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Granite Downstream Production Dependent Size and Profitability Assessment: an application of Mathematical-based Artificial Intelligence Model and WipFrag Software

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Abstract

The purpose of this research work is to create empirical models for assessing the profitability of granite aggregate production in Akure, Ondo State, aggregate quarries. In addition, an Artificial Neural Network (ANN) model for granite profitability was developed. A structured survey questionnaire was used to collect data for the study. The data extracted from the case study mine for this study includes granite marketing operations, royalty, production costs, and mine production information. In this study, the efficacy of granite fragmentation was assessed using the WipFrag software. The relationship between particle size distribution, blast design, blast efficiency, and uniformity index were analyzed using the WipFrag result. The optimum blast design was also identified and recommended for mine production. The result revealed that large burden distances result in bigger X50, X80, and Xmax fragmentation sizes. A burden distance of 2 m and a 2 m spacing were identified as the optimum burden and spacing. The finding revealed that blast mean size and 80% passing mesh size have a positive correlation. The result from this study indicated that the uniformity index has a positive correlation with blast efficiency and a negative correlation with maximum blast fragmentation size. The prediction accuracy of the developed models was evaluated using the coefficient of determination (R2), root mean square error (RMSE), and mean square error (MSE). The error analysis revealed that the ANN model is suitable for predicting quarry-generated profit.

1. Introduction

Mining has played a crucial role in fostering national development and driving technological progress over the course of several centuries. According to Osasan, a robust mining sector, similar to other industries, serves as a fundamental basis for the economic development of a nation [1]. Quarrying, which is a sub-division of the broader mining industry, plays a fundamental role in the construction sector of any economy. Solid minerals are inherently interconnected with the evolution and development of human society and civilization. According to Hirooka [2], the advancement of civilization and the process of democratization, together with the global push for industrial economic growth, have led to a heightened requirement and desire for robust mineral resources. There is a parallel increase in technological advancements, construction activities, and building

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projects to this surge in mineral demand. According to [3], the growing need for industrial rock commodities is crucial for maintaining our technologically driven society, necessitating the study of these resources. Based on the findings of the United States Geological Survey, it has been determined that Africa possesses a substantial quantity of granite deposits and exhibits a significant potential for the occurrence of precious and base metals [4]. Additionally, the country in question acts as a significant global supplier of several key minerals and metals, boasting a substantial share of around 30% of the world's mineral reserves. Notably, it possesses a dominant position in the reserves of platinum, chromium, and tantalum, accounting for approximately 80% of the global supply. Furthermore, it holds a significant portion of the world's reserves for gold, diamond, cobalt, manganese, and phosphate, amounting to over 40% of each respective resource. According to the findings of Mattew and Emmanuel, the presence of Africa's extensive mineral resources can be attributed to the continent's geology, as these minerals are closely linked to the lithological properties of the continent [3]. Africa is primarily characterized by the prevalence of Precambrian basement crystalline rocks, which consist of schist, gneisses, green schist, and granites. Additionally, Africa serves as a significant source, accounting for nearly 80% of the global supply of solid minerals [5]. According to [3], despite the significant potential for income that natural resources have for African countries, ongoing conflicts and political instability have resulted in a regrettable situation where this potential wealth remains unrealized. According to [6], from the 1980s to the present, Africa's level of investment in mineral exploration has been noticeably deficient in comparison to other significant mineral-producing regions around the world. According to the Metal and Economics Group [7], the global mining industry allocates approximately 10% of its yearly production value on exploration activities, but Africa's expenditure in this regard amounts to only around 1%. Although Africa possesses over 30% of the worldwide mineral and metal resources, the allocated budget for mineral exploration in 2010 amounted to around $1.4 billion, representing a mere 13% of the total global expenditures for that year [7]. Melodi *et al.* [8] argue that inadequate marketing practices have a negative impact on the production and supply of quarry end products, resulting in limitations in the supply rate between producers and industrial customers. The origins of mineral exploration and the mining business in Nigeria may be dated back to the early 20th century, specifically 1903–1904, during the period of colonial rule. It was during this time that the colonial government formed the Mineral Surveys of Southern and Northern Nigeria [9].

Historically, the extractive sector in Nigeria was predominantly controlled by the government, leading to adverse consequences for the mineral extraction sector following the discovery of oil in 1956 [3]. After the occurrence of the oil boom, both the government and industry redirected their attention towards this emerging resource, resulting in the country's economic development centered predominantly on oil income. Consequently, the agriculture and solid mineral sectors were marginalized. Nigeria is widely recognized for its significant contributions to the natural resources industry, particularly in the production of oil and gas. It holds the sixth position globally in terms of oil and gas output [10]. Granite is classified as an igneous rock predominantly consisting of quartz, feldspar, micas, amphiboles, and several trace minerals [11]. The diverse hues and textures of granite are attributed to the presence of different minerals, their varying quantities, and the extent of modification [12]. Rock aggregate, a primary constituent in engineering applications including roads, airports, bridges, and water projects plays a pivotal role in the development and implementation of a nation's infrastructure. Aggregate is one of the priciest building materials, according to a study by [13]. According to reference [14], quarrying is a type of mining where rock or mineral extraction takes place within a single bench. Mine-extracted materials are well-recognized as essential components in contemporary civil engineering and construction projects. Stone products play a crucial role in meeting various societal demands by supplying essential minerals. These minerals are predominantly utilized in the construction of concrete structures, including residential buildings, bridges, and roadways. Quarried rock blocks find application in the construction industry as face materials for buildings, provided they undergo cutting, shaping, and carving procedures. Additionally, rough blocks serve as protective armor in marine defense structures. Moreover, quarried materials indirectly contribute to various industrial production processes, such as the manufacturing of toothpaste, cosmetics, paints, and plastic.

Granite mining in Nigeria offers economic growth, job opportunities, and infrastructure development. Predictive models can improve profit by optimizing extraction, reducing waste, and forecasting market demand [15]. The mining sector, encompassing quarrying activities, is a significant portion of Nigeria's gross domestic product (GDP), amounting to 37% [16]. The process of granite aggregate production encompasses several stages, including the controlled fragmentation of the stone through blasting, the extraction of the stone using heavy machinery, the transportation of the stone on vehicles, and the subsequent crushing of the materials into different sizes [17]. As stated by [18], the improvement of granite project profitability involves strategizing and managing the quarry through some elements such as a technical aspect, a specifically targeted economic aspect, and a more comprehensive economic aspect that encompasses financial and business factors that impact the quarry's performance within the industry as a whole. The significance and possibilities of granite aggregate production within Nigeria's mineral sector are of considerable importance, although the monitoring of its production has not been sufficiently conducted to comprehensively ascertain its profitability. Although there is considerable interest among governments in promoting the industrial utilization of granite, there is a dearth of empirical evidence regarding the profitability of aggregate granite manufacturing. Thus this study is very important for figuring out how profitable granite aggregate will be in the future because it looks at the current profit margin in producing granite aggregate and the market structure of the area being studied. Granite rock blasting operations entail drilling holes into the granite, loading them with explosives, and detonating the explosives to break the rock into manageable chunks [16]. As explained by Frank *et al*. [18], while blasting operations are effective for quarrying, challenges include controlling fragmentation, minimizing environmental impact, and ensuring worker safety, making precise blasting techniques crucial for successful granite extraction. The constraints of granite production caused by blast results include increased fracturing and rock degradation, resulting in more waste material and less usable stone. Excessive blasting can also cause safety concerns, environmental challenges, and increased production costs, all of which have an impact on the overall efficiency of granite quarrying.

According to the research conducted by Taiwo *et al*. [19], the blast fragment uniformity index is utilized to assess the uniformity of fragment sizes that arise from an explosion. Additionally, Morin and Ficarazzo provide a definition of blast fragment size homogeneity [20]. The homogeneity index normally ranges from 0.6 to 2.2. The value of 'n' determines the shape of a curve [21]. Chung and Katsabanis [22] noted that a uniformity value of 0.6 indicates a lack of uniformity in the muck pile, whereas a value of 2.2 signifies a uniform muck pile where the majority of pieces are in close proximity to the 50% passing size. According to multiple research works, it has been observed that in order for a blast outcome to be considered favorable, the blast design parameters must be well designed and the fragmentation must possess a uniformity index equal to or greater than unity. Sereshki and Hoseinie [24] worked on ways to design the optimum burden distance for good fragmentation using a case study of the Sungun copper mine in Iran. Their comparison results show that the Anderson, Pears, Allsman, Langefors, and energy transition methods give a good representation of the optimum burden. A well-executed blast design offers several benefits in mining and construction, as Kahraman and Kilic mention [25]. [26, 27] explained that blast design with adequate modification enhances safety by controlling fragmentation, minimizing flyrock, and reducing ground vibrations, ensuring a secure working environment. The issue of environmental impacts is mitigated as controlled blasting also minimizes air overpressure and limits the release of dust and gases [28–30].

According to Manashti *et al*., WipFrag is a visual analysis framework used to assess the particle size distribution of blasted rock. To analyze fragment sizes, several images are collected to ascertain the size of the fragmented particles and the regularity of the blast outcome, as explained by several authors [32–34]. The present study aims to evaluate and analyze the uniformity index of the quarry under investigation using WipFrag software. This assessment will be conducted in order to investigate the potential correlation between the blast uniformity index and two key variables: maximum fragmentation boulder (MFB) and blast efficiency. Cunningham [35] elucidated the significance of investigating the correlation between blast fragmentation size distribution and uniformity index. The comprehension of these two variables is of utmost importance as it facilitates the optimization of explosives utilization, enhances the efficiency of material handling, and guarantees consistent product quality, consequently augmenting blasting efficiency within these sectors. Linear models were formulated to predict MFB, blast efficiency, and blast fragmentation size using traditional methodologies.

The utilization of empirical models for predicting the profitability of granite mines is limited due to their inability to account for the internal complexities within the input parameters, leading to inaccurate estimations [35, 36]. In many cases, the utilization of blast fragmentation size and uniformity index have been identified. Doktan [37] investigated the effect of fragmentation size and uniformity index on truck shovel fleet performance to improve shovel productivity. Doktan [37] developed a relationship between loader dig times and blast fragment mean size (X_{50}) and uniformity index in his findings, as shown in Equation (1).

$$LDT = K - Z \times X_{50} \times n \quad (1)$$

where LDT id the loader digging time in minute, k and z are constant equal to 8.9942 and -0.068706, respectively, X_{50} is mean fragmentation, and n is uniformity index.

To improve loading operation at Gol-e-Gohar mine, Osanloo and Hekmat [38] conducted a study on the relationship between the blast fragmentation size distribution and the shovel productivity. In their findings, the noted that blast fragmentation properties have an effect on bucket fill factor, swell factor, job efficiency and rock density. Using Fragmentation mean size, 80% passing size and uniformity index, they establish a prediction model for shovel loafing productivity as illustrate in Equation (2).

$$PD = 1769 - 9.63d_{50} + 444.45n - 3.37nd_{80} \quad (2)$$

where d_{50} is the average particle size, n is the uniformity coefficient, and d_{80} represent 80% weight of material less than a certain size.

It was found that there exists an inverse relationship between shovel productivity and the size of blast fragmentation particles, whereby larger particles result in decreased production. The model also proposes that d_{80} values, which guarantee increased shovel output, should fall within the range of 200 to 400 mm. The aforementioned research failed to consider the comprehensive influence of blasting efficiency, including the effects of oversize and undersize particle sizes on the profitability of production and the efficiency of blasting in relation to the primary crusher's gape.

1.1. Significance of study

In order to mitigate the deficiencies of empirical predictors and overcome the constraints in evaluating the profitability of granite aggregate, an Artificial Neural Network (ANN) was employed to construct empirical models for the prediction of the overall profit of granite aggregate. In this study, the efficacy of granite fragmentation had been assessed using the utilization of WipFrag software. The relationship between particle size distribution, blast design, blast efficiency and uniformity index were analyzed using the WipFrag result. The optimum blast design was also identified and recommended for the mine for optimum blast production. To the best of the author's knowledge, this is the first study to estimate quarry profitability by incorporating soft computing models into a mathematically driven equation using the machine learning layers of weight and bias. The author also noted that the knowledge gape between fragmentation size distribution, uniformity index, blast design block size and uniformity index had been bridged with detail analysis in this study.

1.2. Description of studied area

Akure is the largest city and capital of Ondo State in South-Western Nigeria. According to the 2006 census, the city has a population of 484,798 people [39]. Akure is located between 7°15' 9.22" N and 5°11' 35.23" E (see Figure 1). On the outskirts of Akure, rock engravings dating back to the Mesolithic period have been discovered. Granite and Charnokite are the most important rocks in Akure. According to [40], the old granite and metamorphic rock formation in the location axis consists primarily of amphibolite and gneisses.

Two quarries (Q1 and Q2) located at Akure north were considered as case study in this study as shown in Figure 1.

2. Research Methodology

The research methodology employed in the quarry case study included the gathering of production cost data, sales data, and market reports. The data utilized in this study was obtained from a combination of primary and secondary sources, specifically mining data records. The data was collected with the purpose of assessing the production attributes of granite and developing predictive models for the profitability of quarry mining operations. The study technique is depicted in Figure 2.

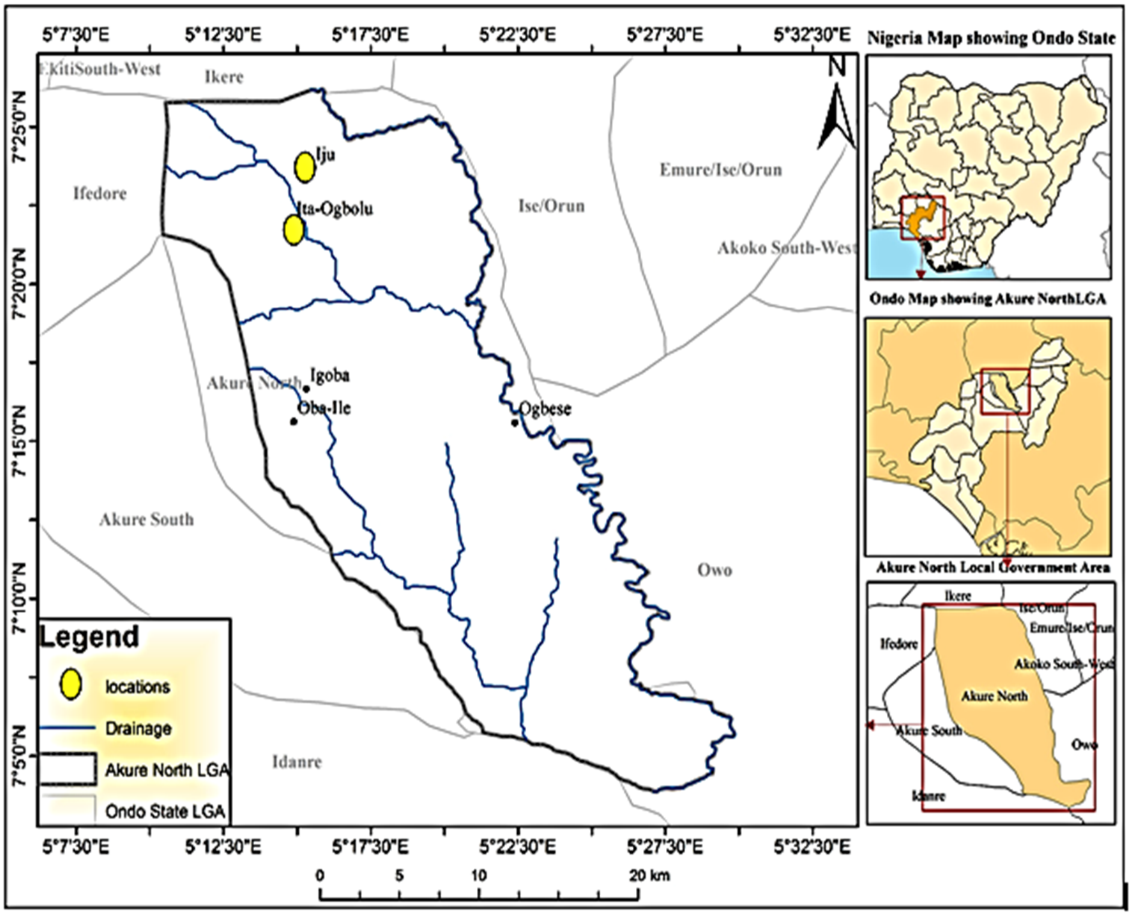


Figure 1. Geological map of Ondo state showing Q1 and Q2.

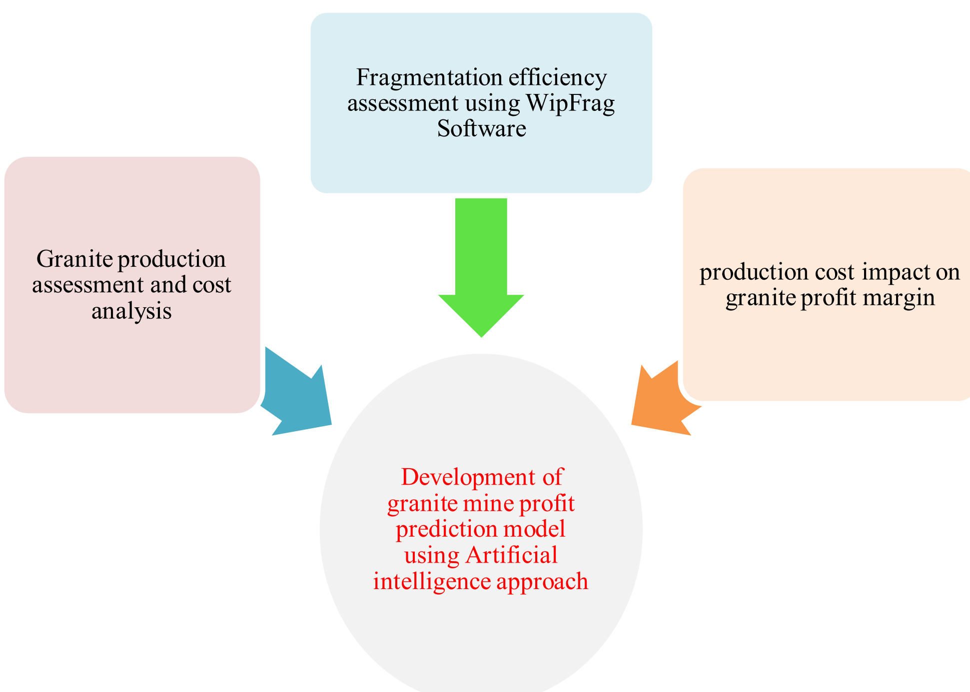


Figure 2. A flow chart of the empirical modeling work.

2.1. Primary data collection

The study employed a comprehensive and meticulously designed survey questionnaire to gather primary data, encompassing information on mine production rate, pricing, and sales. The survey questionnaire was purposefully crafted to monitor many aspects of the granite value chain at the quarries examined in the case study. These aspects include production rate, supply prices, production volumes, and transaction costs in both the source and final markets. The determination of the sample size was calculated based on the methodology outlined in reference [41], as seen in Equation (3).

$$N = \frac{z^2.p.q}{e^2} \tag{3}$$

where N is sample size, z is confidence interval (z-value, 1.96 at 95%), p is 0.5% (the expected proportion of the population of the granite traders), q is 1-0.5 and e is 8% (the allowable margin of error).

Therefore, N is approximately 140 samples (70 from Q1 and 70 from Q2). Royalty paid per tone was calculated based on the payment standard per ton as published by Nigeria Ministry of Mine and Steel Development [42].

2.2. Data analysis method

For analyzing the data collected from the granite industry and developing a sale profitability predictive model, two types of data analysis will be used: descriptive statistics and soft computing analysis. The proposed prediction models were developed using 45 datasets from two case study quarries.

2.3. Fragmentation evaluation

The image analysis technique was used to study and analyze five blasting operations. During the charging, blasting, and post-blast operations, each blast round will be monitored. Blast design parameters will be measured for the blast rounds, and an image of the blast outcome will be obtained for efficiency evaluation. Separately, the acquired blast images were examined with WipFrag software, and the blast fragmentation efficiency was determined using the mine's main crusher inlet size in mm. In this study, blast efficiency was determined by examining the link between the blasted material's 80% passing size and the primary crusher's input size. A smaller 80% passing size with respect to the crusher's inlet indicates improved efficiency. The relationship between particle size distribution, blast design, blast efficiency, and uniformity index were analyzed using the WipFrag result. The optimum blast design was identified and recommended for the mine for optimum blast production.

2.4. ANN model development

The input and output data for the models were extracted from mine production records for a minimum of eight years at the first and second quarters. The ANN and MVR models each had five input parameters and one output parameter (see Table 1). The inputs considered for modeling are those that are most sensitive to the literature outputs. The inputs are interconnected, which means that changing one parameter affects the other. These inputs and outputs are fed into a MATLAB-based ANN system to determine the best model for profit generation.

Table 1. Model input and output parameter representation.

Model input parameters	Input symbols	Model output parameters	Output symbols
Total production	TP	Generated Profit	GP
Total product cost	TPC		
Royalty	R		
Total revenue	TR		
Other expenses	OE		

The Bayesian Regularization algorithm was used to train the ANN model. This algorithm is typically slower, but it can produce good generalization for difficult, small, or noisy datasets. Training is halted based on adaptive weight minimization (regularization). A set of targets is chosen for the given set of inputs. The network computes some outputs using transfer functions using random weights (i.e. transig and logsig). The optimized model is applied to a series of Q1 and Q2 production data in order to optimize fragmentation.

2.4.1. Development of a multivariate regression model

A multivariate regression model is a statistical procedure that is used to determine the relationship between dependent and independent variables. The established model predicts the values of a target (dependent) variable based on the values of a set of independent variables. In general, the multi variants model is created using Equation (4).

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (4)$$

where β_1, β_2, … β_n are the coefficients of regression model, β_0 is the intercept, $\hat{Y}$is the predictive value, x_1, x_2, …, x_n are the independent variables.

2.5. Evaluation of developed model performance

The best network architecture is chosen after successful training, validation, and testing with various network architectures. To evaluate the developed model, three evaluator indices include; root mean square error (RMSE, Equation 5), Mean Square error (MSE, Equation 6), and coefficient od determination (R^2, Equation 7) [43].

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(Z_p - Z_a)2}{N}} \quad (5)$$

$$\text{MSE} = \frac{\sum_{i=1}^{N}(Z_p - Z_a)2}{N} \quad (6)$$

$$R^2 = \sum_i \frac{(Z_p - Z_a)2}{\sum(\text{Ypredi})2} \quad (7)$$

where Z_p is the predicted output, Z_a is the measured output, and N is the number of inputs–output data pairs.

3. Results and Discussion

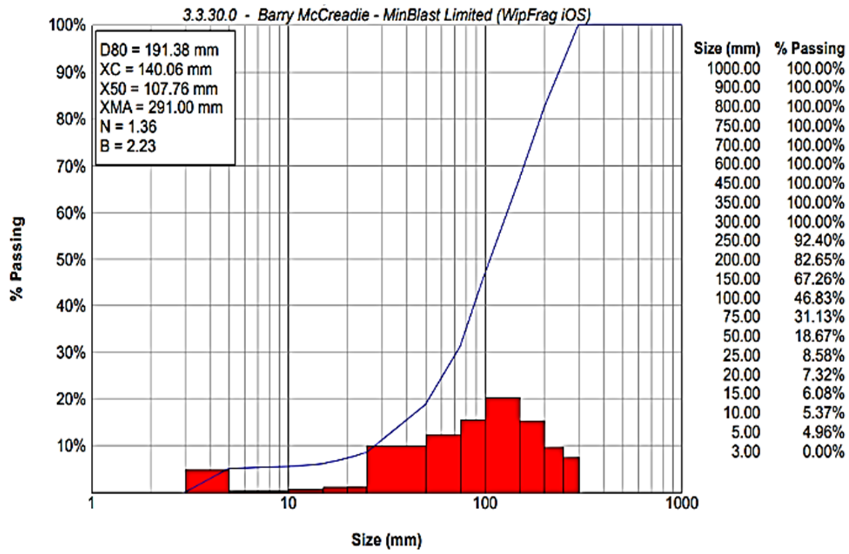
The results and findings of the research are presented in this section.

3.1. Blast efficiency result

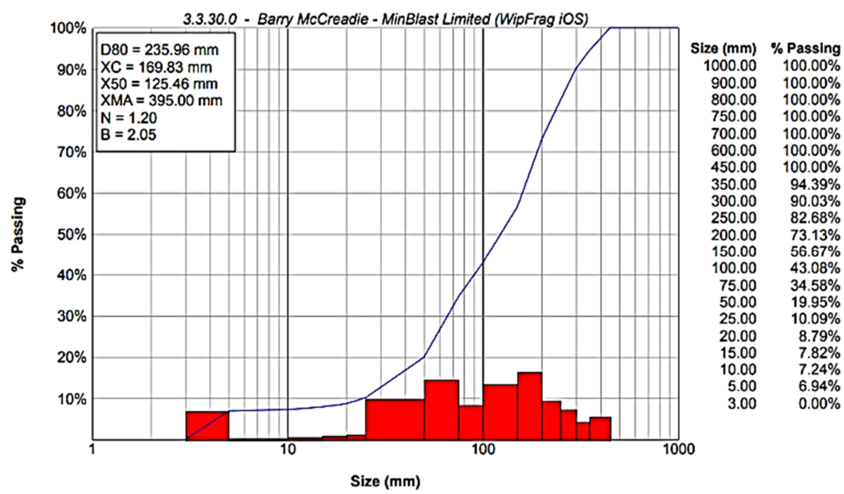
The result from five production blast were collected and evaluated using WipFrag software and primary crusher in let size. The fragmentation analysis result from the five-production blast is presented in Figure 3. Table 2 presents the blast fragmentation analysis result and the blast design parameters. The result shows that the case study mine blast has uniformity ranging from 1.05-1.36, mean size of 107-160.45 mm, 80% passing size of 191.38-245.86, and blast efficiency of 50.53-65.82%. The result shows that change in burden distance affects the fragmentation size distribution of blasted rock. Burden distance refers to the distance between the blasthole and the free face or the rock that is being blasted. The result revealed that large burden distance result in bigger Fragmentation size including X_{50}, X_{80}, and X_{max} fragmentation size. Burden distance of 2 m and 2 m spacing was identified as the optimum burden and spacing as illustrated in Figure 4.

Table 2. Blast fragmentation efficiency result.

	X_{50} (mm)	X_{80} (mm)	X_{max} (mm)	n	Efficiency
Blast-1	107.76	191.38	291	1.36	65.825
Blast-2	125.46	235.96	395	1.2	57.86429
Blast-3	160.45	277	421	1.05	50.53571
Blast-4	131.97	245.86	387	1.36	56.09643
Blast-5	121.42	232.63	421	1.22	58.45893
Burden (m)	**Spacing (m)**	**Hole diameter (mm)**	**Depth (m)**	**Stemming length (m)**	
1	2	90	10	2.5	
2	2	90	10	2.5	
2.5	2	90	10	2.5	
1.5	2	90	10	2.5	
2	2	90	10	2.5	
	Crusher gape	Clearance			
	700	560			



(a)



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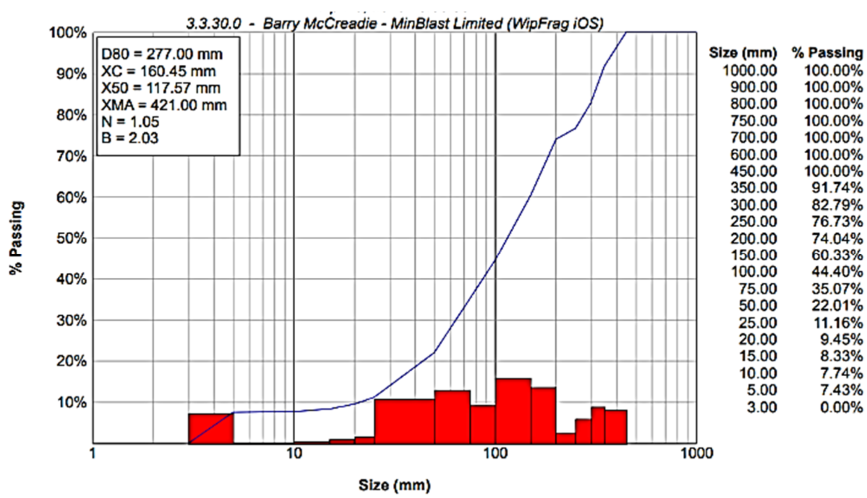
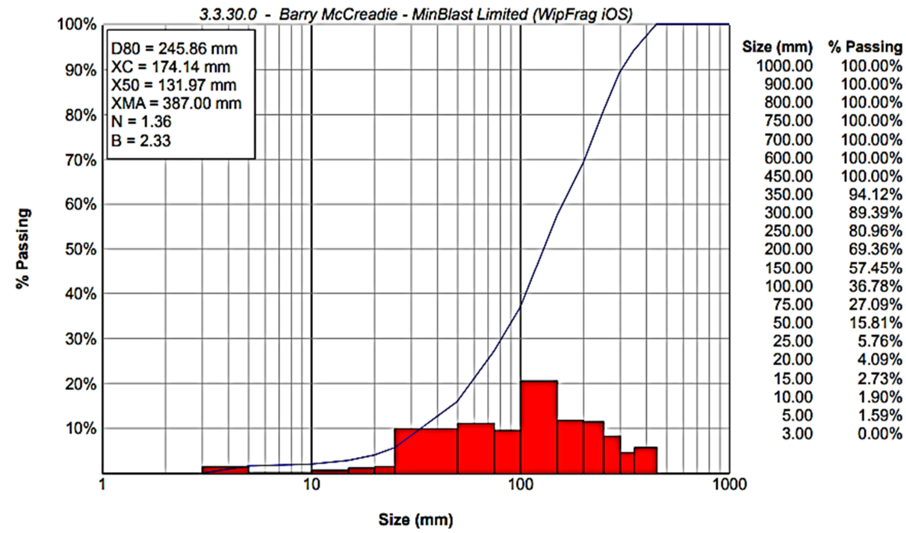


(c)

Figure 3. Fragmentation analysis result with size distribution rate.



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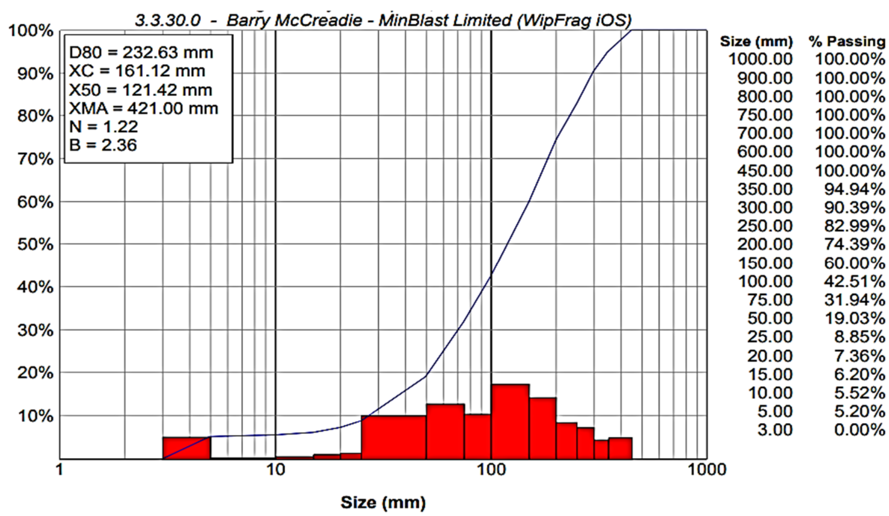


(e)

Continuous of Figure 3. Fragmentation analysis result with size distribution rate.

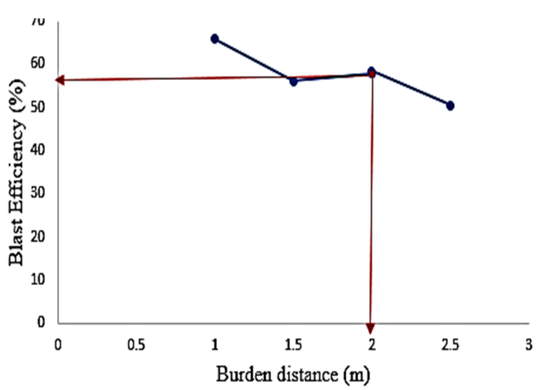


Figure 4. Relationship between blast efficiency and burden distance.

4.1. Relationship between blast efficiency and uniformity index

Figure 5 presents the relationship between blasting efficiency (BE), maximum blast fragment size (MBF), and uniformity index (n). As mentioned by Jug *et al*. [44], the higher this value, the more uniform the fragmented material will be. The result from this study indicated that uniformity index has a positive correlation with blast efficiency and negative correlation with Maximum blast fragmentation size. The blast efficiency was found to increase as blast fragmentation uniformity improves.

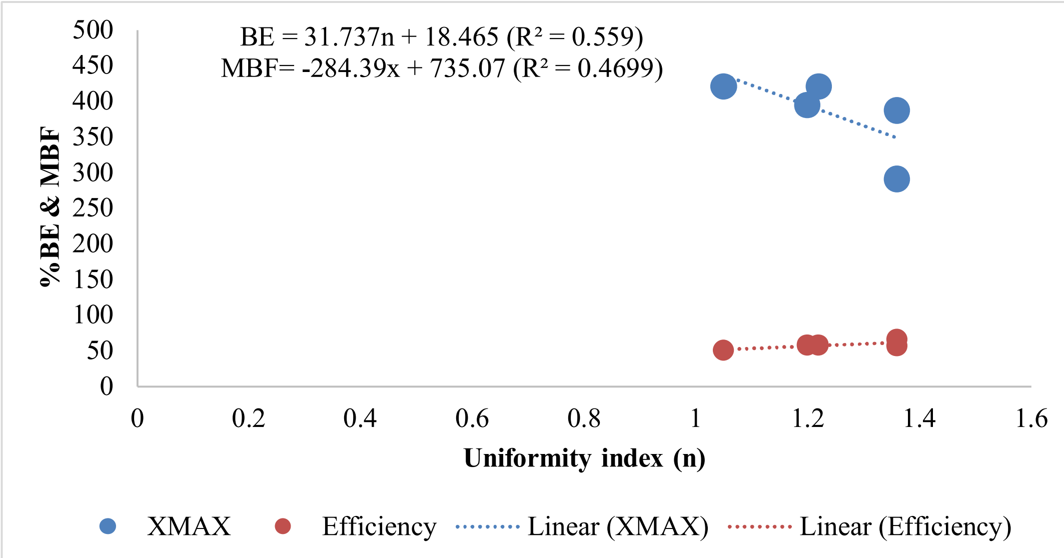


Figure 5. Relationship between MBF, BE, and uniformity index.

Figure 6 present the relationship between fragmentation 50% and 80% passing size. The findings revealed that blast mean size and 80% passing mesh size for each of the blast round have a positive correlation relationship.

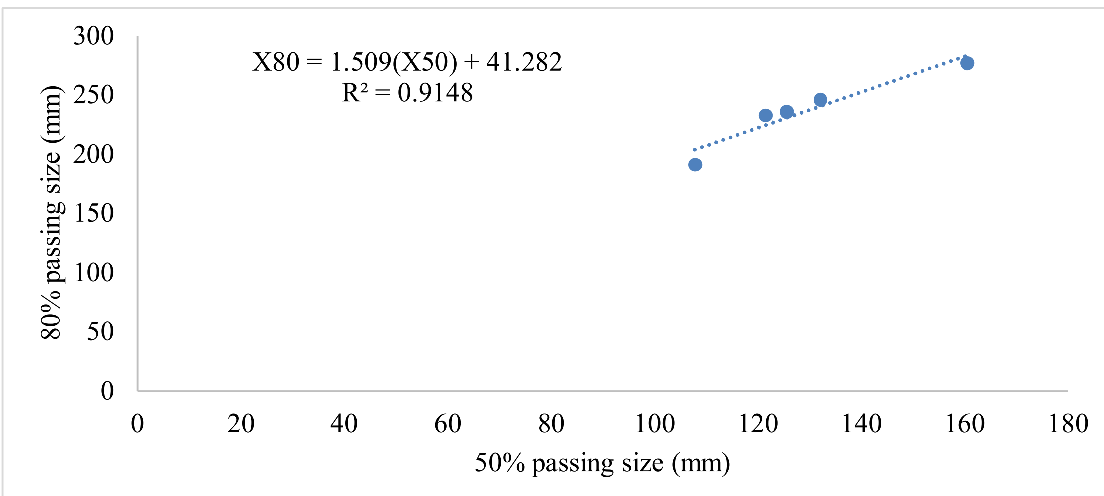


Figure 6. Relationship between mean fragmentation size and 80% passing size mesh.

5. Granite Production Assessment Analysis

5.1 Number of years in operation by selected quarries

Figure 7 shows that 17% of the selected quarries have been in business for 1 to 5 years, while the majority (83%) have been in business for 6 to 10 years. This finding implies that the majorities of the studied quarries are no longer new to the industry and must have attained a reasonable level of professionalism in order to improve their operational efficiency.

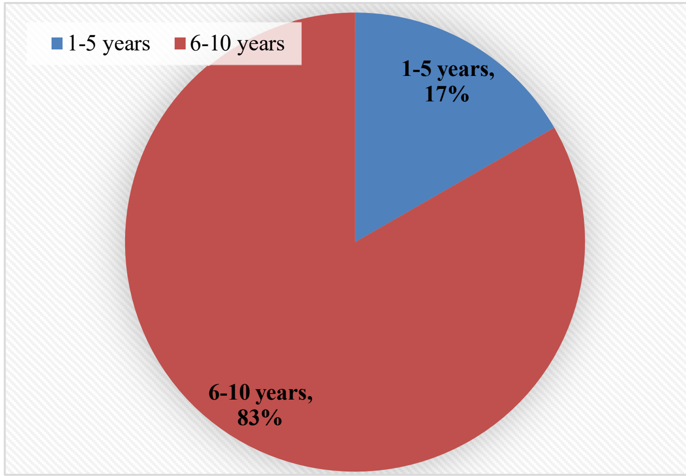


Figure 7. Number of years in operation Q1 and Q2.

5.2. Annual production capacity of quarries

Figure 8 shows that Q1 has higher production at the start of the early years (year one and two data). The annual production capacity of the Q1 and Q2 mines ranges from 891830 to 411930 tons per year and 675500 to 455500 tons per year, respectively. It was discovered that Q1 produces more than Q2, as shown in Figure 8.

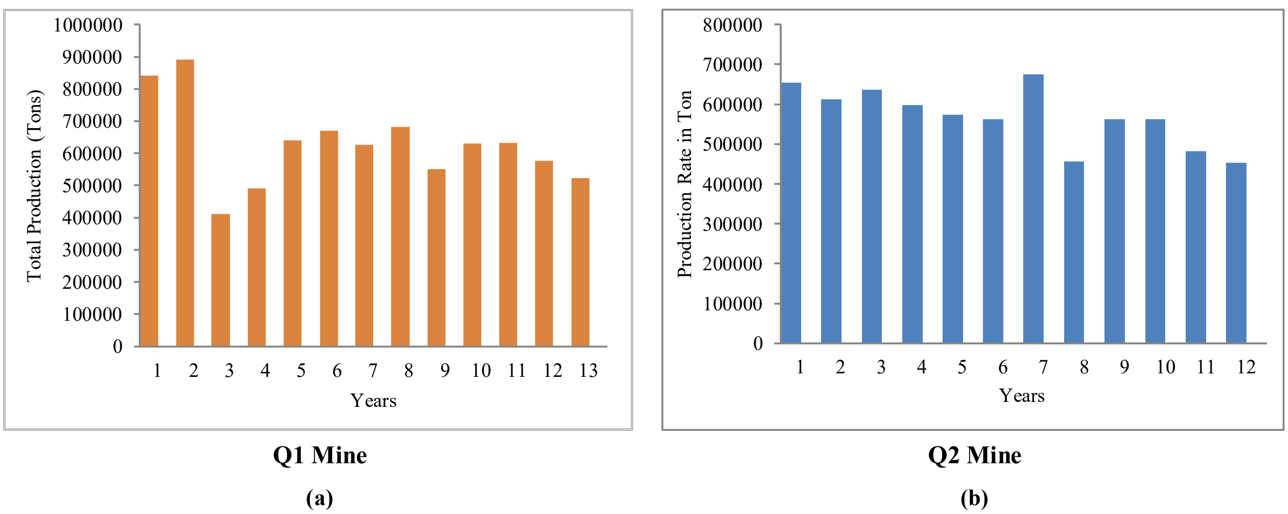
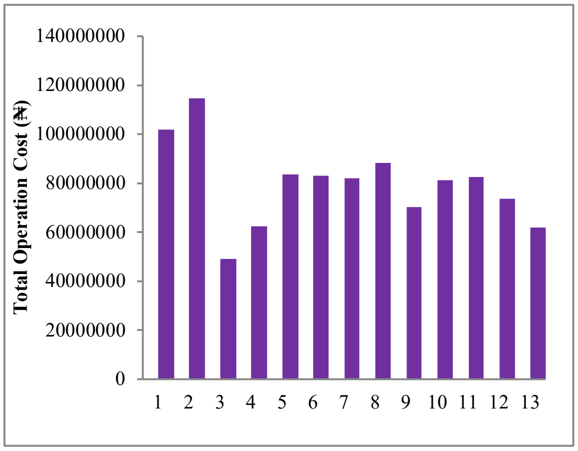


Figure 8. Annual production capacity.

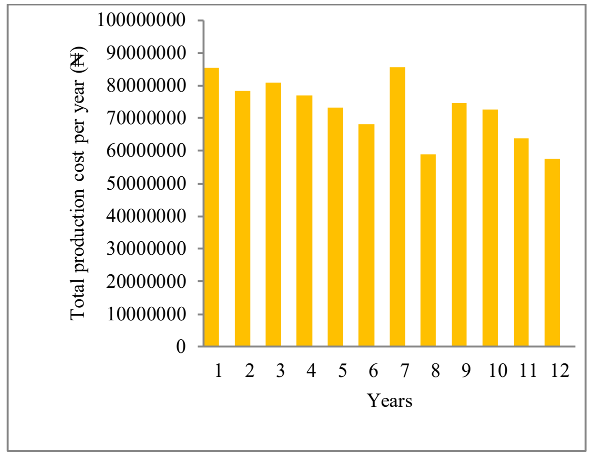
5.3. Operational cost per year

The result in Figure 9 reveals that the average total production cost per year for Q1 and Q2 ranges from ₦ 114,600,000 to ₦ 40030693.6 and ₦85,81,07,60 to ₦ 58,98,11,60, respectively. The production rate of granite depended mainly on the total amount of capital incurred on the operation in the mine as noted by [45] on the evaluation of Bench Drilling Phase of Diamond Wire Sawing Technique cost for Granite Mining. As shown in Figure 9, the production cost was found to increase in a positive correlation order with the production rate.



Q1 Mine

(a)



Q2 Mine

(b)

Figure 9. Mine operational cost per month a. Q1 mine, b. Q2 mine.

6. Profitability model development result

6.1 ANN model results

For the development of the model proposed in this study, the Bayesian Regularization training algorithm with architecture 5-6-1 was used. The training revealed that the Bayesian algorithm takes significantly longer to train data than other ANN training algorithms. Figure 10 depicts the training performance graphs and interface. The Bayesian Regularization algorithm was used in the network's training. The Bayesian Regularization algorithm typically takes more time but can produce good generalization for small datasets. As indicated by variable weight minimization, the model training terminates (regularization).

Figure 11 compares the predicted values of the developed ANN model to the actual Generated Profit value. The prediction result shows a strong coefficient of determination (R^2) = 0.996 close to unity between the predicted Generated profit and the calculated Generated profit from the best ANN model. The developed ANN model was extracted into mathematical equations using the weight and bias of the optimum model input, hidden and output layers. Equation (8) shows the mathematical equation developed from optimum proposed model.

$$N1 = 1.4689 \mathrm{Tanh}\,(0.27288TP - 0.5051TPC - 0.2732OE + 0.2878R + 0.2491TR - 0.9578)$$

$$N2 = -0.0031 \mathrm{Tanh}\,(0.3721TP - 0.375TPC - 0.3967OE + 0.4038R + 0.3327TR - 0.2911)$$

$$N3 = 1.0322 \mathrm{Tanh}\,(0.0722TP - 0.3122TPC - 0.3634OE + 0.2766R + 0.3051TR + 0.0407)$$

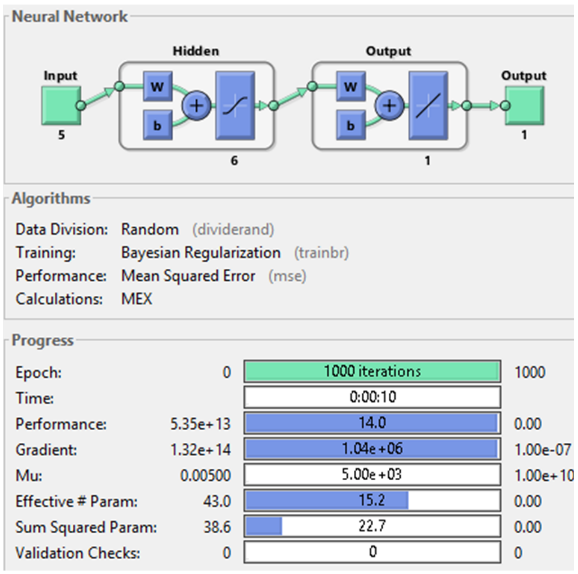
$$N4 = -2.7454 \mathrm{Tanh}\,(0.2297TP + 0.4373TPC + 0.2129OE - 0.4757R - 0.3784TR - 0.2151)$$

$$N5 = 1.7737 \mathrm{Tanh}\,(0.2166TP - 0.44843TPC - 0.3325OE + 0.3249R + 0.2398TR - 0.8092)$$

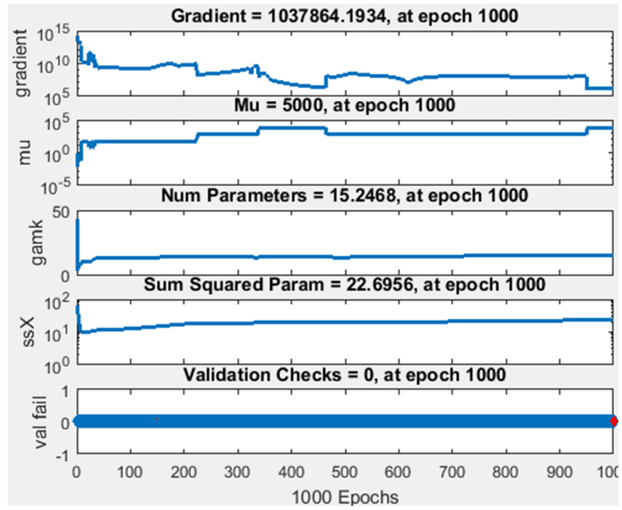
$$N6 = -1.3820 \mathrm{Tanh}\,(- 0.3161TP + 0.5293TPC + 0.5153OE - 0.2723R - 0.4666TR - 1.1801)$$

$$GP = [\mathrm{Tanh}\,(N1 + N2 + N3 \ldots\ldots + N6) - 0.0127] \quad (8)$$

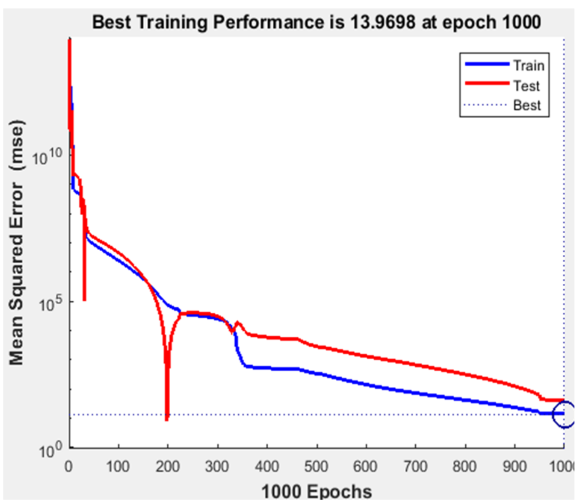
where TP is Total production rate, TPC is total production cost in ₦, OE is the other expense in ₦, TR is total revenue in ₦, and GP is generated profit.



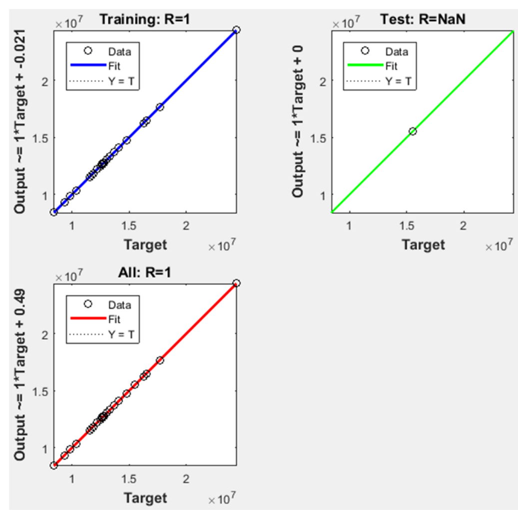
(a)



(b)



(c)



(d)

Figure 10. ANN model training and validation coefficient of correlation: (a), (b) training algorithm architecture; (c), (d) training response and training regression.

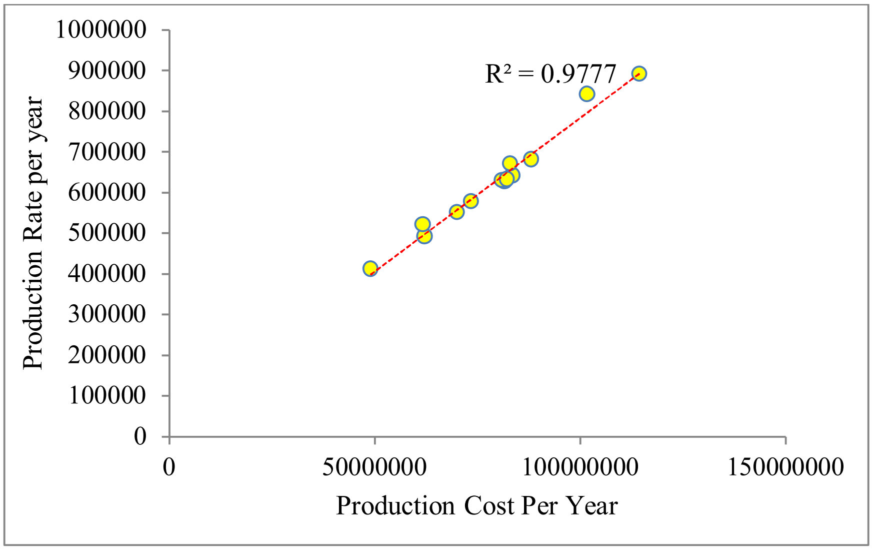


Figure 11. Relationship between production rate and production cost.

6.2. Multivariate regression model result

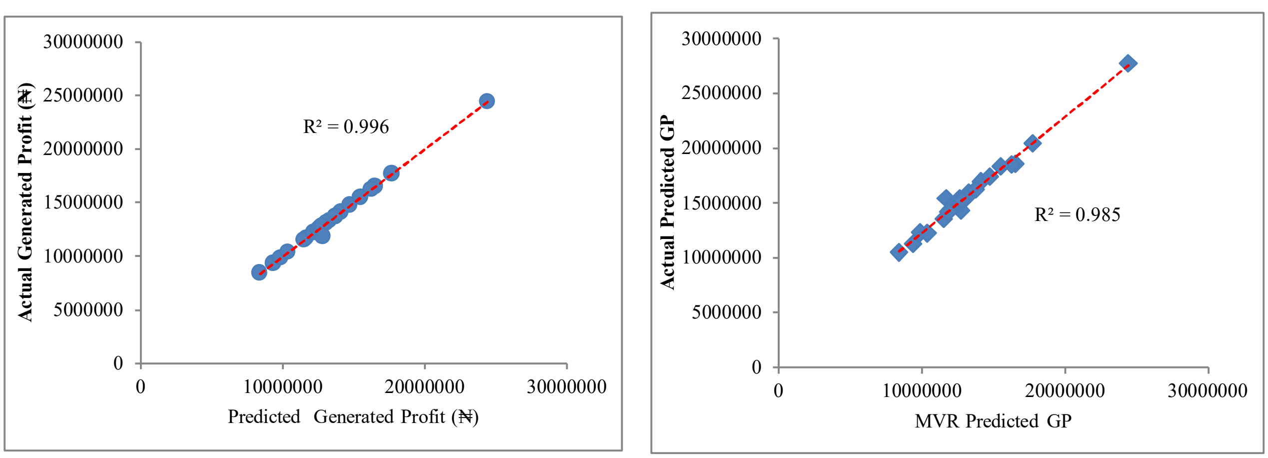
The MVR model was developed using the collected data set in SPSS© Window. The result from the modeling was transformed into mathematical equations. Eq (9) shows the MVR model developed for the prediction of Generated Profit in granite quarries.

$$GP = -1.914e - 12TP + 0.0023TPC - 48.5OE + 0.00006R + 0.5TR -1.386e - 10 \quad (9)$$

where TP is Total production rate, TPC is total production cost in ₦, OE is the other expense in ₦, TR is total revenue in ₦, and GP is generated profit.

6.3. Comparison between MVR and ANN developed model prediction performance

The model was validated with the training dataset and visualized as presented in Figure 12. The obtained coefficient of correlation (R^2) value for the empirical model is 0.985 and it is suitable for predicting generated profit.



(a) **(b)**

Figure 12. Model evaluation result, a. ANN, b. MVR.

The model performance was evaluated using three model prediction evaluators including RMSE, MSE. The error analysis result is presents in Figure 13. The result shows that the ANN model have the lowest RSME and MSE value.

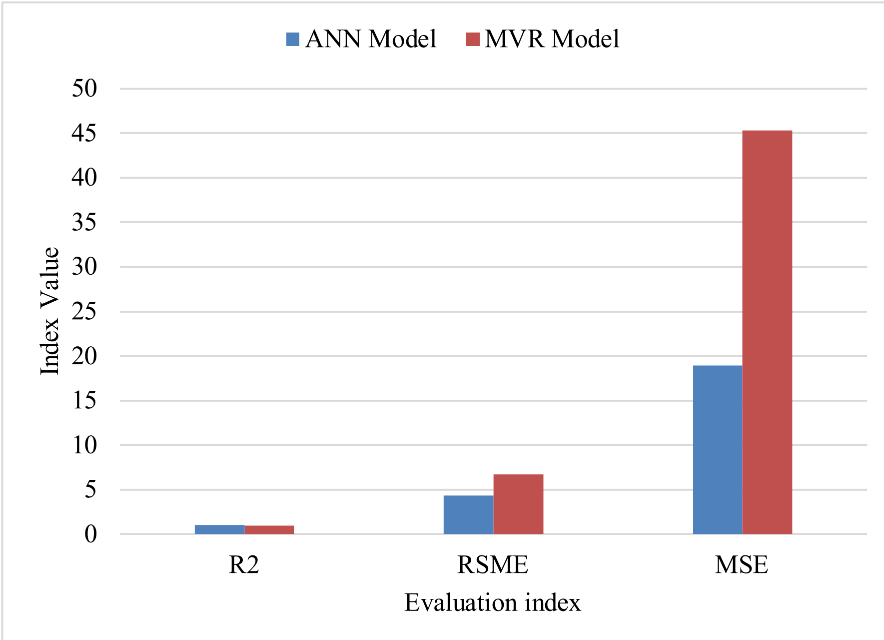


Figure 12. Error analysis result for MVR and ANN models.

The result of the performance indices as indicated that the ANN models are more accurate than MVR model predicted values. The evaluation result also indicated that ANN model with 5-6-1 network architecture has the lowest RMSE, MSE, and highest coefficient of determination (R^2) closer to unity, making it the best predictive model.

7. Conclusions

Granite mining in Nigeria offers economic growth, job opportunities, and infrastructure development. Predictive models can improve profit by optimizing extraction, reducing waste, and forecasting market demand. Predicting granite, mine profits with AI models helps optimize resource allocation, plan investments, and enhance sustainability by minimizing waste, thus ensuring a more efficient and profitable mining operation. This study developed artificially intelligent empirical prediction models for determining the profitability of granite aggregate production. The study's specific objectives include investigating the operation characteristics of the selected granite aggregate quarries in the case study area, assessing the blast production and efficiency of the case study mine, conducting a profitability analysis of granite aggregate production in the selected quarries, developing an ANN and an MVR empirical model for predicting granite aggregate overall profit, and comparing the developed models using three model performance indicators. The data for this study was gathered using a formal survey questionnaire. The information gathered included information on granite marketing operations, royalty, production costs, and the number and relative importance of various participants in terms of flow volume. The study utilized descriptive statistics, MATLAB 2017© and SPSS16.0© software in analyzing and modeling the data collected from granite traders in the studied areas.

The following conclusions were drawn from the results of the analysis:

1. The result revealed that large burden distance result in bigger Fragmentation size including $X_{50,}$ $X_{80,}$ and X_{max} fragmentation size. Burden distance of 2 m and 2 m spacing was identified as the optimum burden and spacing.
2. The findings revealed that blast mean size and 80% passing mesh size for each of the blast round have a positive correlation relationship.
3. The result from this study indicated that uniformity index has a positive correlation with blast efficiency and negative correlation with Maximum blast fragmentation size.
4. The mine characteristics were such that 17% of the selected quarries had been in business for 1 to 5 years, while the majority (83%) had been in

business for 6 to 10 years. This finding implies that the majority of the studied quarries is no longer new to the industry and must have attained a reasonable level of professionalism in order to improve their operational efficiency. It was discovered that Q1 has higher production at the start of early years (year one and two data). The annual production capacity of the Q1 and Q2 mines ranges from 891830 to 411930 tons per year and 675500 to 455500 tons per year, respectively. It was discovered that Q1 produces more than Q2. Furthermore, the average total production cost per year for Q1 and Q2 ranges from N114,600,000 to N40030693.6 and from N85,81,07,60 to N58,98,11,60, respectively. The production cost was discovered to rise in tandem with the rate of production.

5. ANN and MVR soft computing were used to create two models. The ANN model was built with a 5:6:1 training architecture and a Bayesian algorithm. The developed model was converted into four neuron series expression mathematical equations. The ANN model has a coefficient of determination (R^2) of 99.6%, an RSME of 4.355, and an MSE of 474.0668. The MVR model was created using SPSS software, and it provided a 98.5% coefficient of correlation with the actual measured blast efficiency values, as well as high RSME and MSE values. Due to the high prediction error, the RMSE and MSE show that the model is unsuitable for predicting generated profit in a typical quarry. The two models' prediction accuracy was compared using the R^2, RMSE, and MSE model evaluators. The accuracy evaluation reveals that the ANN model is more accurate than the MVR model. As a result, the ANN model can reasonably predict granite quarry blast efficiency with a high degree of accuracy.

The authors' future work will focus on assessing the effect of blasting efficiency on loading operation and overall mine profit and operation cost. This study will also assess the impact of explosive energy on particle size distribution using deep learning motivated image analysis approach.

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ارزیابی اندازه و سودآوری وابسته به تولید پایین‌دستی گرانیت: کاربرد مدل هوش مصنوعی مبتنی بر ریاضی و نرم‌افزار WipFrag

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چکیده:

هدف از این کار تحقیقاتی ایجاد مدل‌های تجربی برای ارزیابی سودآوری تولید سنگدانه گرانیت در معادن سنگدانه آکوره، ایالت اوندو است. علاوه بر این، یک مدل شبکه عصبی مصنوعی (ANN) برای سودآوری گرانیت توسعه داده شد. برای جمع آوری داده‌ها برای تحقیق از پرسشنامه پیمایش ساختاریافته استفاده شد. داده‌های استخراج شده از معدن مطالعه موردی برای این مطالعه شامل عملیات بازاریابی گرانیتی، حق امتیاز، هزینه های تولید و اطلاعات تولید معدن است. در این مطالعه کارایی تکه تکه شدن گرانیت با استفاده از نرم افزار WipFrag مورد ارزیابی قرار گرفت. رابطه بین توزیع اندازه ذرات، طراحی انفجار، راندمان انفجار و شاخص یکنواختی با استفاده از نتیجه WipFrag مورد تجزیه و تحلیل قرار گرفت. طراحی بهینه انفجار نیز شناسایی و برای تولید معدن توصیه شد. نتیجه نشان داد که فواصل بارسنگ بزرگ منجر به بزرگتر شدن اندازه‌های خردایش X50، X80 و Xmax می‌شود. فاصله بار ۲ متر و فاصله ۲ متر به عنوان بار و فاصله بهینه شناسایی شد. یافته‌ها نشان داد که اندازه متوسط انفجار و اندازه مش عبور ۸۰ درصد همبستگی مثبت دارند. نتایج حاصل از این مطالعه نشان داد که شاخص یکنواختی با راندمان انفجار همبستگی مثبت و با حداکثر اندازه خردایش حاصل از انفجار همبستگی منفی دارد. دقت پیش‌بینی مدل‌های توسعه‌یافته با استفاده از ضریب تعیین (R2)، ریشه میانگین مربعات خطا (RMSE) و میانگین مربع خطا (MSE) ارزیابی شد. تجزیه و تحلیل خطا نشان داد که مدل ANN برای پیش‌بینی سود تولید شده از معدن مناسب است.

کلمات کلیدی: راندمان انفجار، شاخص یکنواختی، خردایش حاصل از انفجار، گرانیت، اقتصاد معدنی.