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Evaluation of mining workers impact on production: an application of TOPSIS-CRITIC based multiple criteria decision making approach

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ABSTRACT

The productivity of the quarry during the wet season heavily depends on how well the personnel adjusts to the mine's environmental conditions and management plans. The improvement of granite production through workers' impact identification and mining advancement decision-making in Ondo State, Nigeria, has been considered in this study. The rate of granite production and the factors influencing workers' efficiency were assessed using a well-structured survey and descriptive-analytic technique. To improve the production rate, the Multiple Criteria Decision-Making (MCDM) technique was used to select the most productive pit depending on a number of key labor impact factors. Health and safety in employment, the energy crisis, market conditions and level of competition, on-site accidents, natural disasters, and language barriers were some of the factors identified as external influencer factors affecting mine labor efficiency in granite quarrying. Finally, using the criteria's significance through the inter-criterion (CRITIC) approach, the mine workers' influence on production was estimated and utilized for the best pit selection. The result of the MCDM revealed that the five pits (Pit 1, Pit 2, Pit 3, Pit 4, and Pit 5) had the following decision performance scores: 0.659, 0.617, 0.5, 0.5, and 0.5, respectively. This made Pit 1 the best production pit to be considered during the rainy season. The optimal solution was validated with the 2021 production report. The report shows that production from Pit 1 had the highest revenue of $16,000 Per annum, the lowest dewatering cost, and the highest production rate compared to the other four pits.

Keywords: *Mining, Production improvement, Granite aggregate, TOPSIS score analysis, Decision-making approach..*

1. Introduction

An exploration study published by the United States Geological Survey in 2015 indicated that Africa has a wealth of granite deposits and a great potential for precious and base metals. According to the survey report, about 30% of the world's mineral reserves are located in Africa. Nigeria is a mineral-rich country where the mining industry provides a solid foundation for future development and innovation. The nation is renowned for its vast industrial rock and ore deposits, thriving large-scale and small-scale mining operations. Mining has played an important role in national growth and technological progress for ages. As a subset of the mining industry, rock aggregate quarrying provides essential raw materials for the construction industry, road construction, industrial production, and processing. This essential and demand-driven possibility makes improving aggregate rock production vital and crucial. The success of an aggregate mine depends significantly on how well it functions and its level of productivity. The most important factors determining mine productivity are the relationship between the mine management and the workers, the possibility of worker skill improvement, mine safety, operation task assignment approach, and mine pit accessibility. These helps to determine the real Gross Domestic Product (GDP) realized for every working hour in the mine. Yi and Chan mentioned that labor productivity is a way to measure how much a country or industry produces per hour, while labor efficiency is the amount of work done or completed per hour [1]. Mishra and Mohanty also mentioned that the principal factors affecting the mining industry's production rate are operation, marketing and management, human resources, finance, resource and utility, corporate affairs, corporate social responsibility, and the environment [2]. Even though the production of granite aggregates is limited due to challenges in extraction work, Mata et al. pointed out that the granite market is very competitive for both producers and wholesalers due to the control

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impact caused by sellers, as studied in two case studies in Nigeria [3]. The enhancement of mine worker production rates and extraction advancement rates will support mine material extraction rates. Some of the previously discovered approaches for mine production improvement include direct investment in or providing incentives for changes in technology and human or physical capital to enhance productivity and pyramid-shift profit margins. Kaplan and Norton indicated in their study that productivity makes an organization successful, supports goal achievement, gives people what they want, and keeps its strategic and financial health in good shape [4]. Despite knowing this golden rule, several constraints still hinder the efficiency of human resource management in mine, causing fluctuation in production with limited classification work carried out to understand their influences. Several approaches have been considered as the way forward to improving mine labor productivity. For example, Bonham et al. applied data mining techniques as an approach to quantify the relative influence of design and installation characteristics on labor productivity [4].

Research results at the industrial level have revealed that productivity enhances the profit margin of an industry and keeps customers in good relations with the company as their demands are met on time [5]. Mine material production tends to depend on the response of mine workers, who provide labor effort to the mine working frame and system. The various operation units in mining function with no less than 30% human input, which varies depending on job assignment and the availability of technological innovation. Based on this, most mines' monthly production changes depending on factors like weather, mining method, equipment use, available personnel, and their skill level [6]. Taking weather as an example, Aygei and Tetteh [7] show that during the rainy season, loading and hauling operations from the pit to the beneficiary plant slow down, mainly due to the inaccessibility of some regions or areas in the mine. In either case, it is easy to see how changes in the environment and general well-being affect productivity through the supply rate and process output rate at the downstream level. In the same way, a shift in mine production during the rainy season through proper planning and decision-making can definitely enable high mine efficiency and productivity growth [8]. Nevertheless, sufficient information about the challenges faced by mine workers and their influence on productivity also supports changes in production rates. It has been mentioned that industrial output and production depend on both internal and external constraints. For example, a difference in production cost can cause a difference in the number of granite aggregates produced [9]. Likewise, Abraham and Kirk examined the variation in the production rate of manufacturing plants in the USA [10]. They discovered that production machine shocks during manufacturing are a key determinant of the cross-sectional variations in output. Based on this, the impact of production rate on the mining industry can be considered proportional to workers' productivity. To understand the various impacts of mine workers/labor on the production rate, this study used statistical analysis with a primary database of mine workers to provide array of classified information about workers' constraining factors. The second section of this work also provides a decision-making technique for granite production pit selection during the rainy season based on multiple criteria.

1.1. Description of the study areas

Akure is the state capital and a major metropolis of Ondo State in south-western Nigeria (see Fig. 1). Akure is located at coordinates 7° 15′ 9.22′′ N and 5° 11′ 35.23′′ E. The case study area is located in the northern part of Akure, as shown in Fig. 1.

2. Multiple Criteria decision making application review

Several factors affect the production rate of a mine, including the equipment selection effect, deposit geological factors, drilling and blasting productivity factors, and mining method recovery efficiency [11]. The work of Alinaitwe et al. [12] revealed several factors, including incompetent supervisors, a lack of skills from the workers, rework, a lack of tools and equipment, poor construction methods, poor communication, inaccurate information, and harsh weather conditions, as some of the most significant problems affecting workers' productivity in the mine. Surface mining operations are known for open-atmosphere activities with high task contributions to dewatering and drainage control during the rainy season [13]. This study, apart from understanding the contribution of granite quarry workers to run-off mine productivity, also considered the best approach for the selection of operating pits during different stages of operation and seasons in the mine's life. The rate of production in mines with more than one production pit generates diversity in terms of resource distribution and production decision-making. This study proposed the use of the MCDM techniques for the selection of the most efficient quarry pit during the life of the mine. This technique has been used in many studies, including engineering and management studies [14]. Based on the need to improve production rates in mines during the rainy season and at different stages of mine's life, the influence of workers on run-off mine availability and profitability needs to be well studied. For the past decade, several authors have employed the MCDM techniques as a foundational decision-making approach. Bascetin et al. applied the MCDM technique to select the best mining tools [15]. Naghadeh et al. used the Fuzzy Analytic Hierarchy Process (FAHP) to find the best underground mining method [16]. Aghajani and Osanloo used the AHP-TOPSIS method to choose loading and hauling tools for open-pit mines [17]. Table 1 shows some of the references discussing the application of the MCDM. The method for ordering performance by similarity to the ideal answer (TOPSIS) is a good way to address the real-world MADM or MCDM (multi-attribute or multi-criteria decision-making) situations [18]. Chakraborty [19] says that TOPSIS is founded on the basic idea that the best solution is the one closest to the positive ideal solution and farthest from the negative ideal solution. An overall measure is used to rank the alternatives based on how far away they are from the best options [19, 20].

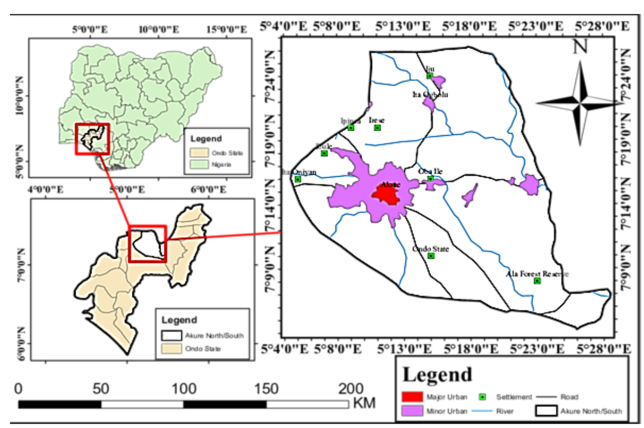

Fig. 1: Location map showing Akure state map.

The granite mining operation in Akure had taken on a new dimension due to the high demand for granite aggregates in construction work. To the best of the author's knowledge, this is the first study to analyze the influence of mine workers' constraints using both traditional approach and MCDM. This study assesses the process of making right decision about production pit selection during the rainy season in a granite quarry by first understanding the labor productivity limiting factors using the part principle approach [6] and then compares the rate of impact generated by the identified factors using the Multiple Criteria Decision-Making (MCDM) approach. Through the part principle approach, the study identified the 20% constraint factors that affect mine workers' productivity by 80% on-site in the case study mine pits, along with the most effective ways to solve the identified key constraints. Five criteria were established for the MCDM analysis with a weight target on a null hypothesis that if mine workers are paid well but do not have much to do, production tends to go up in an exponential way. This was extended to cover the safety of the mine, the mine management relationship with workers, and the assigned task rate using five production pits.

Table 1: Review of application of TOPSIS.

Reference	Topic	Year
Okul et al. [20]	A method based on SMAA-topsis for stochastic multi-criteria decision making and a real-world application	2014
Jumaah et al. [18]	Technique for order performance by similarity to ideal solution for solving complex situations in multi-criteria optimization of the tracking channels of GPS baseband telecommunication receivers	2018
Abidin et al. [17]	Technique for Order Performance by Similarity to Ideal Solution (TOPSIS)-entropy methodology for inherent safety design decision-making tool	2016
Lin et al. [22]	Score function based on the concentration degree for probabilistic linguistic term sets: an application to the TOPSIS and VIKOR	2021
Balcerzak [23]	Quality of institutions in the European Union countries. The application of TOPSIS based on entropy measure for objective weighting	2020
Mijalkovski et al.[24]	Underground mining method selection with the application of TOPSIS method	2022
Li et al.[25]	Mining Method Optimization of Difficult-to-Mine Complicated Ore body Using Pythagorean Fuzzy Sets and TOPSIS Method	2023
Alhassan et al.[26]	Mercury Risk Reduction in Artisanal and Small-Scale Gold Mining: A Fuzzy AHP-Fuzzy TOPSIS Hybrid Analysis	2023
Ozdemir [27]	The use of Integrated AHP-TOPSIS Method in Selection of optimum Mine Planning for Open-Pit Mines	2023

3. Data Collection and Analysis methodology

3.1. Quarry mine design parameters

The case study quarry has five production pits for granite aggregate extraction. The mine slope dip and dip direction were measured using a compass clinometer in accordance with ISRM [28], using the window technique as suggested by Saliu and Akande [29]. Table 2 presents the characteristics of five pits as obtained directly from the mine during the visitation.

3.2. Statistic data collection

To understand the influence of mine labor on the production rate, a primary database was collected from the mine management which include information on the number of mine workers' working hours, average production per hour, average labor task per hour, company payment response, company level of empowerment, and mine pit accessibility. The database was used to determine the various constraints affecting the production rate of the case study granite mine. The safety of five pits slopes was accessed from the discontinuity properties using the kinematic analysis approach as described in Taiwo et al. [30]. To classify the database from the survey into internal and external factors affecting mine production, t-test analysis was used to examine 14 selected internal factors as key factors affecting the granite production rate. The t-test null hypothesis was that the identified internal factors have an impact on labor productivity. Descriptive figures, such as a table, frequency, and percentage contribution were used to evaluate each factor's effect on the quarry production rate. The production rate and level of worker involvement were determined through a structured survey to assess the constraints to optimal productivity. The schematic approach applied for the study objectives is summarized in Fig. 2.

During the MCDM matrix development, Eq. (1) was used to determine work done per person as a factor of time, alongside with the productivity estimation using Eq. (2) as an index number for the whole.

$$Labour\ Productivity = \frac{TPO}{TNW} \tag{1}$$

$$Productivity = \frac{TWP}{TPC} \tag{2}$$

Where TPO is the total production output in Tonnes/hr, TNW is the total number of worker assigned to task per hour (Man/hr), TWP is the total worth of production in Naira, and TPC is the total production cost in Naira [31].

3.3. Multiple decision making analysis

The case study quarry uses the open-pit mining technique for granite aggregate production and has five alternative loading pits. In an attempt to increase its production rate, the company intends to make decisions on the best loading pit with the highest production rate based on the following attributes, depending on the minimum number of workers:

1. Labour Task,
2. Company Payment Response,
3. Company Level of Empowerment
4. Mine safety, and Mine Accessibility.

The TOPSIS technique with criteria importance through inter-criteria (CRITIC) weighting techniques was used in this study to determine the most critical attributes affecting quarry production based on workers' conditions. Five decision criteria (worker task assigned, company worker payment response, mine safety, and pit accessibility) were ranked using the TOPSIS technique. Five production pits from the case study granite aggregate company were considered as alternative loading options in the company for run-off-mine supply to the mill. A survey was conducted with 70 mine workers on how the five selected attributes affect mine production in the five production pits. A full list of mine workers' average responses based on selected key attributes is given in Table 3.

In this study, a numerical value is assigned to each linguistic variable in Table 3 using the scale explained in Table 4. The five attributes/criteria are classified into benefit and non-benefit-based factors depending on their relationship with workers' performance. The attribute matrix is presents in Table 5.

To determine the weight of each criterion, the Criteria Importance Through Inter-Criteria (CRITIC) technique proposed by Diakoulaki et al. [32] was used. The method is based on the standard deviation which uses correlation analysis to measure the value of each criterion. The attributes decision matrix is first normalized using Eq. (3) for the benefit factor and (4) for non-benefit factor.

$$\rho_{ij} = \frac{y_{ij}-y_j^{Min}}{y_j^{Max}-y_j^{Min}} \quad i=1,\ldots,m;\ j=1,\ldots,n \tag{3}$$

$$\rho_{ij} = \frac{y_{ij}-y_j^{Max}}{y_j^{Max}-y_j^{Min}} \quad i=1,\ldots,m;\ j=1,\ldots,n \tag{4}$$

The linear correlation coefficient between the criteria values in the matrix is calculated using Eq. (5).

Table 2: The quarry mine design parameters.

Parameters	Bench height	Slope angle	Slope Direction	Max Blast Hole Number	Production Capacity	Remark
Pit 1	6m	80^0	165^0	86	600T/day	active
Pit 2	6m	70^0	235^0	90	500T/day	active
Pit 3	9m	78^0	185^0	100	760T/day	active
Pit 4	9m	72^0	305^0	80	600T/day	active
Pit 5	6m	82^0	265^0	90	800T/day	active

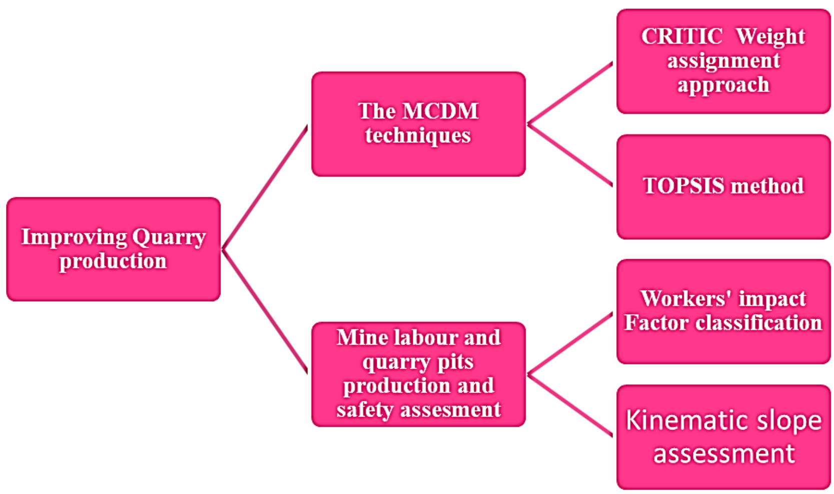

Fig. 2 The research objectives flow sheet.

Table 3. Alternative and Attributes for Production.

Attributes	Alternatives				
	Pit 1	Pit 2	Pit 3	Pit 4	Pit 5
Task	High	Medium	Low	Medium High	High
Company Payment response	High	Medium High	Low	Medium	Very High
Company Level of Empowerment	Medium	High	Very High	Low	High
Mine Safety	Very High	High	Low	Medium	Low
Accessibility	High	Medium	Medium	High	very high

Table 4. Assigned Numerical Values of Linguistic Variables.

Benefit based	Relative intensity	Non Benefit based
Very High	1	Low
High	3	Medium
Medium high	5	Medium high
Medium	7	High
Low	9	Very High

Table 5. Weight age for the criteria.

Attributes	Non-Benefit-based	Benefit-based	Benefit-based	Benefit-based	Benefit-based
Weight-age	0.16	0.23	0.24	0.28	0.09
	Task	Company Payment Response	Company Level of Empowerment	Mine Safety	Accessibility
Pit 1	3	7	3	9	7
Pit2	7	5	7	7	5
Pit 3	9	1	9	1	5
Pit 4	5	3	1	3	7
Pit 5	3	9	7	1	9

$$\rho_{ij} = \frac{\sum_{i=1}^{m}(\rho_{ij}-\ddot{\rho_j})\times(\rho_{ik}-\ddot{\rho_k})}{\sqrt{\sum_{i=1}^{m}(\rho_{ij}-\ddot{\rho_j})^2\sum_{i=1}^{m}(\rho_{ik}-\ddot{\rho_k})^2}} \text{i=1,......,m; j=1,........,n} \tag{5}$$

The weight of each criterion is calculated using Equation (6 and 7).

$$\beta_j = \sigma_j \times \sum_{k=1}^{n}(1-v_{jk}) \tag{6}$$

$$w_j = \frac{\beta_j}{\sum_{k=1}^{n}\beta_k} \tag{7}$$

Where σ_j is the standard deviation, ρ_{ij} is the normalized critical matrix value, ρ_{ij} is the matrix coefficient of correlation, and $w_j$is the critical variable weight.

The TOPSIS approach was applied to ranking the labor-dependent productivity of the five pits using Table 5. The normalized attribute and Calculate Weighted Normalized Matrix were calculated using Eqs. (6) and (7), respectively.

The ideal best and ideal worst contributions of both benefit- and non-benefit-based attributes were computed using the minimum value for the non-benefit attributes and the maximum value for the benefit attributes for the ideal best. For the ideal worst, the minimum value was considered for the benefit attributes and the maximum value for the non-benefit attributes, respectively.

$$\overline{X}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n}x_{ij}^2}} \tag{6}$$

$$v_{ij} = x_{ij} \times w_j \tag{7}$$

The Euclidean distance from the ideal best and ideal worst for all the attributes was calculated using Eqs. (8) and (9).

$$S_i^+ = \left[\sum_{j=1}^{m}(\boldsymbol{V_{ij}} - V_j^+)^2\right]^{0.5} \tag{8}$$

$$S_i^- = \left[\sum_{j=1}^{m}(V_{ij} - V_j^-)^2\right]^{0.5} \tag{9}$$

The TOPSIS performance score was calculated using Eq. (10). The ranking was based on the highest score, illustrate the most profitable pit based on labor relation.

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{10}$$

4. Results and Discussion

This section presents the results of the descriptive analysis and the MCDM analysis. The responses from the mine administration staff and pit workers are detailed in section 4.1.

4.1. Quarry Company Profile

Table 6 presents the statistics of the information gathered from the survey carried out at the five production pits. The table is detailed appropriately in the results discussion section. The current level of production capacity was also assessed based on the available equipment capacity. The results show that the mine is currently underutilizing its mining machinery due to the challenge of making the right decision between pit productions in different sections.

The result also revealed that the mine has enough workers on-site daily (see Table 5). It also shows that both skilled and unskilled workers are essential to the success of these businesses. Although it is possible that this is unrelated to the fact that utilizing exclusively skilled personnel results in higher operational expenses, it is still true that hiring unskilled workers will reduce those costs, according to the respondents' opinion. Fig. 3 shows the pits' beneficial daily output data and working environmental conditions based on the worker interaction influence. The results show that favorable mine working conditions support a high daily production rate, while unfavorable working conditions hamper production. Fig. 3b shows the contribution of working environment conditions to the production rate. Based on the survey conducted, most responses revealed that fairly good working conditions support a high production rate. Most working pits are influenced by other factors that have a multicollinear influence on production rates. To clarify the factors influencing mine production, further findings were conducted on the dependent factors influencing the production rate based on the various pit working capacities, as presented in Section 4.2.

Table 6. Company Profile.

(n = 70)	Freq.	%
Production on daily basis		
Favourable	56	80.9
Undecided	9	12.9
Unfavourable	5	7.1
Kind of Labour used		
Skilled	8	11.4
Unskilled	14	20.0
Both	48	68.6
There are equipments to meet labor and production level		
Yes	50	71.4
No	20	28.6
Current level of utilisation of production capacity (%)		
100	1	1.4
90	11	15.7
80	27	38.6
70	24	34.3
Less than 70	7	10.0
Working environment		
Good	23	32.9
Fairly Good	45	64.3
Bad	2	2.9
Very Bad	0	0.0
Labour unrest		
Frequent	12	17.1
Not Frequent	58	82.9

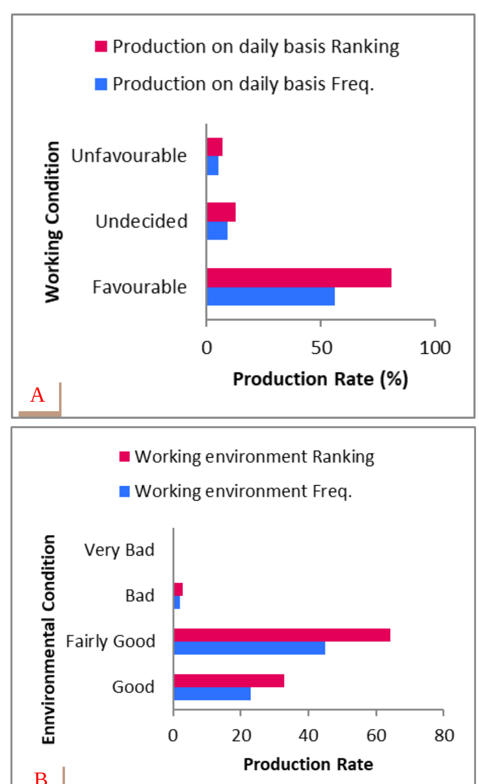

Fig. 3. Production rate and working environment assessment.

4.2. Factors influencing Granite production rate

To understand the contribution of granite mine workers to the production rate and the various factors controlling their contribution, 70 workers were surveyed using a structured questionnaire and interview approach. According to the findings presented in Table 7, the majority of the granite mining pits (92.9%) used an open-pit mining approach due to the primary mineral they worked on. Similarly, on average, mine pit workers operate on a shift-by-shift basis, because they are involved in sequential mining operations depending on material availability in the pit. The survey results revealed that labor and technology contribute significantly to increased granite crude productivity, as also mentioned in [33–34]. The findings show or indicate or represent or illustrate that the contribution of mine workers influences the granite production rate.

Table 7. Production and mine worker assessment results.

(n = 70)	Freq.	%
Mining Method		
Open pit	65	92.9
Open cast	5	7.1
Shift of Operation		
1	35	50.0
2	32	45.7
3	3	4.3
Operator on duty per shift		
1 - 5	20	28.6
5 - 10	30	42.9
10 - 20	10	14.3
Above 20	10	14.3
Productivity level influenced by labor and technology		
Yes	70	100.0
No	0	0.0
Skilled labor involved in one shift		
1 – 5		
5 – 10	45	67.1
Above 10	13	18.6
	10	14.3
Unskilled labor involved in one shift		
1 – 5	19	27.1
5 – 10	21	30.0
Above 10	30	42.9

To understand the influence of the division of labor on the production rate, a task assignment ratio based on workers' strengths was also assessed. The findings presented in Fig. 4 show that for skilled labor, production rates increased substantially when divisions were within 1–5 capacity range. While for unskilled labor, higher capacity contributes significantly to production rate increments, The results also revealed that task assignment has a considerable impact on the performance of mine workers and likewise influences the production rate.

4.3. Constraints to Optimal Productivity

Focusing on optimizing mine production rate, the internal constraints that affect quarry production were identified from the responses of the mine worker and administrative staff population samples. The report's exclusive summary shows that rate payments, level of motivation or commitment, level of empowerment, level of skill and experience, level of familiarity with current job conditions, and adequacy of method employed are among the internal constraints affecting mine productivity. The results showed that some of the internal constraints affecting on-site labor are similar to those that Alinaitwe identified eralier [9]. The level of skill and experience of mine workers has a significant influence on on-site labor productivity performance, according to our findings. Nevertheless, the results show that workers' experience improves their intellectual and physical fitness on the job, which directly increases labor productivity [34]. The level of motivation or commitment of the workforce is the next most influential factor. This also aligns with Cooper's [35] conclusion that a contented team can improve work attitudes and result in a significant increase in labor productivity. According to the respondents' conclusion, high levels of workforce motivation and commitment can be achieved through job security, an effective reward system, a culture of openness, trust, loyalty, and the involvement of frontline personnel in decision-making. Health and safety in employment, the energy crisis, market conditions, level of competition, on-site accidents, natural disasters, and language barriers were some of the factors identified as external influencing factors. Similarly, one of the influential factors rated is the health of the workforce, which determines how well workers will be able to utilize resources for maximum productivity. The finding also revealed that labor empowerment through conferences and training can lead to considerable improvements in production rates. As [36] noted, the results demonstrate that rapid technological advancement is one of the most significant external factors affecting labor productivity. The 14 factors selected for the t-test analysis were examined as internal influences on the mine production rate. Based on the T-test results presented in Table 8, cal-t = 0.906, df = 68, and sig. = 0.368, the null hypothesis that the identified internal determinants have an impact on labor productivity in the mine is accepted. The MCDM helps to improve the case study of mine production decision-making by considering internal labor impact relations, as presented in Section 3.4.

4.4. Quarry safety assessment Result

The safety of the case study mine slope was assessed using kinematic analysis techniques with Dip 6.0© software. The five pit slopes were considered and the results are present in Fig. 5a-e.

Table 9 presents the interpretation of the kinematic analysis for plane, wedge, and toppling failure mechanisms. The findings show that all the pits are stable and safe from plane failure mechanisms (See Figs. 5a–e). Two joint sets were identified in pit 1 with dips and dip directions of 13/217 and 54/213, respectively. Likewise, in pit 2, three joint sets with high critical levels were identified with dips and dip directions of 27/74, 24/74, and 24/44, respectively. Pit 3 was recognized with three joint sets with dip and dip directions of 36/323, 62/52, and 03/031, respectively. The joint set was assessed with a 47.22% wedge failure possibility, a 6.7% toppling failure critical level, and an 84.27% plane failure possibility, making its safety attributes low. Furthermore, in pit 4, three joint sets were identified with dip and dip directions of 60/220, 73/135, and 07/101, respectively. Pit 5 was identified with two joint sets with joint orientations of 52/200 and 09/199, respectively. As presented in Table 9a and b, the failure critical level for wedge and toppling failure is high in pit 2 and pit 3.

The safety result and other databases on mine worker task assignment, payment response, level of empowerment, and pit accessibility were used to create a 5 by 5 alternative and attribute matrix for the computation of the proposed MCDM weight age criteria. The MCDM result is presented in subsection 4.5.

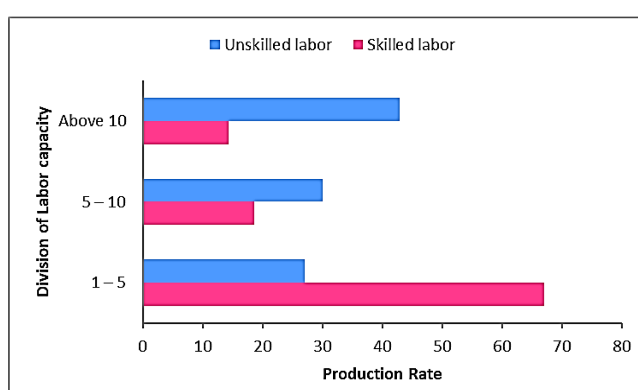

Fig. 4. The influence of the division of labor capacity on the production rate.

Table 8. Statistic analysis results on the impact of internal factors on productivity.

Internal factors selected	B	Beta	t – value	p – value
Constant	6271.091		3.023	0.004
Payment time	157.771	0.35	0.159	0.874
Lenders' high interest rate	-1158.495	-0.170	-1.112	0.671
High cost of material and machinery	-2646.354	-0.403	-3.200	0.542
Operation rate	265.023	0.25	0.240	0.411
Level of empowerment	448.837	0.066	0.475	0.637
Level of skill and experience of workforce	497.726	0.076	0.553	0.482
Level of familiarity with current job condition	-1312.143	-0.201	-1.551	0.127
Workforce absenteeism	-301.941	-0.052	-0.387	0.700
Level of staff turnover	611.692	-0.088	-0.596	0.553
Health of the workforce	-1282.876	-0.088	-1.274	0.208
Adequacy of plant and equipment employed	126.410	-0.187	0.144	0.886
Adequacy of method employed	581.174	0.080	0.606	0.347
Adequacy of technology employed	19.228	0.003	0.021	0.984
Lack of training and education	467.262	0.079	0.562	0.562

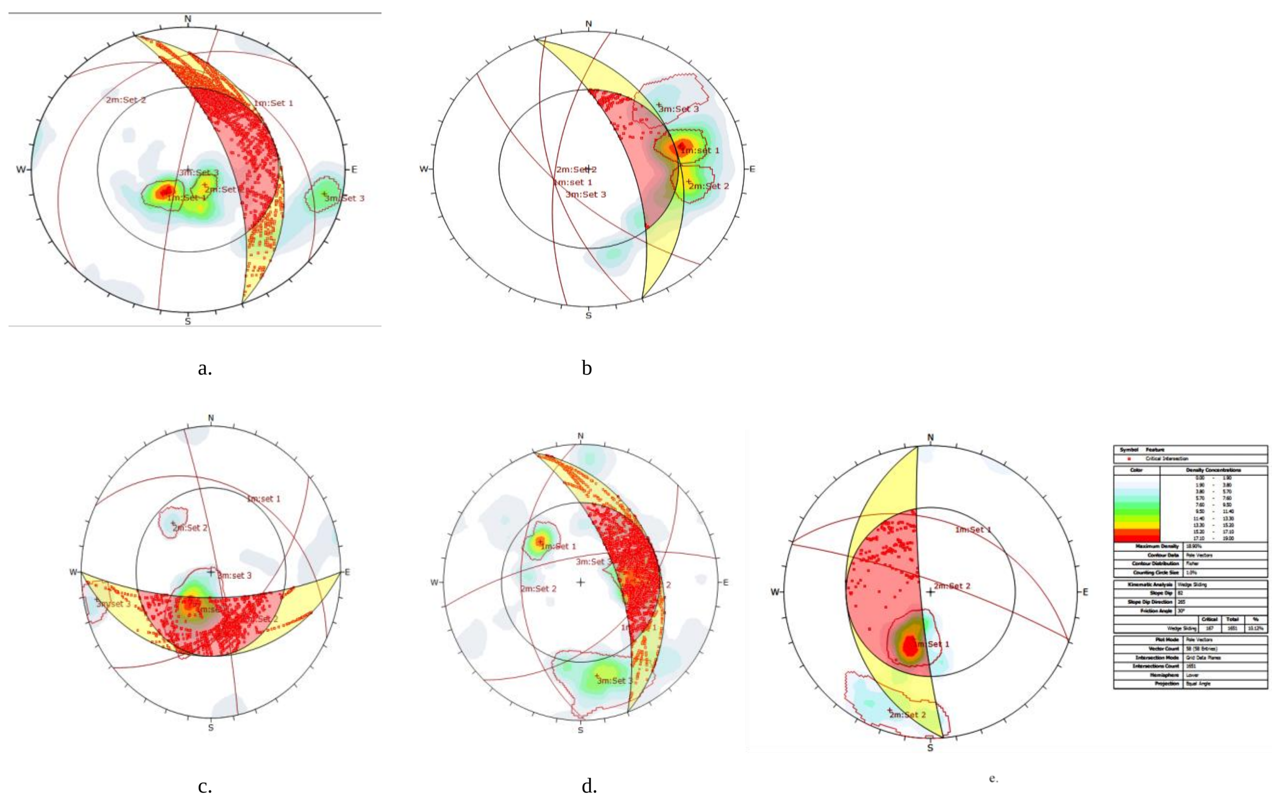

Fig. 5. The kinematic analysis results for the slope safety assessment.

4.5. MCDM Result

The MCDM result for the five production pits is presented in Table 10. The ideal best and ideal worst values for task, company payment response, level of company empowerment, mine safety, and accessibility are 0.08 and 0.239, 0.175 and 0.019, 0.164 and 0.018, 0.114 and 0.013, 0.052 and 0.029, respectively (see Fig. 6). The five pits (Pit 1, Pit 2, Pit 3, Pit 4, and Pit 5) have the following decision performance scores: 0.659, 0.617, 0.5, 0.5, and 0.5, respectively.

As shown in Fig. 7, Pit 3 has the greatest Euclidean distance from the ideal, followed by Pit 5, and Pit 4 has the east ideal value. According to Eq. (10), the TOPSIS performance score depends on both the ideal worst and ideal best Euclidean values. A low ideal Euclidean value shows a high production rate. The TOPSIS analysis also revealed that Pit 1 hasthe highest probability of producing more material, considering the company's payment response, mine accessibility, mine safety, company level of empowerment, and task assigned to it.

4.6. Validation of Pit 1 production rate using 2022 production database

The MCDM analysis revealed pit 1 as the most productive pit in the mine based on the selected key decision attributes. The mine's granite aggregate production database for the year 2021 was used in this study or investigation to validate the study results. The summary of the production is presented in Table 11 and Fig. 8. The report shows that production from Pit 1 has the highest revenue of $16,000 per annum, the lowest dewatering cost, and the highest production rate as compared to the other four pits.

Table 9a . The kinematic analysis results for the five pits slope safety (Pit 1&2).

Pit 1			Safety Assessment Level	
Joint set 1			**Plane Failure**	Critical level
Plunge	13		Overall	0.73%
Trend	217		**Wedge Failure**	
Joint set 2			Critical level	10.29%
Plunge	54		**Toppling Failure**	
Trend	213		Critical level	0.74%
Pit 2			Safety Assessment Level	
Joint set 1			**Plane Failure**	Critical level
Plunge	27		Overall	Safe
Trend	74		**Wedge Failure**	
Joint set 2			Critical level	0.48%
Plunge	24		**Toppling Failure**	
Trend	98		Critical level	
Joint set 3			Set 1	63.77%
Plunge	24		set 2	12.50%
Trend	44		set 3	15.15%

Table 9b. The kinematic analysis results for the five pits slope safety (Pit 3, 4& 5).

Pit 3			**Safety Assessment Level**	
Joint set 1			**Plane Failure**	Critical level
Plunge	36		Set 1	32.94%
Trend	323		set 2	84.27%
Joint set 2			**Wedge Failure**	
Plunge	62		Critical level	47.22%
Trend	52		**Toppling Failure**	
Joint set 3			Critical level	6.70%
Plunge	3			
Trend	31			
Pit 4			Safety Assessment Level	
Joint set 1			**Plane Failure**	Critical level
Plunge	60		Overall	7.94%
Trend	220		**Wedge Failure**	
Joint set 2			Critical level	15.52%
Plunge	73		**Toppling Failure**	
Trend	135		Critical level	1.33%
Joint set 3				
Plunge	7			
Trend	101			
Pit 5			Safety Assessment Level	
Joint set 1			**Plane Failure**	Critical level
Plunge	52		Overall	Safe
Trend	200		**Wedge Failure**	
Joint set 2			Critical level	0.67%
Plunge	9		**Toppling Failure**	
Trend	199		Critical level	20.69%

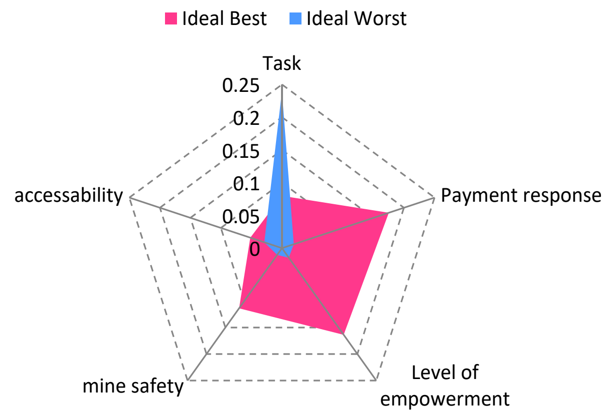

Fig. 6. The illustration of score analysis results for the ideal worst and ideal best values.

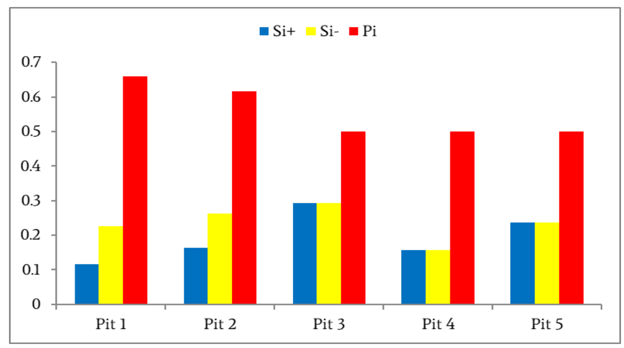

Fig. 7. The illustration of score analysis results for the Euclidean distance for the ideal worst and best values.

5. Conclusion

A mining company's productivity is the single most important factor in its overall performance and profitability. Therefore, it is important to understand what causes productivity to rise or fall. The study identifies the primary constraints that affect the granite production rate in relation to mine workers in Akure, Nigeria. In total, twenty-two (22) components were found in this study, and they were divided into internal and external production determinant factors.

Table 10. The TOPSIS Performance score result.

Euclidean distance from the ideal best (S+)and ideal worst (S-)									
	Task	Payment response	Level of empowerment	mine safety	accessibility	Si+	Si-	Pi	Rank
PIT 1	0.080	0.136	0.055	0.114	0.040	0.116	0.225	0.659	1
PIT2	0.186	0.097	0.127	0.088	0.029	0.163	0.263	0.617	2
PIT 3	0.239	0.019	0.164	0.013	0.029	0.292	0.292	0.500	3
PIT 4	0.133	0.058	0.018	0.038	0.040	0.157	0.157	0.500	3
PIT 5	0.080	0.175	0.127	0.013	0.052	0.237	0.237	0.500	3
			Ideal best (V+) and ideal worst (V-)						
V+	0.080	0.175	0.164	0.114	0.052				
V-	0.239	0.019	0.018	0.013	0.029				

Table 11. The report of production assessing the MCDM model prediction.

Pits	Average cost of production ($/yr)	Cost of dewatering Per year ($/yr)	Total production Per year (Tons/month)	Total revenue ($/yr)
1	35,400	1300.26	15,000	**16,000**
2	21,350	1700.24	9,000	14,450
3	24,56.25	1680.55	10,400	12,000
4	23,680	1250.75	8,500	8,000
5	25,340	1800.20	9,200	7540
		$ @ ₦650		

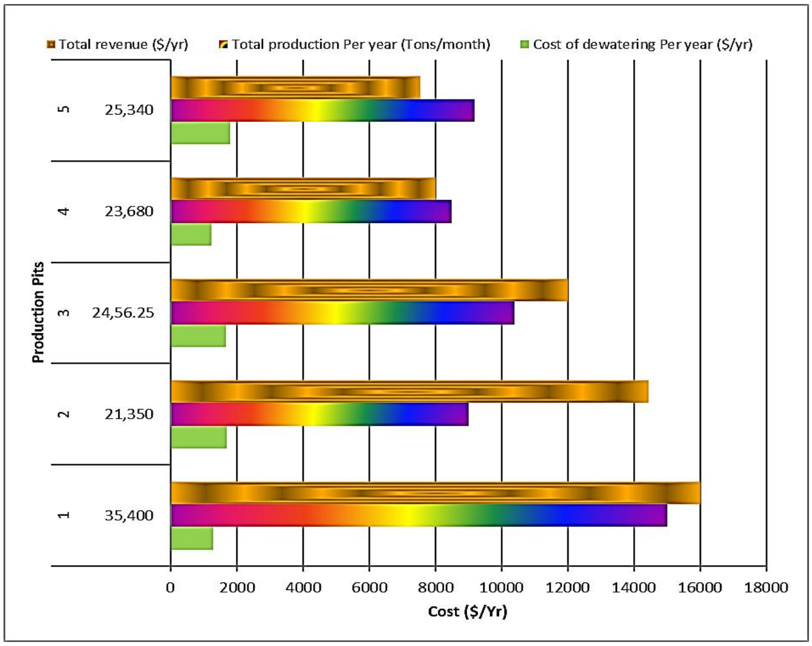

Fig. 8. The production and revenue assessment summary for year 2021.

The study also applied the TOPSIS multiple criteria decision-making techniques to determine the best loading pit in terms of the production rate based on the following attributes: labor task, company payment response, company empowerment level, mine safety, and mine accessibility. The study revealed that mine workers' contributions and efficiency have a outstanding impact on production rates. The most influential factors identified were those classified as internal constraints, which influence workers as a result of mine management and decision-making. According to the decision-making analysis technique's result, mine pit 1 was selected, as having the highest likelihood of generating more material during the rainy season, taking into account the following factors: company payment response, mine accessibility, mine safety, company degree of empowerment, and tasks allocated to workers.

Based on the study findings, the following recommendations are given:

- Routine meetings with all site engineers, depending on research results, should be scheduled for companies seeking to implement projects successfully.
- Pits should also prioritize increasing the expertise, experience, and motivation of their employees due to the labor-intensive nature of quarry operations, as highlighted by the TOPSIS research.
- . Increasing the number of apprenticeships available and implementing modern quarrying processes might lead to enhanced on-site labor productivity in the mine.

The limitation of the study being restricted to granite quarrying is a drawback. However, the author's future work will include other industrial rocks and metallic mines to expand the application scope of the multiple criteria decision-making technique as an approach for improving mine production.

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Availability of data and materials

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Competing interests

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Authors' contributions

Melodi: Data collection, Manuscript drafting and proof reading, and statistical analysis

Taiwo: Data analysis, result Visualization, MCDM analysis, manuscript detailing, writing and proofreading.

Raymond and Mojisola: data collection and analysis support, and Manuscript proofreading

REFERENCES

[1]. Yi, W., and Chan, A. P. (2014). Critical review of labor productivity research in construction journals. Journal of management in engineering, 30(2), 214-225.

[2]. Mishra, P. C., & Mohanty, M. K. (2020). A review of factors affecting mining operation. World Journal of Engineering, 17(3), 457-472.

[3]. Mata, M.M., Taiwo, B.O., Itunu, O. A.(2022a). Evaluation of Granite Production and Market Structure for the Improvement of Sales Performance in Ondo and Ogun States, Southwest Nigeria, FUOYE Journal of Engineering and Technology, Vol7(1).

[4]. Bonham, D. R., Goodrum, P. M., Littlejohn, R., & Albattah, M. A. (2017). Application of data mining techniques to quantify the relative influence of design and installation characteristics on labor productivity. Journal of Construction Engineering and Management, 143(8), 04017052.

[5]. Kaplan, R. S., and Norton, D. P. (2001). Transforming the balanced scorecard from performance measurement to strategic management: Part 1. Accounting horizons, 15(1), 87-104.

[6]. Durdyev, S. (2011). Pareto Analysis of On-site Productivity Constraints and Improvement Techniques in New Zealand Building Industry. A Master Thesis presented in Construction Management, Massey Univeristy at Albany, New Zealand.

[7]. Aygei, G., & Tetteh, A. R. (2022). Analysis of the effects of rainfall on production performance of a surface mine in Ghana.

Nigerian Journal of Technology, 41(4), 760-766.

[8]. Tlhatlhetji, M., &Kolapo, P. (2021). Investigating the effects of rainy season on open cast mining operation: The case of WescoalKhanyisa Colliery.

[9]. Reilly, M.C., Zbrozek, A.S., Dukes E.M. (1993). The Validity and Reproducibility of a Work Productivity and Activity Impairment Instrument. Pharmacoeconomics.Vol.4, pp.353–365.

[10]. Abraham, A., and Kirk, W.(2006). The Dynamics of Plant-Level Productivity in U.S. Manufacturing. Working Paper from U.S. Census Bureau, Centre for Economic Studies. http://econpapers.repec.org/RePEc:cen:wpaper assessed on May 6th, 2016.

[11]. Nasirov, S., & Agostini, C. A. (2018). Mining experts' perspectives on the determinants of solar technologies adoption in the Chilean mining industry. Renewable and Sustainable Energy Reviews, 95, 194-202.

[12]. Alinaitwe, M.H., mwakail, J.A and Hansson, B.m., (2007). Factors Affecting the Productivity of Building Craftsmen-Studies of Uganda. Journal of Civil Engineering

and Management, Vol XIII, (3), 169-176'.

[13]. Saputra, A., Adnyano, A. I. A., Putra, B. P., Sutrisno, A. D., Zamroni, A., & Machmud, A. (2023). A review of Open Channel Design for Mine Dewatering System Based on Environmental Observations. International Journal of Hydrological and Environmental for Sustainability, 2(1), 24-31.

[14]. Kumar, A., Sah, B., Singh, A. R., Deng, Y., He, X., Kumar, P., & Bansal, R. C. (2017). A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renewable and Sustainable Energy Reviews, 69, 596-609.

[15]. Bascetin A., (2004). An application of the analytic hierarchy process in equipment selection at Orhaneli open pit coal mine. Mining Technology (Transaction of the Institute of Mining and Metallurgy),Vol. 113, A192-A199.

[16]. Naghadehi. M.Z, Mikaeil,R and Ataei, M. (2009). The application of fuzzy analytic hierarchy process (FAHP) approach to selection of optimum underground mining method for Jajarm Bauxite Mine, Iran. Expert Systems with Applications 36 (2009) 8218–822

[17]. Aghajani, A,. and OsanlooM., (2007). Application of AHP-TOPSIS Method for Loading-Haulage Equipment Selection in Open pit Mines. XXVII International Mining Convention, Mexico.

[18]. Jumaah, F. M., Zaidan, A. A., Zaidan, B. B., Bahbibi, R., Qahtan, M. Y., &Sali, A. (2018). Technique for order performance by similarity to ideal solution for solving complex situations in multi-criteria optimization of the tracki ng channels of GPS baseband telecommunication receivers. Telecommunication Systems, 68, 425-443.

[19]. Chakraborty, S. (2022). TOPSIS and Modified TOPSIS: A comparative analysis. Decision Analytics Journal, 2, 100021.

[20]. Okul, D., Gencer, C., &Aydogan, E. K. (2014). A method based on SMAA-topsis for stochastic multi-criteria decision making and a real-world application. International Journal of Information Technology & Decision Making, 13(05), 957-978.

[21]. Abidin, M. Z., Rusli, R., & Shariff, A. M. (2016). Technique for Order Performance by Similarity to Ideal Solution (TOPSIS)-entropy methodology for inherent safety design decision making tool. Procedia Engineering, 148, 1043-1050.

[22]. Lin, M., Chen, Z., Xu, Z., Gou, X., & Herrera, F. (2021). Score function based on concentration degree for probabilistic linguistic term sets: an application to TOPSIS and VIKOR. Information Sciences, 551, 270-290.

[23]. Balcerzak, A. P. (2020). Quality of institutions in the European Union countries. Application of TOPSIS based on entropy measure for objective weighting. Acta PolytechnicaHungarica, 17(1), 101-122.

[24]. Mijalkovski, S., Efe, O. F., Despodov, Z., Mirakovski, D., &Mijalkovska, D. (2022). Underground mining method selection with the application of TOPSIS method. GeoScience Engineering, 68(2), 125-133.

[25]. Li, S., Huang, Q., Hu, B., Pan, J., Chen, J., Yang, J., ... & Yu, H. (2023). Mining Method Optimization of Difficult-to-Mine Complicated Orebody Using Pythagorean Fuzzy Sets and TOPSIS Method. Sustainability, 15(4), 3692.

[26]. Alhassan, H., Peleato, N., & Sadiq, R.(2023). Mercury Risk Reduction in Artisanal and Small-Scale Gold Mining: A Fuzzy Ahp-Fuzzy Topsis Hybrid Analysis. Available at SSRN 4389592.

[27]. Ozdemir, A. C. (2023). Use of Integrated AHP-Topsis Method in Selection of Optimum Mine Planning for Open-Pit Mines. Archives of Mining Sciences, 35-53.

[28]. ISRM (1978). Suggested Methods for the Quantitative Description of Discontinuity in Rock Masses, Int. Journal Rock Mechanic, Mining Sciences and Geomechanical Abstract, 15, pp. 319-368.

[29]. Saliu, M. A. and J. M. Akande, (2011). Drilling and Blasting Pattern Selection for Fragmentation Optimization in Ray-con Quarry," Journal of Engineering and Applied Sciences, Vol. 2, No. 12, 2007, pp. 1768.

[30]. Taiwo, B. O., Yewuhalashet, F., Ogunyemi, O. B., Babatuyi, V. A., Okobe, E. I., & Orhu, E. A. (2023). Quarry Slope Stability Assessment Methods with Blast Induced Effect Monitoring in Akoko Edo, Nigeria. Geotechnical and Geological Engineering, 41(4), 2553-2571.

[31]. Mata, M.M., Taiwo, B.O., Adamolekun, L.B. (2022b). Improvement of Asphalt production investment in Nigeria through profitability assessment:A case study of oyo state Nigeria construction company, International Journal of Engineering and Advanced. Vol.10(2), pp.1-15.

[32]. Diakoulaki, D; Mavrotas, G; Lefteris, P. (1995), Determining objective weights in multiple criteriaproblems: The CRITIC method. Comp. Operate. Res.22 (7) 763-770.

[33]. Kazaz, A., Manisali, E. and Ulubeyli, S.(2008). Effect of Basic Motivational Factors on Construction Workforce Productivity in Turkeys.

[34]. Enshassi. A., Mohamed. S. Mustafa A.Z. and Mayer. P.E.(2007). Factors Affecting Labour Productivity in Building Projects in the Gaza Strip, Journal of Civil Engineering and Management. Vol .8(4), 24S254

[35]. Cooper, K. G.(1993). The rework cycle: benchmarking for the project manager. Project Management Journal, Vol. 24 No. 1. pp. 17-22.

[36]. Sakarcan. A. S and Thomas. H. R. (1994), 'Forecasting labour productivity using factor model'. Journal of Construction Engineering and Management, ASCE, Vol. 120-1, pp. 228-239