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EFFECTIVENESS OF CONTINUOUS SURFACE MINING SYSTEMS: LESSONS LEARNED FROM SIX DECADES OF LIGNITE EXTRACTION IN WESTERN MACEDONIA, GREECE

The South Field Mine, situated in Western Macedonia, Greece, has used continuous surface mining systems: bucket wheel excavators (BWEs), belt conveyors, and stackers for over four decades of uninterrupted operation. This paper, using the principles of the Lessons-Learned process, tries to identify, document, analyse, and disseminate valuable knowledge and experience acquired in this mine, focusing on the performance indicators and downtimes of BWEs. Quantitative analysis methods were employed to analyse data and detect trends and factors for productive time losses. During a rather crucial period for the mine, due to decarbonisation and energy transition policies, the performance of BWEs exhibited a decline. On the other hand, availability and utilisation remained relatively stable. Mechanical failures and annual maintenance appeared to be the primary causes of downtimes. Non-operating time, connected with the lack of personnel, also had a great impact on operational efficiency. According to the linear regression model, this downtime has the greatest influence on the availability of the BWEs. In conclusion, this research implies the importance of the incorporation of new technologies for monitoring and producing daily and monthly records of the mine activities, which can enhance the overall effectiveness of a continuous mining system.

Keywords: Continuous mining systems; bucket-wheel excavators; availability; utilisation, performance

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1. Introduction

The gradual depletion of mineral-rich deposits, coupled with the increasing demand for minerals, mainly those essential for digital and energy transitions, and the influence of decarbonisation policies have made productivity enhancement and cost reduction top priorities for the mining industry. To address these challenges, mining companies have relied on exploration and productivity improvement. Over the past 150 years, the industry has successfully increased productivity by manufacturing larger equipment and expanding mining operations. However, since 2000, signs of a slowdown have emerged [1].

The concept of intelligent mining has gained traction as a means to enhance productivity while meeting the climate change goals outlined in the Paris Agreement [2]. A key driver of this transformation is Mining 4.0, a technological platform based on Industry 4.0 technologies, such as the Internet of Things (IoT), big data, Artificial Intelligence (Al), and Machine Learning (ML). Mining 4.0 aims to modernise the industry by improving productivity, safety, and environmental sustainability [3].

The digital technologies implemented in mining operations and processing can be categorised into four groups:

(a) Automation and remote operation: Autonomous Load-Haul-Dump (LHD) systems [2] and Haul-Truck (AHSs) systems [4] boost production and help reduce machine downtime, maintenance costs, and fuel consumption, consequently lowering greenhouse gas emissions. Other examples include autonomous drill systems [2], automatic controlled belt conveyors [5], and Unmanned Aerial Vehicles (UAVs) and remote sensing technologies applied in surveys to enhance productivity and improve mine planning [6].

(b) IoT: Real-time monitoring and control systems such as smart sensors that enable real-time data capture from equipment, actuators, and cloud-based data engines support decision-making, optimise operations, data storage and analysis, and improve productivity and safety [7]. IoT applications in communication, video surveillance, and health management have also reduced injuries and fatalities [2].

(c) AI and ML: Both technologies will play an increasingly critical role in intelligent automation, enabling autonomous systems to adapt to dynamic environments, optimise processes, and make informed decisions, including decisions about human safety [4]. These technologies are also used for predictive maintenance, operational optimisation, blasting optimisation, and fuel efficiency. Combined with remote sensing data, they are also used in mineral exploration and drilling [2].

(d) Digital Twinning: This concept refers to developing a digital model of the physical operation. This is possible using the geological and engineering information of the site, but more importantly, using the real-time data generated from the sensors connected across the operation. With the digital twin of a mine, it is possible to perform simulations and predict potential failures or downturns in equipment performance [7].

Furthermore, numerous studies have focused on the performance of mining equipment. Many researchers highlight the role of systematic equipment performance measurement, particularly Overall Equipment Performance (OEE), in improving equipment utilisation and efficiency [8]. In this context, the Mine Production Index (MPi), a modified version of OEE, has been proposed to provide a more realistic assessment of mining equipment effectiveness. Tested in a Swedish mine equipped with five shovels, MPi provided higher and more realistic values than traditional OEE [9].

Based on Lean Manufacturing principles, a tailored Total Productive Maintenance (TPM) approach was implemented in copper mines, focusing on three key pillars: improving the work environment, autonomous and planned maintenance, and developing standards [10]. Additionally, a TPM strategy combined with an OEE model has been applied to assess equipment efficiency in an underground mine [11].

A new methodology called Overall Mining Equipment Effectiveness (OMEE) has been developed to evaluate the efficiency of mining equipment, identify operational weaknesses, and estimate equipment life cycles and maintenance needs. OMEE has been applied in two open-pit coal mines in Spain, based on data collected over 10 years [12]. With the rise of Mining 4.0, the mining industry is steadily moving towards predictive maintenance to correct potential faults and increase equipment reliability. ML is a powerful tool in reliability and fault analysis. With the integration of deep learning into AI, intelligent diagnosis is expected to enhance further predictive capabilities. Future developments should combine data-driven AI methods with failure mechanisms and prior knowledge to improve diagnostic accuracy [13]. However, statistical techniques, geostatistical models, production scheduling, truck dispatching models, and system control methods will continue to play a role in mines that are not yet ready to adopt innovative digital technologies [6].

The present study focuses on continuous mining systems. Although less flexible than loader-truck setups, they offer significant advantages in achieving high production rates and, under certain conditions, can attain high efficiency levels. A notable example of statistical analysis in this area is the study of failure rates and maintenance performance of an SchRs 800.15/1.5 bucket-wheel excavator that operates in a Serbian lignite mine is presented in [14].

The surface lignite mines of Western Macedonia are now in their seventh decade of operation. The accumulated knowledge and experience from operating continuous extraction systems and addressing various challenges, such as the multi-layered structure of the deposit and the presence of hard rocks in the overburden, are noteworthy [15]. Following the EU decarbonisation and energy transition policy, the mines are expected to cease operations in the next few years.

Preserving the knowledge and lessons learned from these operations is very important; it is perhaps as important as implementing land reclamation and addressing the social and economic impacts due to mine closure. This research examines the evaluation of the effectiveness of continuous surface mining systems, focusing on the performance indicators and the downtime analysis of the bucket wheel excavators. Based on the principles of the lesson-learned process, it uses quantitative analysis methods and tries to provide the mining industry with valuable conclusions for future operational efficiency improvement.

2. The study area

Lignite had been a major source of electricity production in Greece for several decades before the expansion of renewable energy sources and the decarbonization efforts led to a sustainability strategy. The Western Macedonia region was the primary location for lignite extraction in Greece, hosting the country's largest lignite-fired power plants with a total installed capacity of about 4,300MW.

South Field Mine (Fig. 1) is the largest mine of Western Macedonia Lignite Centre (WMLC), in terms of acreage, total excavation volumes, and lignite production. Since 1979, when the mine operation began, the total excavations have exceeded 2.6×10^9 fm^3 and the production of lignite has reached 265 million tonnes (Fig. 2). Nowadays, it covers an area of 72 km^2, with an active excavation area of 8 km^2. It is a surface mine developed in two discrete pits, the so-called Sector 6 and Sector 7, currently with five and four horizontal benches, respectively. In the past, the South Field mine had a different layout, with a single pit consisting of ten main benches and some small ones for getting access to the deeper parts of the lignite deposit.

Fig. 1. Map of the West Macedonia Lignite Centre and South Field Mine
(*Source:* https://globalenergymonitor.org/projects/global-coal-mine-tracker/tracker-map/)

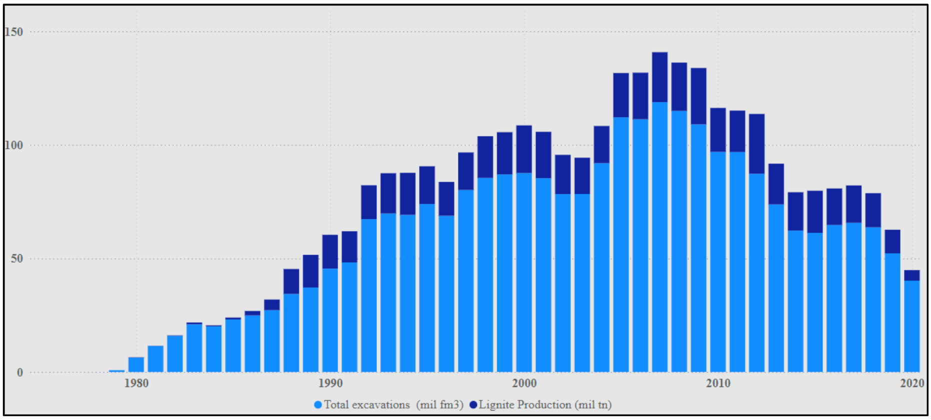


Fig. 2. Annual fluctuation of total excavations and lignite Production in South Field Mine from the beginning of its operation until 2022

The deposit consists of multiple, thin lignite layers separated by calcareous and clayey waste beds. Due to this complexity and the need to achieve high production rates, selective mining techniques are applied using continuous mining equipment. Eleven bucket-wheel excavators (TABLE 1), seven spreaders, and 96 km of belt conveyors have been installed in the mine [16].

TABLE 1

South Field Mine's Bucket Wheel Excavators that were operating in the period 2010-2020

Name	Manufacturer	Type	Capacity (m^3/h)
BWE1	KRUPP	Schrs3700/2,5.30	7586/11100
BWE2	TAKRAF	SRs2000/5.32	4170/6050
BWE3	TAKRAF	SRs2000/5.33	4170/6050
BWE4	TAKRAF	SRs2000/5.34	4170/6050
BWE5	TAKRAF	SRs2000/5.34	4170/6050
BWE6	TAKRAF	SRs 2000/6.33	3970/5760
BWE7	TAKRAF	SRs 2000/6.33	3970/5760
BWE8	KRUPP	Schrs 2300/5.32	4188/6072
BWE9	ETEKA/KRUPP	Schrs 1760/5.32	4207/6100

Additionally, due to the complex stratigraphy and tectonics of the deposit, comparing the operational performance of the South Field Mine with other lignite mines is risky and may lead to incorrect conclusions if not analysed by mining experts. However, earlier publications report that the productivity per employee at the Southern Field Mine is comparable to that of the German Garzweiler mine, while it lags behind the Inden and Hambach mines [17]. Overall, the productivity of the lignite mines in Western Macedonia is among the highest, alongside those of German and Polish mines [18]. Yet, in terms of cost per ton of lignite and even worse, cost per Gcal of lignite, Greek mines are among the most expensive in Europe due to their high stripping ratio and the low calorific value of the lignite produced [19].

3. Material and methods

3.1. The Lessons-Learned Process

This study implemented a Lessons-Learned process to identify, document, analyse, and disseminate the knowledge acquired in the WMLC lignite mines regarding the operational efficiency of continuous mining systems.

The Lessons-Learned process is a common practice in project management and organisational learning. It systematically involves identifying, documenting, and sharing insights from positive and negative experiences. This allows an organisation to learn from the past and apply those lessons to improve future projects and operations.

According to the Guide to the Project Management Body of Knowledge [17], Lessons-Learned represent the knowledge gained during a project that shows how project events have been or should be dealt with in the future to improve future performance. Collecting these lessons and the conclusions from the positive and negative experiences of the past helps to enhance the protocols and principles of a project. The goal is to iterate and capitalise on the positives while avoiding the negatives. The basic principles of this method are presented in Fig. 3. Essentially, the idea is to learn from past mistakes and successes to enhance future projects and endeavours. The literature highlights how failing to learn from past mistakes often leads to their repetition [18-20].

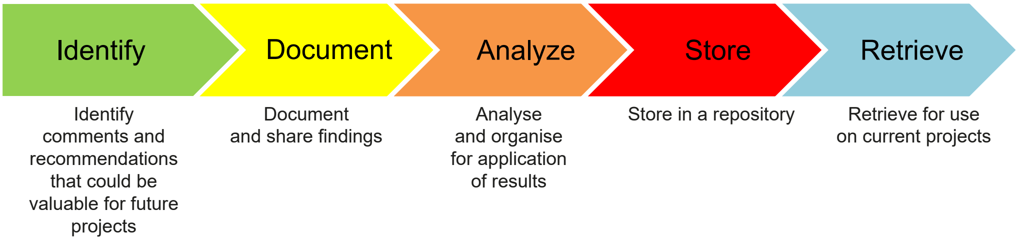


Fig. 3. Basic principles of the Lessons-Learned method

In the framework of the present study, the relevant information was sourced from the data stored in the belt conveyors' control tower software and the mining company's monthly operating reports. Next, various statistical methods presented in the following section were applied to analyse the input data and determine the causal factors of productive operational time losses, such as the failures that reduced equipment availability and the operating conditions that prevented equipment from achieving its theoretical capacity. Finally, the results of this analysis were reported and disseminated through lectures attended by the personnel of the mining company and students of the Department of Mineral Resources Engineering, University of Western Macedonia.

3.2. Quantitative data analysis

Quantitative analysis is a powerful research method that utilises numerical data to establish relationships between variables. It is widely used across natural and social sciences as it allows researchers to test theories and make predictions based on quantifiable evidence [21]. Researchers can use a variety of statistical techniques to analyse quantitative data, ranging from basic descriptive statistics to complex multivariate analyses. One of the key advantages of quantitative research is its ability to generate objective, generalizable findings. Proper data analysis is crucial, as improper techniques can lead to misleading or inaccurate results. Quantitative methods can investigate phenomena through the collection of numerical data and the application of mathematical models and statistical techniques for analysis [22].

Quantitative data analysis typically involves statistical methods to find patterns, trends, and relationships. Some common steps and methods include [23]:

- Descriptive Statistics: This is often the first step, summarising data using measures like mean, median, mode, standard deviation, etc.
- Inferential Statistics: This is used to draw conclusions and make inferences. Examples include hypotheses and estimates to make comparisons and predictions and draw conclusions.

There's a wide range of software available for quantitative data analysis, each with its own strengths and target audiences. In the framework of this study, SPSS, DATAtab, and Microsoft Power BI software packages were used to conduct the quantitative data analysis. Power BI enabled the creation of interactive data visualisations to enhance interpretability. Applying these tools, combined with a solid understanding of the underlying statistical concepts, was crucial to deriving meaningful and reliable insights from the data.

The analysis began with data preparation and cleaning, ensuring the dataset was suitable for further study. This involved handling missing values, removing outliers, and transforming variables. Next, univariate and multivariate analyses were conducted to investigate the relationships between the key variables of interest. Techniques such as correlation analysis, regression modelling, and factor analysis were employed to uncover the underlying patterns and structures within the data [24].

3.3. Bucket Wheel Excavators Performance Indicators

The Public Power Corporation of Greece uses the following indicators/ factors for the evaluation of the performance of the bucket wheel excavators:

Availability (%): It is calculated by the following ratio:

$$Availability = \frac{Productive\,Operating\,Time}{Calendar\,Time} \times 100 \tag{1}$$

Utilisation (%): It is a factor representing the efficient operation of the mine. It is related to the selection of the BWEs, which depends on criteria associated with their technical characteristics and their capacity, as well as with the nature of the excavated material. It is calculated by the following ratio:

$$Utilisation = \frac{Total\,excavations\left(\mathrm{fm}^3\right)}{Maximum\,Capacity\left(\dfrac{\mathrm{m}^3}{\mathrm{month}}\right)(loose)} \times 100 \tag{2}$$

Performance (fm^3/h): It is calculated separately for each BWE by the following ratio:

$$Performance = \frac{Total\,excavations\left(\mathrm{fm}^3\right)}{Productive\,Operating\,Time(\mathrm{h})} \tag{3}$$

where fm^3 are the cubic meters of the in-situ rock volume (i.e. before excavation).

3.4. Analysis of Downtimes

In the framework of this study, the downtimes are distinguished in the groups and subgroups presented in Fig. 4, following the same classification incorporated in the software applied by all the WMLC lignite mines [25]. Scheduled downtimes consist mainly of the BWE's daily and annual maintenance. Unscheduled downtimes are classified into four different sub-groups:

- Failures: They are classified as mechanical, electrical, or related to mining operations or conveyor belts.
- Non-operating time: It includes holidays, strikes, and lack of personnel or personnel replacement.

- Delays: This period mainly involves conducting auxiliary operations at the mine, which are classified as downtime. Examples of delays are the changes in digging level, changes in BWE operating face, BWE movements and manoeuvring, contouring of bench floor, and reloading of excavated material.
- Idle time: Period when the BWE is ready to operate but remains inactive due to a lack of subject, insufficient space for reloading, difficulties in transferring lignite or overburden.

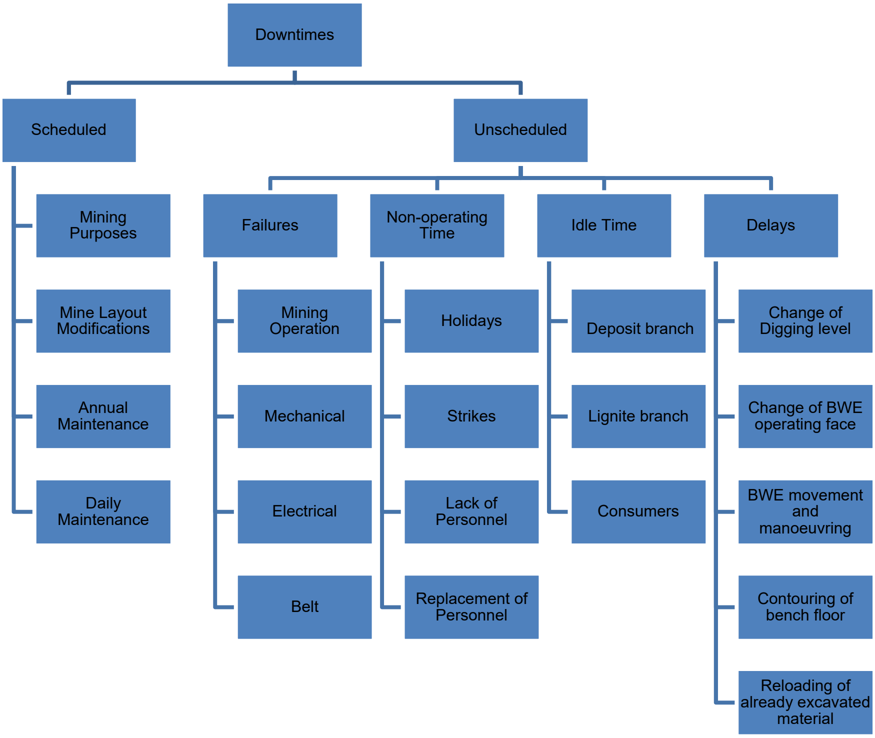


Fig. 4. Downtime Classification

4. Results

4.1. Descriptive statistics

Between 2010-2020, the continuous mining equipment of South Field Mine exhibited a maximum Performance of 1,965 fm^3/h in 2012 and a minimum one of 1,085 fm^3/h in 2020, corresponding to a considerable decrease of 81.16%. In the same period, Availability fluctuated from 27.26% to 36.07%, and Utilization gradually decreased from 10.9% in 2010 to 4.1% in 2020. In Fig. 5, Availability, Utilization, and Performance fluctuations are presented separately for overburden and lignite-bearing strata. At the beginning of the examined period, the three indicators exhibited higher values in lignite strata, with the most remarkable being the Utilization value of 15.1% in lignite strata in 2012, the highest value of the examined period. During this year, the highest deviation in Performance between lignite strata (2,160 fm^3/h) and overburden strata (1,696 fm^3/h) was also recorded. In 2017, Performance values were almost equal, and after this year, higher Performance was noted for equipment operating in the overburden formations.

Fig. 6 demonstrates the annual fluctuation of the three examined indicators for each of the nine BWEs (TABLE 1) that operated in South Field Mine from 2010 to 2020. The highest Performance, Availability, and Utilization values were achieved by BWE1 in 2012, BWE4 in 2019, and BWE8 in 2011, respectively.

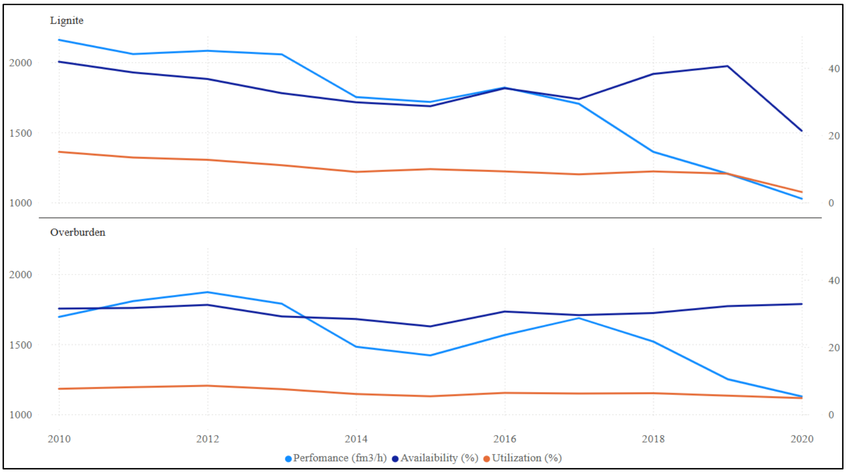


Fig. 5. Fluctuation of annual average Performance, Availability, and Utilisation of continuous mining equipment installed in the overburden and lignite-bearing strata of South Field Mine in the period 2010-2020

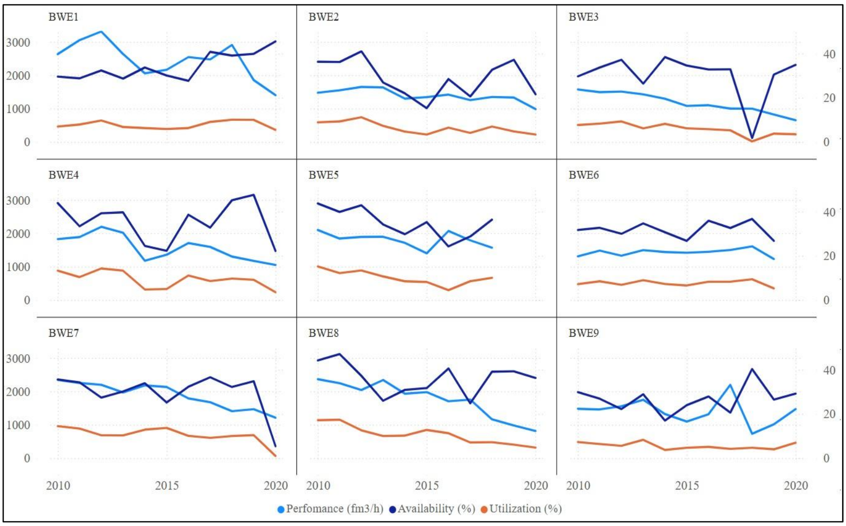


Fig. 6. Annual fluctuation of Performance, Availability, and Utilisation of the nine BWE of South Field Mine in the period 2010-2020

The fluctuation of the annual average productive operating time of South Field Mine's continuous mining equipment between 2010-2020 is presented in Fig. 7. This includes the relevant fluctuations of the five downtime groups and sub-groups presented in Fig. 4. Productive operating time fluctuated from 26.8% (2015 & 2020) to 40.6% (2012). Failures were the main reason for downtimes (Fig. 8), with values that fluctuating between 20.77% (2020) and 33.27% (2012), followed by non-operating time, with values fluctuating between 7.83% (2011) and 23.03% (2020) and scheduled downtimes, with values fluctuating between 10.83% (2010) and 24.39% (2018). Idle Time and Delays showed a smooth variation and low values.

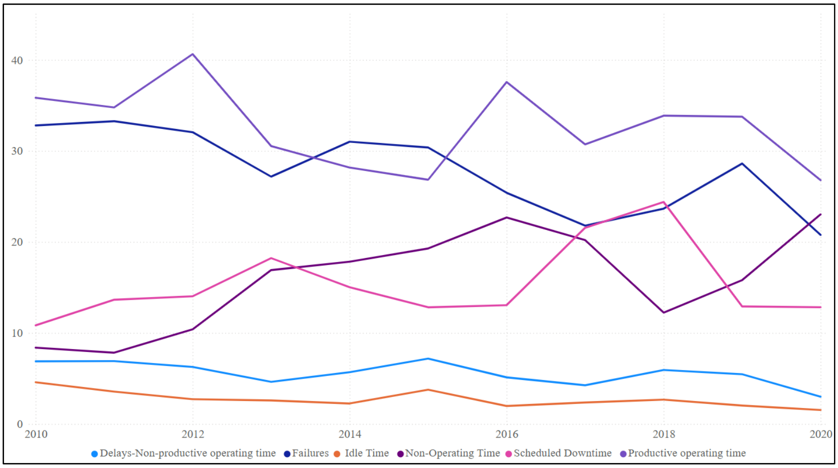


Fig. 7. Annual fluctuation of Downtimes and Productive Operating Time of South Field Mine in the period 2010-2020

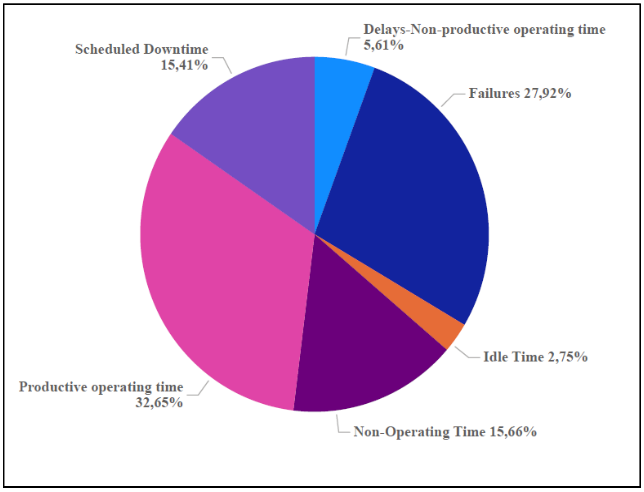


Fig. 8. Distribution of calendar time of South Field Mine in productive operating time and various groups of downtime causes for the period 2010-2020

Focusing on the distribution of downtime in groups and sub-groups, it is obvious from Fig. 9 that the main reason for non-operating time is the lack of personnel, which reaches percentages as high as 81.64%. The lack of personnel results from the WMLC strategy to gradually reduce the participation of lignite in electricity production, which ultimately aims to reach a zero-lignite share by 2028. Thus, WMLC implements voluntary redundancy programs and has limited the hiring of seasonal staff to a minimum. It is worth noticing that the total staff of the South Field Mine in 2010 approached 1,400 employees, while in 2020 it fell below 1,000, with about 35% of them being seasonal.

Furthermore, the most common failures are mechanical (32.32%), followed by those due to mining operations (23.42%), electrical (22.03%), and conveyor belt problems (21.63%). Scheduled downtime was mainly due to the annual maintenance (56.68%). Finally, the major cause of the non-productive operative time was the change in digging level (30.07%), an unavoidable operating scheme in multi-layered deposits that must be exploited with selective mining techniques. Reloading of previously excavated materials, contouring of bench floor, BWE movement and manoeuvring, and change of BWE operating face fluctuated at lower levels.

Finally, by examining the distribution of downtimes and productive operating time per BWE in the same period (Fig. 10), it was found that BWE8 exhibited the highest percentage of productive operating time (39.3%), and the lowest percentage of failures (22.6%). On the contrary, the highest percentage of failures was exhibited from BWE6, which operated in the overburdened strata. The maximum percentage (20.2%) in scheduled downtimes was exhibited by BWE3 and the minimum by BWE7 (10.6%). Failures and scheduled downtimes appeared to have a positive correlation. The last observation perhaps contradicts what would be expected, namely that an increase in scheduled maintenance time, such as the duration of BWEs' annual maintenance, would reduce the number and total duration of failures.

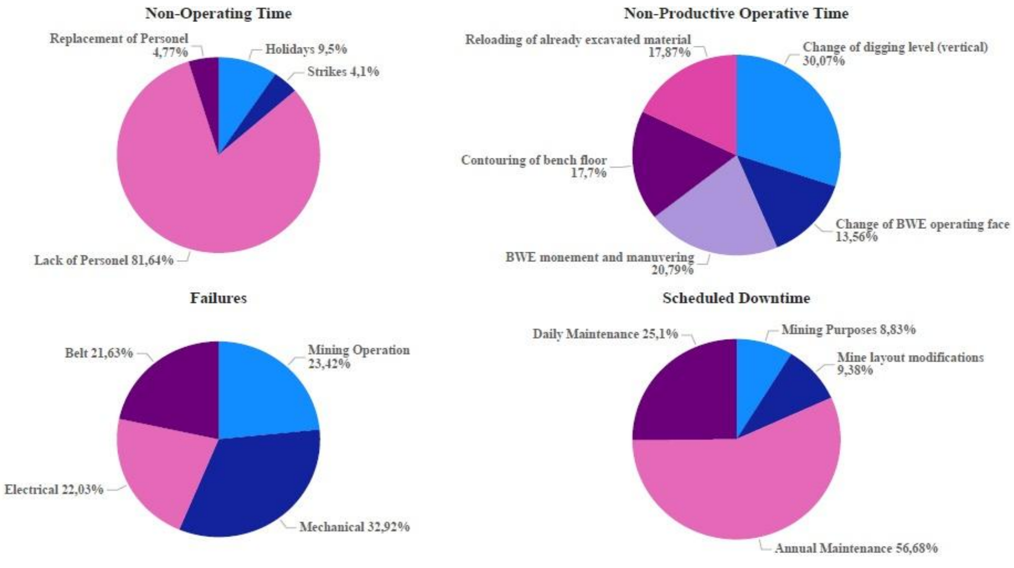


Fig. 9. Distribution of the downtime of South Field Mine's continuous mining equipment in different groups and sub-groups of causes for the period 2010-2020

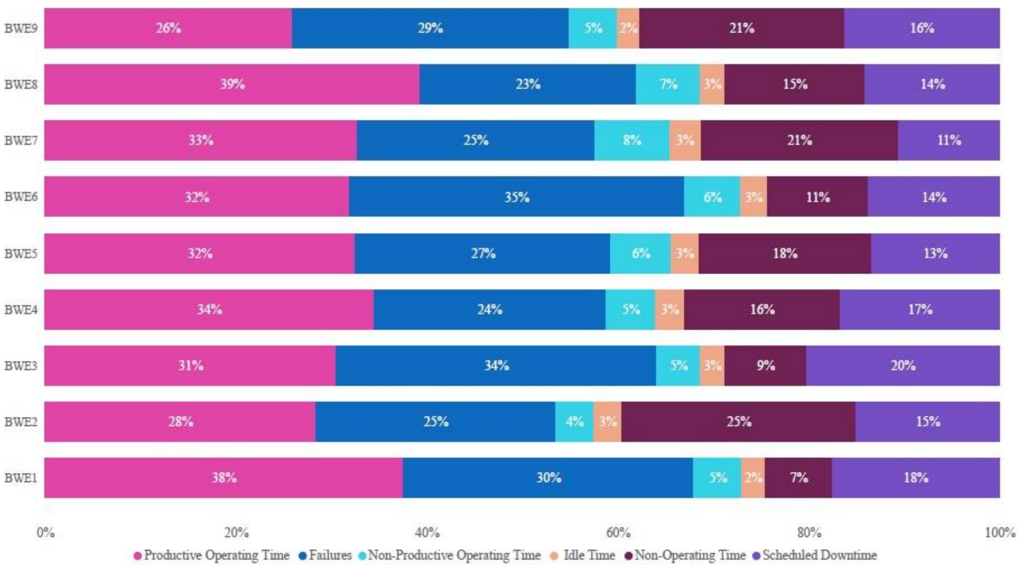


Fig. 10. Distribution of Downtimes and Productive Operating Time per BWE of South Field Mine in the period 2010-2020

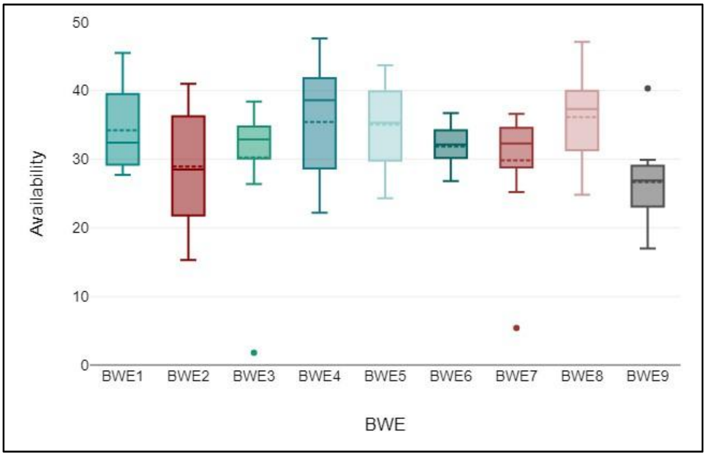
4.2. Inferential Statistics

4.2.1. Hypothesis testing with parametric and non-parametric tests

The test results presented below show that Utilisation and to a lesser extent Performance depend on BWE while Availability does not seem to vary significantly between the nine machines. As far as Performance is concerned, since it is expressed as fm^3/h and not as a percentage, it was expected to be increased in BWE1, which has the highest theoretical capacity. In any case, the correlations observed do not appear to be linked to machine manufacturers.

A discussion on hypothesis testing is included below:

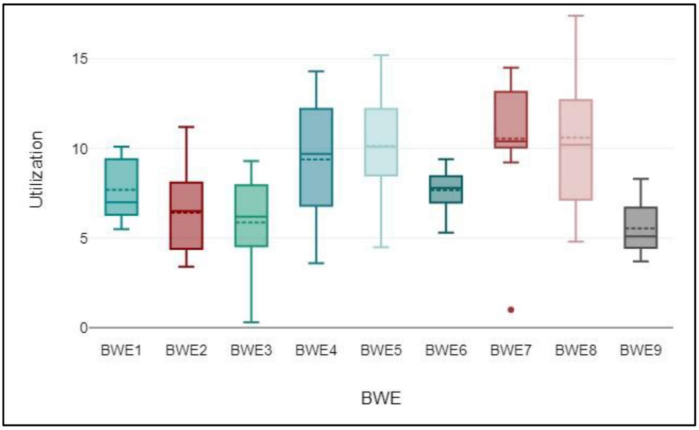
- **Availability by BWE**
  A one-way analysis of variance showed a significant difference between the independent variable of "BWE" and the dependent variable "Availability" ($F = 2.069$, $p = 0.047$). Thus, the null hypothesis that there is no difference between the 9 categories of the independent variable "BWE" concerning the dependent variable "Availability" was rejected (Fig. 11). The Bonferroni post-hoc test was used to compare the groups in pairs to determine which was significantly different. Despite the significant difference determined by the ANOVA test, no pairwise group comparison was significant in the Bonferroni post-hoc test, i.e. all p-values were greater than 0.05.
- **Utilisation by BWE**
  A one-way analysis of variance showed a significant difference between the independent variable "BWE" and the dependent variable "Utilisation" ($F = 5.245$, $p = <0.001$). Thus, the null hypothesis that no difference exists between the 9 categories of the independent variable "BWE" concerning the dependent variable "Utilisation" was rejected (Fig. 12).



	Sum of Squares	Df	Mean Square	F	p
BWE	952.4	8	119.1	2.069	0.047
Residual	5005.9	87	57.5		
Total	5958.3	95			

Fig. 11. Boxplot of Availability by BWE and ANOVA Results

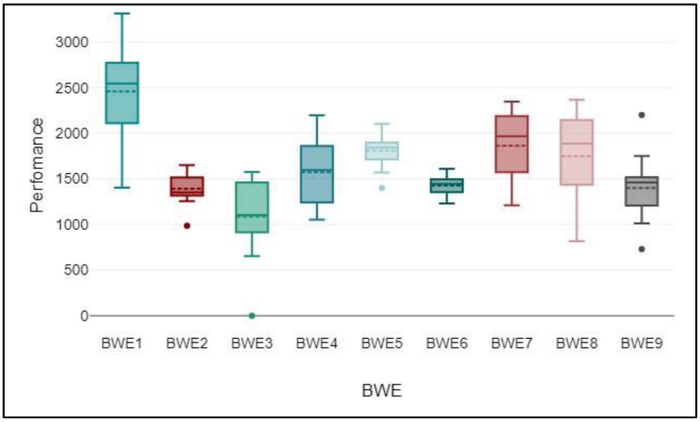
The Bonferroni post-hoc test revealed that the pairwise group comparisons of BWE2-BWE7, BWE2-BWE8, BWE3-BWE7, BWE3-BWE8, BWE5-BWE9, BWE7-BWE9 and BWE8-BWE9 have a p-value less than 0.05. Thus, based on the available data, it can be assumed that these groups are significantly different.



	Sum of Squares	Df	Mean Square	F	p
BWE	350.9	8	43.9	5.245	<0.001
Residual	727.6	87	8.4		
Total	1078.5	95			

Fig. 12. Boxplot of Degree of Utilisation by BWE and ANOVA Results

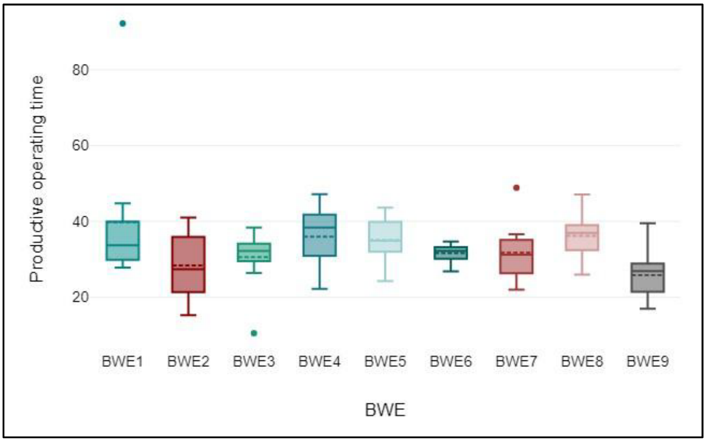
- **Performance by BWE**
  A Kruskal-Wallis test showed a significant difference between the categories of the independent variable "BWE" concerning the dependent variable "Performance" (p = <0.001). Thus, the null hypothesis that no difference exists between the 9 categories of the independent variable "BWE" in the dependent variable "Performance" was rejected (Fig. 13). The Dunn-Bonferroni test revealed that the pairwise group comparisons of BWE1- BWE2, BWE1-BWE3, BWE1-BWE6, BWE1-BWE9, BWE3-BWE5 and BWE3-BWE7 have an adjusted p-value less than 0.05. Thus, based on the available data, it can be assumed that these pairs were significantly different.



	Chi^2	df	p
Performance	40.417	8	<0.001

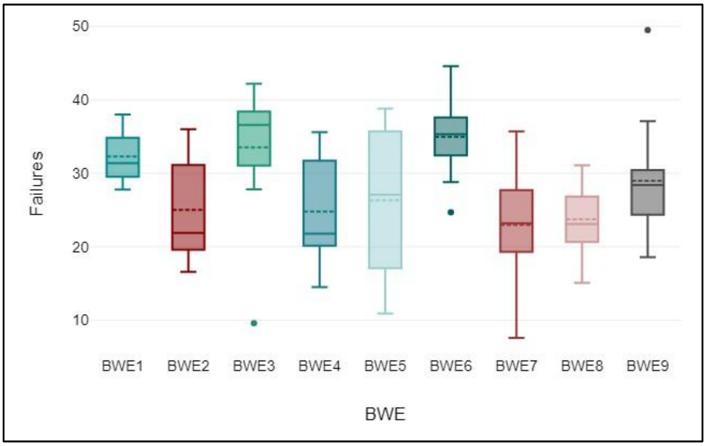
Fig. 13. Boxplot of Performance by BWE and Kruskal-Wallis Test Results

- **Productive Operating Time by BWE**
  A one-way analysis of variance showed a significant difference between the independent variable "BWE" and the dependent variable "Productive Operating Time" (F = 2.55, p = 0.015). Thus, the null hypothesis that no difference exists between the 9 categories of the independent variable of BWE concerning the dependent variable "Productive Operating Time" was rejected (Fig. 14).
  The Bonferroni Post hoc test showed that the pairwise group comparison of BWE1-BWE9 has a p-value less than 0.05. Thus, based on the available data, it can be assumed that the two groups are significantly different.
- **Failures by BWE**
  A one-way analysis of variance showed a significant difference between the categorical variable "BWE" and the variable "Failures" (F = 3.978, p = <0.001). Thus, the null hypothesis that no difference exists between the 9 categories of the independent variable of "BWE" concerning the dependent variable "Failures" was rejected (Fig. 15).
  The Bonferroni post hoc test revealed that the pairwise group comparisons of BWE3-BWE7, BWE6-BWE7, and BWE6-BWE8 have a p-value less than 0.05. Thus, based on the available data, it can be assumed that these groups were each significantly different.



	Sum of Squares	df	Mean Square	F	p
BWE	1644.8	8	205.6	2.55	0.015
Residual	7013.8	87	80.6		
Total	8658.6	95			

Fig. 14. Boxplot of Productive operating time by BWE and ANOVA results



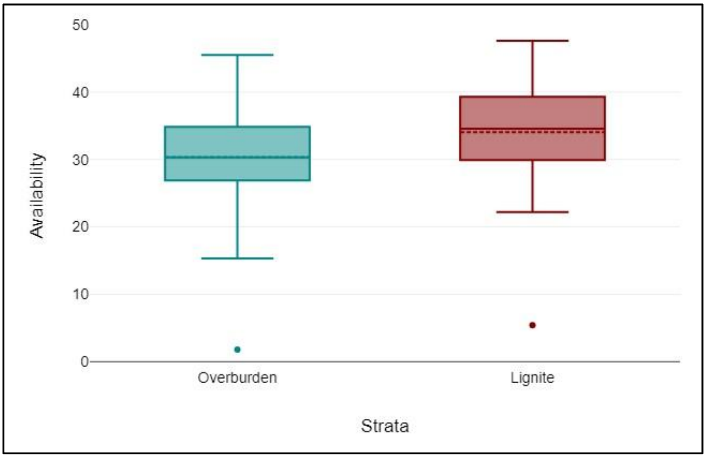
	Sum of Squares	Df	Mean Square	F	p
BWE	1741.6	8	217.7	3.978	<0.001
Residual	4761.5	87	54.7		
Total	6503	95			

Fig. 15. Boxplot of Failures by BWE and ANOVA results

Moreover, the test results showed that the BWEs operated in the lignite-producing benches showed higher Availability, Utilisation, and Performance values than the machines operated in the benches of overburden. This reflects the serious problems arising due to the existence of hard rock formations in the overburden, despite the use of blasting and conventional diesel equipment to remove them before the excavation of these specific mine faces by the BWEs. This effect was so significant that it surpassed the adverse conditions formed in the lignite-producing benches due to the multilayer nature of the deposit and the unavoidable implementation of selective mining techniques that significantly reduced the Utilisation of the machines.

A discussion on strata-related parameters is included below:

- **Availability by Strata**
  The results of the descriptive statistics showed that the overburdened strata had lower values for the dependent variable "Availability" (M = 30.361, SD = 7.4) than the lignite strata (Fig. 16). A two-tailed t-test for independent samples (equal variances assumed) showed that the difference between overburden and lignite strata concerning the dependent variable "Availability" was statistically significant, t(94) = –2.314, p = 0.023, 95% confidence interval (–6.85, –0.523). Thus, the null hypothesis was rejected. Cohen's d value of 0.476 represents a small effect.

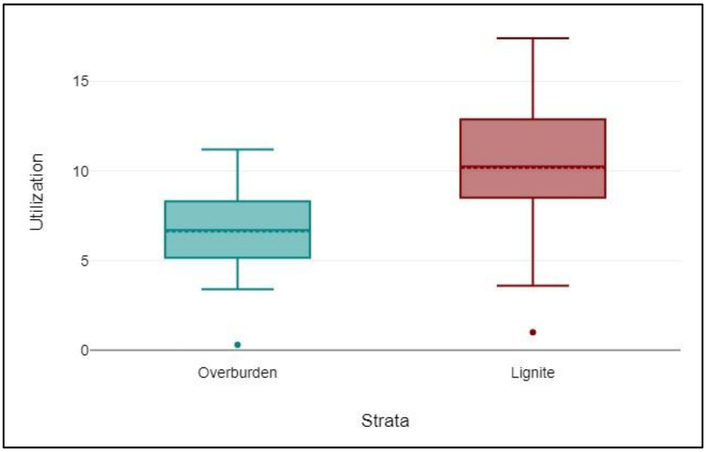


		t	df	p	Cohen's d
Availability	Equal variances	–2.314	94	0.023	0.476
	Unequal variances	–2.285	83.676	0.025	0.47

Fig. 16. Boxplot of Availability by Strata and results of t-test for independent samples

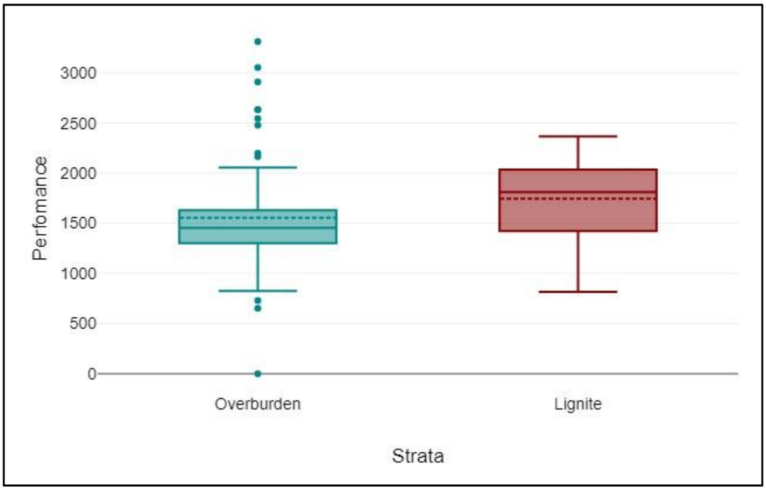
- **Utilisation by Strata**
  A two-tailed t-test for independent samples (equal variances not assumed) showed that the difference between overburden and lignite strata concerning the dependent variable "Utilization" was statistically significant t(63.058) = –5.635, p = <0.001, 95% confidence interval (–4.808, –2.29). Also, Cohen's d value of 1.159 represents a significant effect (Fig. 17).
- **Performance by Strata**
  A Mann-Whitney U-test was conducted to compare the values of "Performance" between overburden and lignite strata. For the given data, a Mann-Whitney U-Test showed that

the difference between overburden and lignite strata concerning the dependent variable "Performance" was statistically significant, U = 789, n_1 = 54, n_2 = 42, p = 0.011. Thus, the null hypothesis was rejected. There is a difference between the overburden and lignite groups concerning the dependent variable of "Performance". The effect size r was 0.26, which is a small effect (Fig. 18).



		t	df	p	Cohen's d
Utilization	Equal variances	–5.984	94	<0.001	1.231
	Unequal variances	–5.635	63.058	<0.001	1.159

Fig. 17. Boxplot of Utilisation by Strata and results of t-test for independent samples

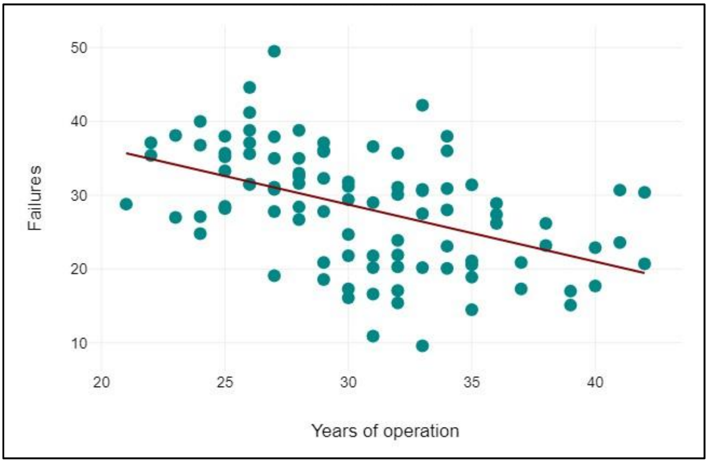


	U	z	asymptotic p	exact p	r
Performance	789	–2.548	0.011	0.011	0.26

Fig. 18. Boxplot of Performance by Strata and results of Mann-Whitney U-Test

4.2.2. Correlation of BWE failures and operating years

The result of the Pearson correlation showed that there was a moderate, negative correlation between years of operation and failures. The correlation between years of operation and failures was statistically significant r(94) = –0.477, p = <0.001 (Fig. 19). This correlation was unexpected since the increased age of a machine is usually connected with a shorter time between failures and a longer duration of repair and maintenance periods. This negative correlation shows that, for machines of the size and complexity of BWEs, systematic preventive maintenance, refurbishment, and technological upgrading of crucial sub-systems, such as electronics and automation, can maintain a machine at high levels of Availability and Performance.



	r	p
Years of operation vs Failures	–0.477	<0.001

Fig. 19. Correlation of BWEs failures and years of operation and results of the Pearson Correlation Analysis

4.2.3. Linear Regression

A multiple linear regression analysis was performed to examine how Availability is affected by the following variables: non-operating time, scheduled downtime, failures, idle time, delays-non-productive operating time, and productive operating time (TABLE 2). The regression model showed that these variables explained 75.46% of the Availability variance (TABLE 3). The following regression model was obtained:

$$\text{Availability} = 73.441 - 0.719\ \text{Non-Operating Time} - 0.714\ \text{Scheduled Downtime} - 0.648\ \text{Failures} - 1.202\ \text{Idle Time} - 0.463\ \text{Delays} + 0.166\ \text{Productive Operating Time}$$

An ANOVA test showed that the effect was significantly different from zero (F = 45.615, p = <0.001, $R^2 = 0.755$).

The standardised coefficient beta was independent of the measured variable and was always between –1 and 1. The larger the amount of beta, the greater the contribution of the respective independent variable to explain the dependent variable "Availability". According to this model, the variable "non-operating time" has the greatest influence on the variable "Availability".

TABLE 2

Regression coefficients

	Unstandardised Coefficients	Standardised Coefficients	Standard error	t	p	95% confidence interval for B	
Model	**B**	**Beta**				**lower bound**	**upper bound**
(Constant)	73.441		7.098	10.34	<0.001	59.336	87.546
Non-Operating Time	–0.719	–1.031	0.082	–8.74	<0.001	–0.883	–0.556
Scheduled Downtime	–0.714	–0.855	0.074	–9.61	<0.001	–0.861	–0.566
Failures	–0.648	–0.655	0.103	–6.30	<0.001	–0.852	–0.444
Idle Time	–1.202	–0.283	0.24	–5.01	<0.001	–1.678	–0.725
Delays	–0.463	–0.137	0.205	–2.26	0.026	–0.871	–0.056
Productive operating time	0.166	0.2	0.057	2.90	0.005	0.052	0.28

TABLE 3

Model Summary

R	**R^2**	**Adjusted R^2**	**Standard error of the estimate**
0.869	0.755	0.738	4.053

5. Discussion and conclusions

The period 2010-2020 held many challenges for the South Field Mine due to the changes in the Public Power Corporation business strategy brought about by the energy transition strategy and the gradual withdrawal of Greece's lignite-fired power plants. While the number of personnel began to decrease and investments were limited, high targets were set for mine productivity and equipment performance to keep the total cost of lignite-based kilowatt-hours as low as possible despite the enormous cost increase due to the European emissions trading scheme.

This development is reflected in the results of the present study. The downward trend of total excavations and lignite production was also evidenced in the Performance of the BWEs. The maximum annual average BWE Performance was exhibited in 2012. Since then, a gradual reduction has been observed up to 2020. On the other hand, Availability and Utilisation were not affected to the same extent as Performance. Availability exhibited a considerable recovery in 2016, 2018, and 2019, while Utilisation showed a smooth decrease without sharp fluctuations during the examined period.

The downtime analysis showed that the primary causes were mechanical failures and scheduled annual maintenance. In addition, the correlation analysis showed that the BWEs that remained out of operation for long annual maintenance periods exhibited high downtime percentages due to failures. The statistical analysis also showed that this fact was not related to the age of the equipment. It is worth noticing that the year of manufacture of South Field Mine's BWEs varies from 1978 to 1989.

The overall operating efficiency of continuous mining equipment was also impacted by the increase in non-operating time resulting from the lack of personnel. Although annual lignite demand decreased significantly during the examined period, the production targets were impossible to achieve without continuing the exploitation of all mine benches and all excavation faces. For this reason, no BWE stopped operating, and the mine management made significant efforts to keep safe distances (advancement) between the machines by transferring personnel from one BWE to another. In addition, the retirement of experienced technical staff affected many sectors of the operating procedure.

The inferential statistics with hypothesis testing revealed significant differences in performance indicators across different BWEs and different strata types. They pointed out the higher Utilisation percentages and Performance values of BWEs operated in lignite strata, except BWE1, which has significantly higher theoretical capacity than all the other BWEs. Moreover, the statistical tests confirmed that BWEs operated in benches where hard rock formations appeared and exhibited increased downtime due to failures. In future research work, it would be useful to conduct a comparative analysis of the performance values of continuous mining equipment installed in South Field Mine and other mines of WMLC, where hard rock formations do not exist but the type and age of BWEs are similar.

Nevertheless, the Lessons-Learned approach attempted in this paper could not be applied without the data, especially the data derived from the downtime recording software installed in the belt conveyors control tower of the South Field Mine [26]. Thus, the following conclusions can be drawn:

- It is impossible to obtain the engineering and technical knowledge incorporated into a production system without first identifying and documenting it.
- Lessons-learned procedures must be implemented on time, long before starting a productive activity during the closure phase. The South Field Mine has already suffered the consequences of knowledge losses due to the early retirement of personnel as part of the energy transition.

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