all personnel who fill out the report.
- The creation of an online SQL database that would function as a data warehouse for collecting all accessible data relevant to mining mechanization
- This data would then be processed into graphs and dashboards via Power BI or another business intelligence system and subsequently shared with the users who manage the mining mechanization operation.

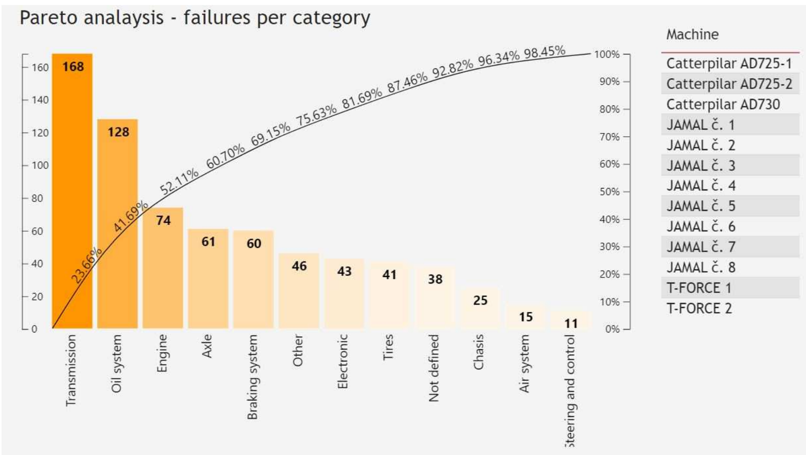

Fig. 5. Pareto analysis – failures per category

We used the power BI function to create the Pareto analysis shown in Figure 5 using the extracted data from the table. The number of individual categories can be seen in the graph. The graph displays the number of failures by category of occurrence as well as the Lorenz curve of the total number of individual defects. Individual brands or specific vehicles can be filtered using the filters in the created set, providing us with data that allows us to specify the occurrence of failures related to model maintenance more precisely. From the graph, we can easily see that the three most represented categories in our case accounted for 52.11% of the total number of failures. Categories were associated with the transmission, oil system and engine. A total of 9 categories caused the remaining 47.89% of vehicle breakdowns. By eliminating these three shortcomings, we would be able to reduce the overall failure rate by more than 50%. It means that we should focus mainly on these three categories or the first 5 categories, which make up almost 70% of the total volume of failures that caused the truck to be not available.

At the same time, the fact that, despite the high number of outages, the company fulfils its production plan by more than 95% on average cannot be overlooked. This can be explained by the fact that the company has a large fleet of trucks, and even if all of them were available, only a portion of them would be used on any given day.

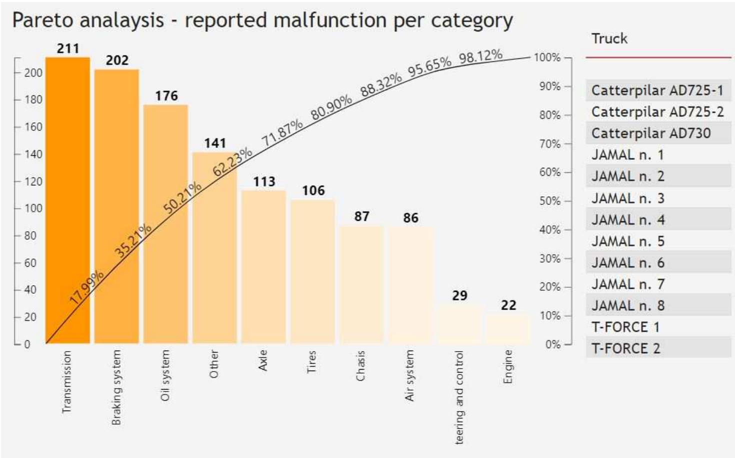

Fig. 6. Pareto analysis – reported malfunction per category

Since the information about the recorded failures and various abnormalities in the operational functioning of trucks is recorded even if the vehicle is capable of operation, we also created a Pareto analysis shown in Figure 6. They are also divided into categories according to their character. As a result, we can observe that more than 50% of the reports were in the first three categories. Data on small electronic problems were filtered from the graph. In 2021 there were 640 reports containing some type of electronic problem. These were faults such as:

- All types of headlight faults
- Air conditioning malfunction

These disorders were excluded from the Pareto analysis due to their low relevance. They were often neglected, and in some trucks, the failure occurred for several weeks in a row. Both Pareto analyses, in connection with the developed sets, provide us with much information that we can use appropriately in the management of trucks. One of the main disadvantages of applying Pareto analysis is that it does not provide a root cause of why the fault occurred. To determine or identify the root causes of the defect, it is necessary to analyze all the factors that affect the operational capability of trucks. The analysis also does not provide information about the severity of the error or any problem. It only shows qualitative data.

However, in our case, it considers the number of hours the vehicle was not available due to a malfunction or failure. Based on these findings, we were unable to justify the extent to which the time the truck was out of service was proportional to the severity of the failure. The length of this time is affected by the severity of the failure, maintenance levels, as well as purchasing operations that affect spare part availability.

Discussion and conclusions

The progressive development of information technology and the pursuit of sustainable development bring new challenges for mining companies. One of the options for solving the requirements is an in-depth analysis of the processes performed in the company, which is made possible by the use of appropriately selected KPIs. BI visualization programs are a very useful tool for processing and evaluating key performance indicators. Identifying KPIs as measures and metrics tailored to the mining company to monitor processes and make decisions based on reliable data is an essential part of the improvement in company performance.

The aim of our article was to demonstrate the use of business intelligence software in which, through the developed dashboards, it is possible to analyze and evaluate some key performance indicators in the management of mining mechanization. It was impossible to process complete data for mining mechanization due to the low quality of the input data. Nevertheless, based on the analysis of data for trucks, we were able to develop several dashboards that can be helpful for the managers and supervisors of logistic operations in the mining company. Thanks to the obtained knowledge, they are able to focus their attention on the most critical areas and implement changes that will lead to improvement. If we wanted to proceed to process all data in Power BI, it would be necessary first to change the data acquisition process. If the changes were successfully implemented, the company would have a very powerful tool to monitor the performance and utilization of mining mechanization. However, the magnitude of the impact cannot be provided as there is no existing metric we can use to estimate the result of such implementation. The analysis we created with Power BI can undoubtedly be useful for the company; further improvements are the subject of our next research, which will lead to more complex solutions.

References

Ambrisko, L.; Marasova Jr., D.; Grendel, P.; Lukac, S. (2015). Application of logistics principles when designing the process of transportation of raw materials, *Acta Montanistica Slovaca*, 20, 141-147.

Andrejiova, M., Grincova, A., Marasova, D. (2019). Failure analysis of the rubber-textile conveyor belts using classification models. *Engineering Failure Analysis*, 101, 407-417.

Akbar, R., Oktaviani, R., Tamimi, S., Shavira, S. and Rahmadani, T. (2017). Implementasi business intelligence untuk menentukan tingkat kepopuleran jurusan pada universitas. *Jurnal Ilmiah Informatika*, 2(2), 135-138.

Campbell, J. and Jardine, A. (2001). *Maintenance excellence*. New York: Marcel Dekker.

Campbell, J. (1995). *Uptime*. New York: Productivity Press.

Chaudhary, S., (2004). *Management Factors for Strategic BI Success*. In book: Business Intelligence in the Digital Economy, 191-206.

Durrant-Whyte, H., Geraghty, R., Pujol, F., Sellschop, R. (2015). *How digital innovation can improve mining productivity*. Available from: www.mckinsey.com/industries/metals-and-mining/our-insights/how-digital-innovation-can-improve-mining-productivity.

Gowthami, K,. and Kumar, M. R. P. (2017). Study on Business Intelligence Tools for Enterprise Dashboard Development, *International Research Journal of Engineering and Technology*, (4), 4, 2987–2992.

Grincova, A., Berezny, S., Marasova, D. (2009). Regression model creation based on experimental tests of conveyor belts against belt rips resistance, *Acta montanistica Slovaca,* 14 (1), 113-120.

Kalakota, R., and Robinson, M. (1999). E-business: Roadmap for success. Addison-Wesley.

Koch, A. (2003). OEE industrial standard v. 2.0. Aarle Rixtel, Bloom Consultancy.

Krajčík, V. (2022). Digitalization of SMEs and their perceptions regarding public interventions and supports of digitalization: Evidence from mining and iron industries. *Acta Montanistica Slovaca*, (27), 100-116.

Laudon, K.C., Laudon, J.P. (2015). *Management information systems: Managing the digital firm*. Pearson Educación, 672.

Liautaud, B., Hammond, M. (2002). E-business intelligence. Turning information into knowledge into profit. New York: McGraw-Hill.

Lukacs, Z. (2001). Standardization of definitions for benchmarking.

Marasova, D., Saderova, J., Ambrisko, L. (2020). Simulation of the Use of the Material Handling Equipment in the Operation Process. *Open Engineering*, 10(1), 216-223.

Moubray, J. (1997). *Reliability-centered maintenance*. Industrial Press Inc., 448.

Moss, L. T., Alert, S. (2003). Business intelligence roadmap – The complete project lifecycle for decision support applications. Addison-Wesley, 543.

Paraszczak, J. (2005). Understanding and assessment of mining equipment effectiveness. *Mining Technology*, 114(3), 147-151.

Powell, B. (2018). Mastering Microsoft Power BI: Expert Techniques for Effective Data Analytics and Business Intelligence. Packt Publishing.

Saderova, J., Ambrisko, L. (2020). Computer simulation as one of the tools for modelling of the work cycle of loading and transport of the raw material at a quarry, *Mining Science* 2020, 27, 199-208.

Talib, F., Rahman., Z. (2010). Studying the impact of total quality management in service industries. *International Journal of Productivity and Quality Management*, 6(2), 155-168.

Wiebmer, J., Widdifield, L. (1997). Cost per ton imporement ideas for undeground equipment. paper no. 97-169. SME Annu. Meeting. Denver.