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Profitability Assessment of Granite Aggregate Production and the Development of a Profit Assessment Model

Melodi Mbuyi Mata, Blessing Olamide Taiwo, Afolabi Ayodele David

Abstract—The purpose of this research 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 and multivariate predicting models for granite profitability were developed in the study. A formal survey questionnaire was used to collect data for the study. The data extracted from the case study mine for this study include granite marketing operations, royalty, production costs, and mine production information. The following methods were used to achieve the goal of this study: descriptive statistics, MATLAB 2017, and SPSS16.0 software in analyzing and modeling the data collected from granite traders in the study areas. The ANN and Multi Variant Regression models' prediction accuracy was compared using a coefficient of determination (R^2), Root Mean Square Error (RMSE), and mean square error (MSE). Due to the high prediction error, the model evaluation indices revealed that the ANN model was suitable for predicting generated profit in a typical quarry. More quarries in Nigeria's southwest region and other geopolitical zones should be considered to improve ANN prediction accuracy.

Keywords—National development, granite, profitability assessment, ANN models.

I. INTRODUCTION

FOR centuries, mining has made significant contributions to national development and technological advancement. According to Osasan, a thriving mining sector, like any other, provides a solid foundation for a country's growth [1].

Quarrying, a subset of mining is a foundational component of any economy's construction sector. Thus, solid minerals are inextricably linked to human progress and civilization. According to [2], the evolution of civilization and democratization, as well as the massive drive for industrial economy development around the world, has resulted in an increase in the need and demand for solid minerals, alongside an increase in technology, construction, and building activities.

Reference [3] also stated that, in order to sustain our technologically based society, demand for industrial rock commodities is increasing, and exploration for these commodities is essential. According to the United States Geological Survey, Africa has an abundance of granite deposits and a high potential for precious and base metals [4]. It is also a major producer of several strategic minerals and metals, holding approximately 30% of the world's mineral reserves; 80% of global platinum, chromium, and tantalum reserves; and more than 40% of gold, diamond, cobalt, manganese, and phosphate reserves. Mattew and Emmanuel also stated that Africa's abundant mineral deposits are not unrelated to the continent's geology, as minerals are directly associated with the lithological characteristics of the continent [3].

Africa is dominated by Precambrian basement crystalline rocks composed of schist, gneisses, green schist, and granites, and it hosts and supplies approximately 80% of the world's solid minerals [5]. Reference [3] also noted that, the despite the enormous amount of wealth that mineral resources should translate into for African countries, incessant wars and an unstable political situation have created an unfortunate situation in which 'potential wealth' has become a 'present course. According to [6], mineral exploration investment in Africa has been extremely low when compared to other major mineral producing regions of the world since the 1980s until today.

In accordance with the Metal and Economics Group [7], the mining industry worldwide spends about 10% of its annual production value on exploration, while Africa only spends about 1%. Despite the fact that Africa has more than 30% of the world's mineral and metal resources, the mineral exploration budget in 2010 was approximately $1.4 billion, accounting for 13% of global budgets in 2010 [7]. According to Melodi et al., poor marketing reduces the rate of production and supply of quarry end products and limits the supply rate between the producer and the industrial users [8]. Mineral exploration and the mining industry in Nigeria can be traced back to 1903/1904, when the then colonial government established the Mineral Surveys of Southern and Northern Nigeria [9]. In the past, the extractive industry in Nigeria was dominated by the government, and as a result, the discovery of oil in 1956 harmed the mineral extraction industries [3]. Following the oil boom, the government and industry shifted their focus to this new resource, causing the country to develop a monolithic economy based solely on oil revenues. As a result, other industries such as agriculture and solid minerals were pushed to the margins.

Nigeria is best known in the sector of natural resources for its oil and gas production, ranking sixth in the world [10]. Granite is an igneous rock composed primarily of quartz, feldspar, micas, amphiboles, and a variety of trace minerals [11]. These minerals, as well as their variations in abundance

Melodi Mbuyi Mata, Blessing Olamide Taiwo, and Afolabi Ayodele David are with Department of Mining Engineering, Federal University of Technology, Akure Nigeria (e-mail: taiwoblessing199@gmail.com).

and alteration, give granite its various colors and textures [12]. The raw material rock aggregate is used in engineering applications such as roads, airports, bridges, and water structures. It is crucial in the design and construction of a country's infrastructure. Aggregate is one of the most expensive building materials [13].

Quarrying is a type of mining method in which rock or minerals are extracted in a single bench, according to [14]. Also, from [14], the end product materials from the quarries include marble, gravel, granite, and limestone, which are considered necessary in modern civil engineering and construction works. It is also known that over the centuries, stones have played critical roles in the lives of the entire human race [14]. It provides minerals to meet many societal needs, as stone products are primarily used in concrete structures such as houses, bridges, and roads. Quarried rock blocks are used for facing buildings when cut, shaped, and carved; rough blocks are used as amour in sea defenses, and in less direct ways, it is used in industrial production processes involving toothpaste, cosmetics, paints, and plastic. Reference [15] emphasized the use of quarry dusts for soil "re-mineralization." As a result, quarrying is the only source of these raw materials in many parts of the world where mineral deposits such as hard rock and sand and gravel are available. The broad industrial sector of mining, which includes quarrying, accounts for 37% of Nigeria's GDP [16].

Granite aggregate production involves producing minimal breaks in the stone (blasting), extracting the stone with heavy machinery, securing the stone on a vehicle for transportation (hauling), and crushing the materials into various sizes (processing) [17]. According to [18], the project task of planning and operating a granite quarry consists of at least three components: a technical component, a narrowly focused economic component, and a more broadly based economic component, which includes financial and business elements that influence quarry performance within the industry at large.

The importance and potential of granite aggregate production in Nigeria's mineral sector cannot be overstated, but its production has not been adequately monitored to understand profitability. Despite various governmental policy interests in increasing the industrial use of granite, empirical evidence on aggregate granite production profitability is lacking. This research is therefore critical in order to predict the performance of the granite aggregate profit by demonstrating the current granite aggregate production profit margin and how the current granite market in the case study area is structured.

Using empirical models, an attempt was made to improve the granite aggregate profit evaluation. Because of their inability to address the internal complexities in the input parameters, these empirical models were generally unsuccessful. Furthermore, they only allowed a limited number of inputs and could not predict multiple outcomes. To address the shortcomings of empirical predictors and resolve the limitation in granite aggregate profitability assessment, an ANN will be used to develop empirical models for predicting granite aggregate overall profit.

Description of the Study 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 [19]. Akure is located between 7°15' 9.22" N and 5°11' 35.23" E (see Fig. 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 [20], the old granite and metamorphic rock formation in the location axis consists primarily of amphibolite and gneisses.

II. Research Methodology

In the case study quarries, the research method used in this study includes collection of the production cost data as well as sales and market report information. The data for this study came from both primary and secondary mine data records. The information was gathered in order to evaluate the granite production characteristics and to create prediction models for the profitability of quarry mine operations.

A. Primary Data Collection

Primary data, such as mine production rate, price, and sales information, were collected in this study using a detailed and well-structured survey questionnaire. The survey questionnaire was specifically designed to track the production rate, supply prices, production volumes, and transaction costs in the source and final markets along the granite value chain in the case study quarries. The sample size was computed according to [21] as shown in (1):

$$N = \frac{z^2 . p . q}{e^2} \tag{1}$$

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).

According to [22], there is no formula for determining the number of interviews needed for each stage or segment of the marketing chain. Several hundreds of producers, thousands of consumers, dozens of rural traders, dozens of wholesalers, and thousands of retailers are frequently found for the marketing of a single type commodity from one production area (origin) to one urban market (destination). As a result, establishing a fixed procedure (e.g., a certain percentage of the estimated population of a specific type of participant) may be excessive for some segments of the study and insufficient for others. As a result, for this study, sampling by segments with no size restrictions will be used.

B. Analysis of Market Performance

Marketing costs and price variation over time were used to evaluate market performance. Marketing costs included operating costs that were proportional to the volume and level of business transacted [23]. Buying costs (purchase price multiplied by tons of granite, government marketing fee, broker payment), transportation costs, and selling costs were all included. The cost was considered in the context of a potential trader's initial capital requirement. As shown in (2), gross margin was calculated as the difference between buying and selling prices for individual traders.

$$\text{Net margins} = \text{TR-OC} \quad (2)$$

where TR is the total revenue, and OC is the operation cost.

Royalty paid per tone was calculated based on the payment standard per ton as published by Nigeria Ministry of Mine and Steel Development [24].

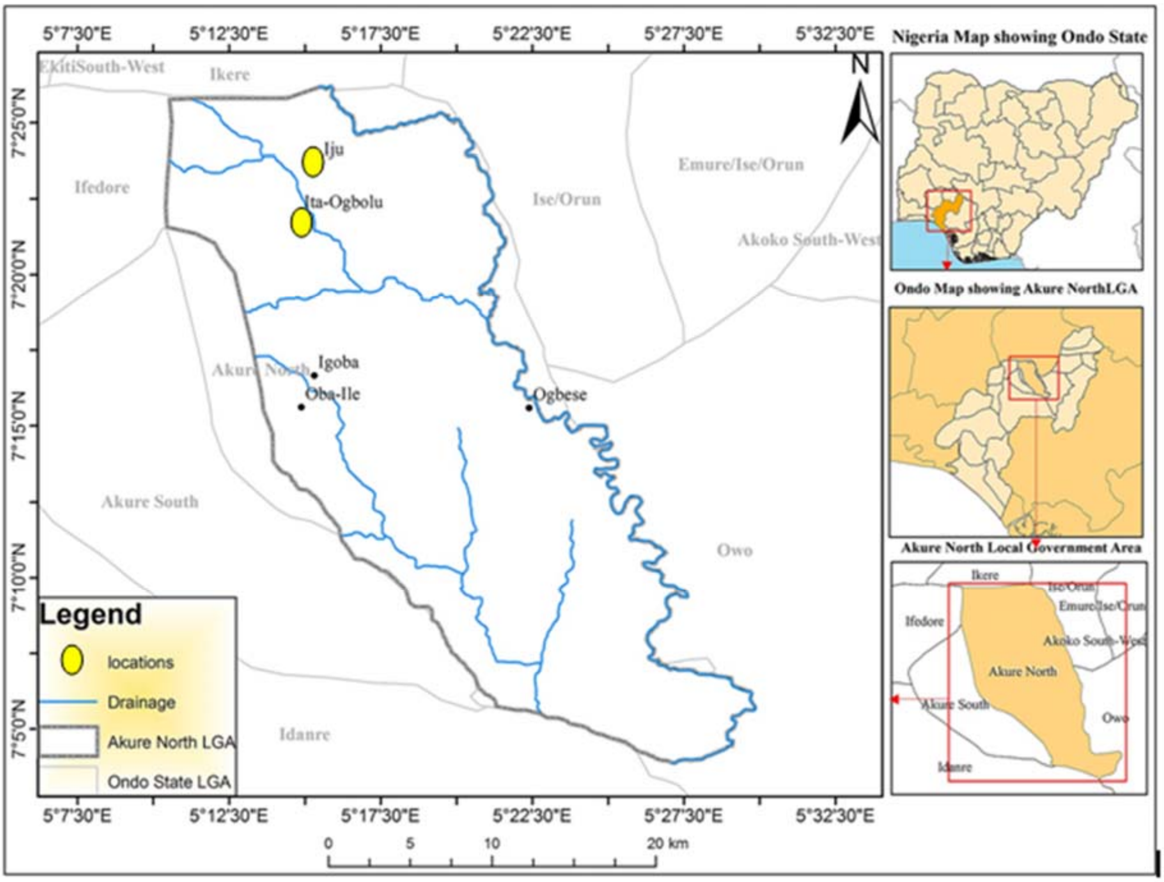


Fig. 1 Geological Map of Ondo State showing Q1 and Q2

TABLE I
MODEL INPUT AND OUTPUT PARAMETERS AND THEIR SYMBOLS

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		

C. 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 25 datasets from the case study quarries.

D. ANN Model Development

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 I). 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.

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.

E. 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 (3):

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{3}$$

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.

F. Evaluation of the Developed Model Performance

The best network architecture is chosen after successful training, validation, and testing with various network architectures. Reference [25] used (4)-(6) to compute the MSE, RMSE, Maximum Relative Error (MRE), and Determination coefficient (R^2) for various models:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (ypredi - ymeasi)2}{N}} \tag{4}$$

$$\text{MSE} = \frac{\sum_{i=1}^{N} (ypredi - ymeasi)2}{N} \tag{5}$$

$$R^2 = \sum_i \frac{(\text{Ypred} - \text{Ymeas})2}{\sum(\text{Ypredi})2} \tag{6}$$

where Ypred is the predicted output; Ymeas is the measured output, and N is the number of input–output data pairs.

III. Results and Discussions

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

A. Number of Years in Operation by the Selected Quarries

Fig. 2 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.

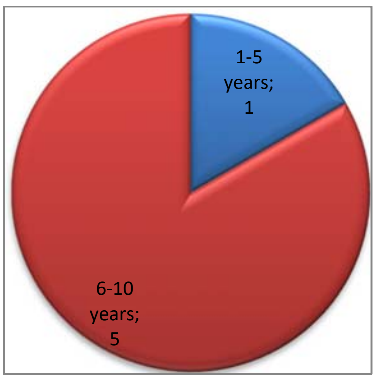
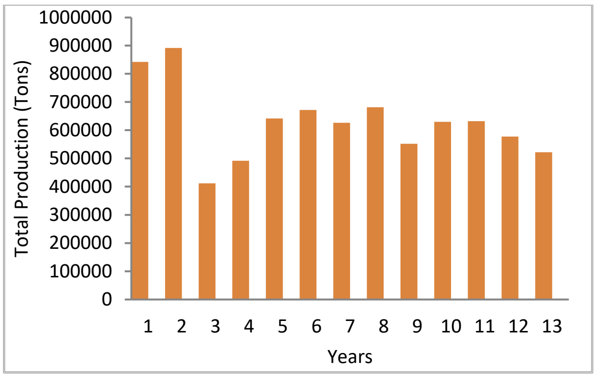


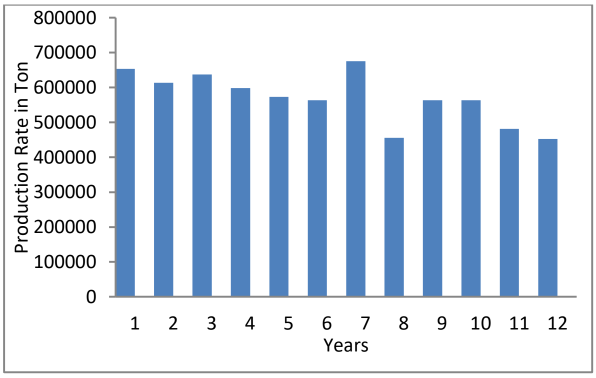
Fig. 2 Number of Years in Operation Q1 and Q2

B. Annual Production Capacity of the Quarries

Fig. 3 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 Fig. 3.



(a) Q1 Mine



(b) Q2 Mine

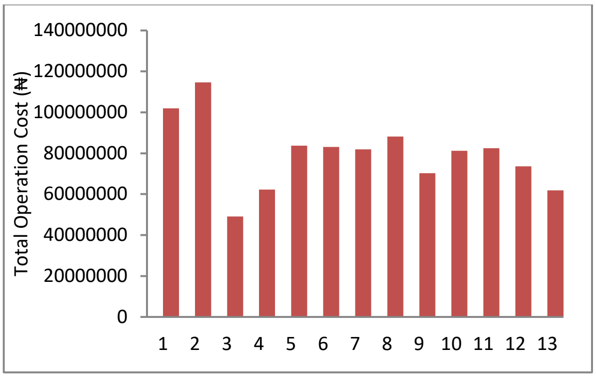
Fig. 3 Annual Production Capacity

C. Operational Cost per year

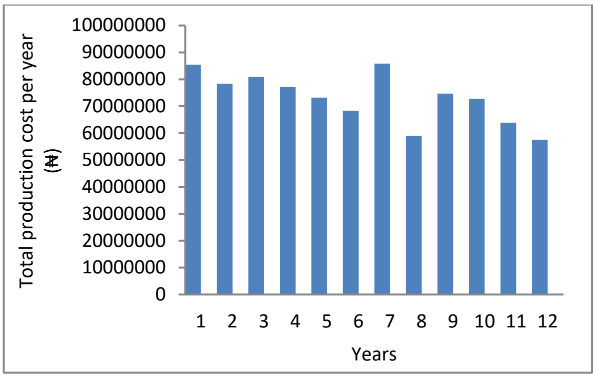
The result in Fig. 4 reveals that the average total production cost per year for Q1 and Q2 ranges from ₦ 114,600,000 to ₦ 40030693.6 and ₦85,81,07,60 to ₦ 58,98,11,60 respectively. The production rate of granite depended mainly on the total amount of capital incurred on the operation in the mine as noted by [26] on the evaluation of Bench Drilling Phase of Diamond Wire Sawing Technique cost for Granite Mining. As shown in Fig. 5, the production cost was found to increase in a positive correlation order with the production rate.

D. ANN Model Development Result

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. Fig. 8 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).



(a) Q1 Mine



(b) Q2 Mine

Fig. 4 Mine Operational Cost per month a.Q1 Mine, b.Q2 Mine

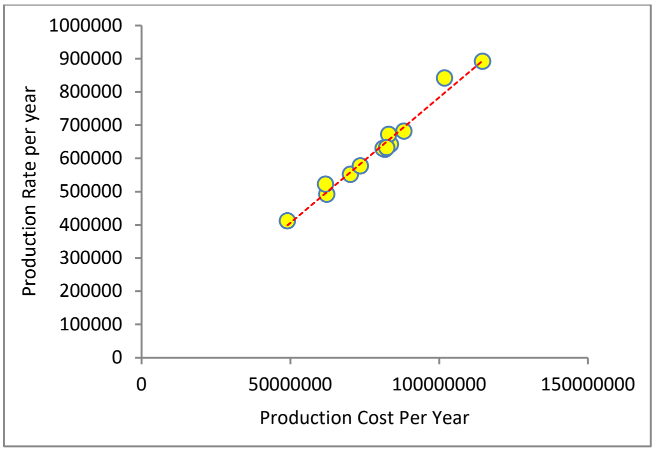


Fig. 5 Relationship between production rate and production cost

Fig. 6 compares the predicted values of the developed ANN model to the actual Generated Profit value. The prediction result shows a strong coefficient of determination (R2) = 0.996 close to unity between the predicted Generated profit and the calculated Generated profit from the best ANN model.

Equation (7) shows the general form of the principle of operation of the ANN model as noted by [27].

$$p_j = f_{sig/purlin}\{b_0 + \sum_{k=1}^{n}[fsig(\mathrm{bnk} + \sum_{i=1}^{m} \mathrm{wik}\Gamma\mathrm{i})wk \times \ldots]\} \quad (7)$$

where, n is the number of neurons in the hidden layer; b0 is the bias in the output layer; bnk is the bias in the kth neuron of the hidden layer; wik is the weight of connection between the ith input parameter and the hidden layer; wk is the weight of link between the kth of the hidden layer and the single output neuronΓi is the input variable i; pj is the output variable; and fpurlin and fsig are the linear and nonlinear transfer functions, respectively.

Equation (8) shows the mathematical equation developed from optimum proposed model.

N1 = 1.4689Tanh (0.27288TP – 0.5051TPC - 0.2732OE + 0.2878R + 0.2491TR - 0.9578)

N2 = -0.0031Tanh (0.3721TP – 0.375TPC - 0.3967OE + 0.4038R + 0.3327TR - 0.2911)

N3 = 1.0322Tanh (0.0722TP – 0.3122TPC - 0.3634OE + 0.2766R + 0.3051TR + 0.0407)

N4= -2.7454Tanh (0.2297TP+0.4373TPC +0.2129OE -0.4757R-0.3784TR-0.2151)

N5 = 1.7737Tanh (0.2166TP – 0.44843TPC -0.3325OE + 0.3249R + 0.2398TR - 0.8092)

N6 = -1.3820Tanh (- 0.3161TP + 0.5293TPC + 0.5153OE - 0.2723R - 0.4666TR - 1.1801)

GP = [Tanh(D1 + D2 + D3 …… + D6) - 0.0127] (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.

To validate the accuracy of the extracted mathematical equations, the prediction values from (8) were compared with the model predicted blast efficiency as shown in Fig. 8. The compared experiment shows unity (R^2 = 1) coefficient of determination.

E. Multivariate Regression Model Result

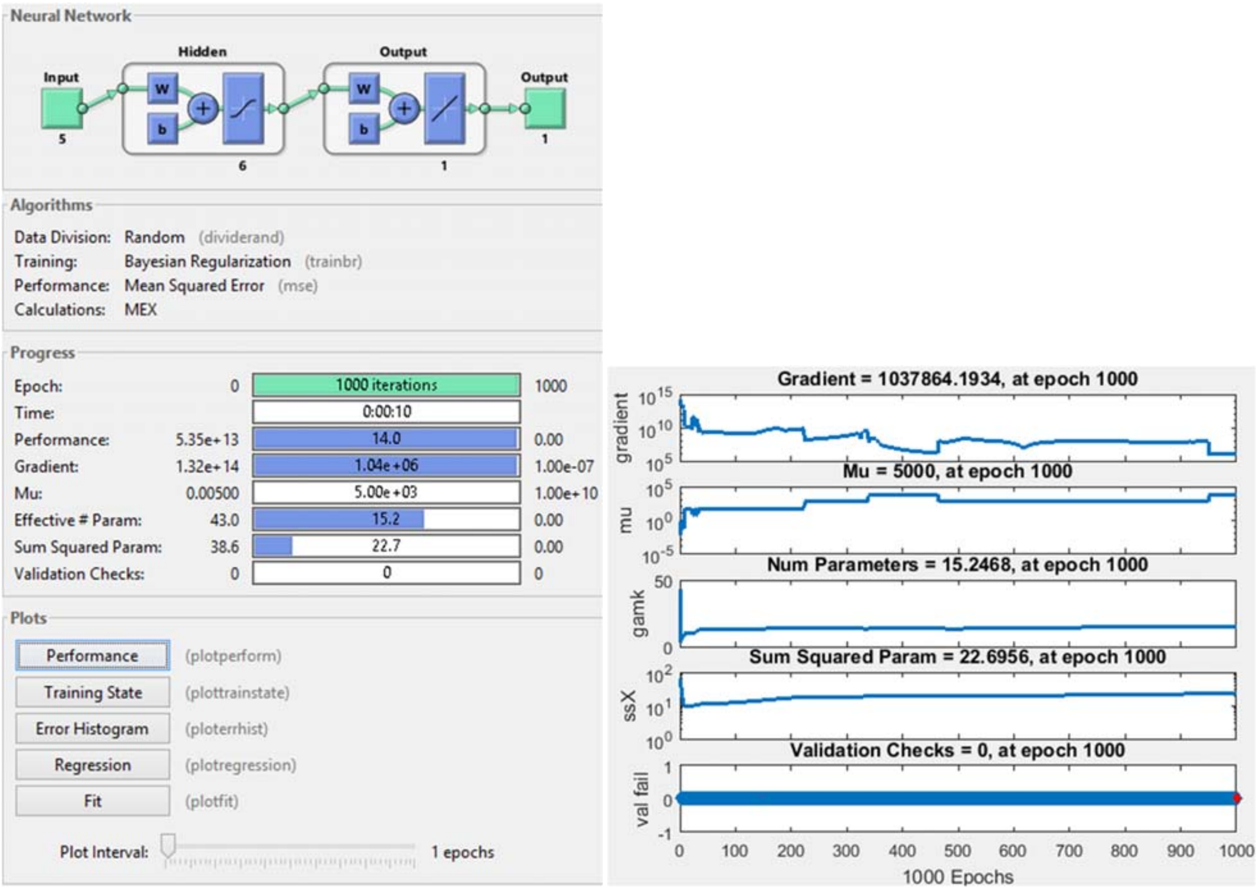
The MVR model was developed using the collected data set in SPSS© Window. The result from the modeling was transformed into mathematical equations presented in (9):

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

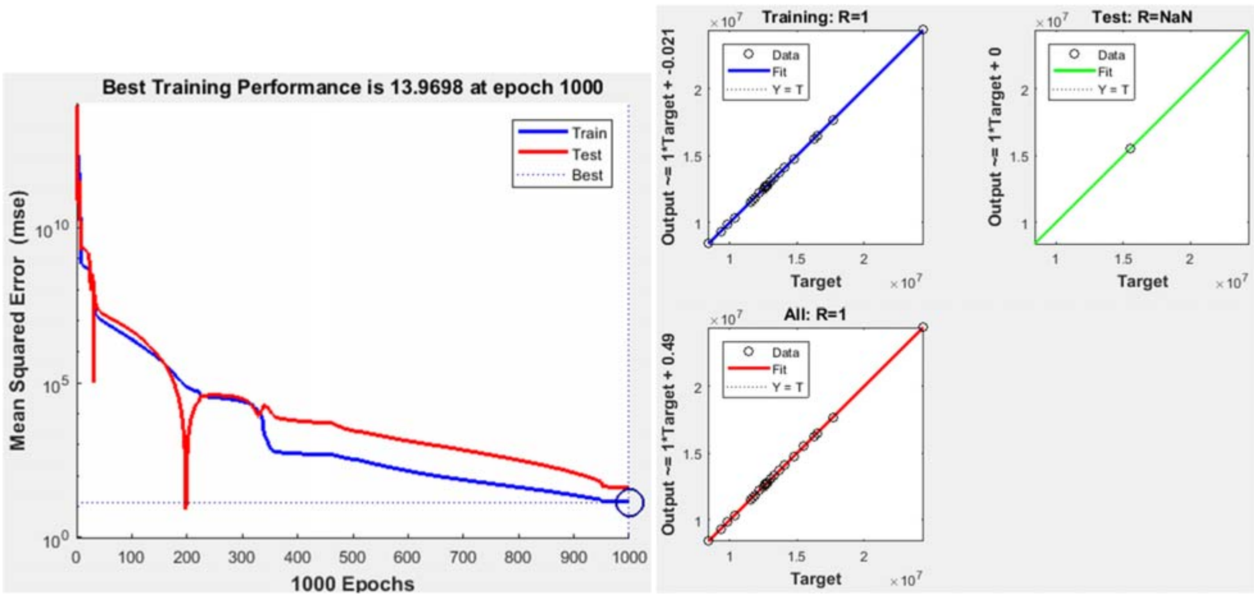
where TP is Total production rate, TPC is Total Production cost in ₦, OE is the other expense in ₦, TR is Total Revenue in ₦, and GP is Generated Profit.

The Model was validated with the training dataset and visualized as presented in Fig. 9.

Equation (9) shows the MVR model developed for the prediction of Generated Profit in granite quarries. The obtained coefficient of correlation (R^2) value for the empirical model is 0.985 (see Fig. 9) and it is suitable for predicting Generated Profit.



(a) (b)



(c) (d)

Fig. 6 ANN Model Training, and validation Coefficient of Correlation: (a), (b) Training Algorithm architecture; (c), (d) Training response and Training Regression

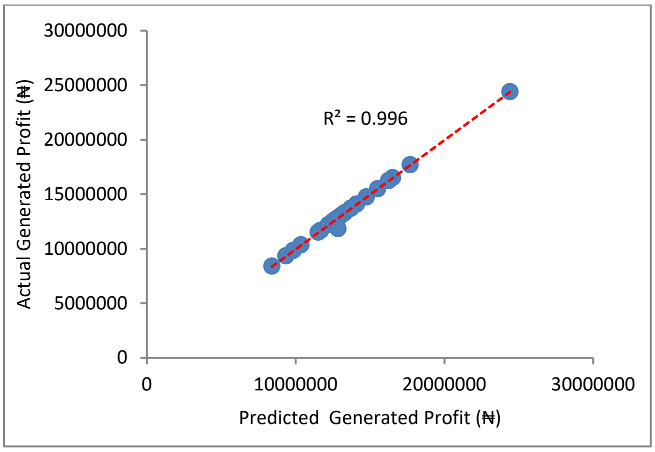


Fig. 7 Model Evaluation Result

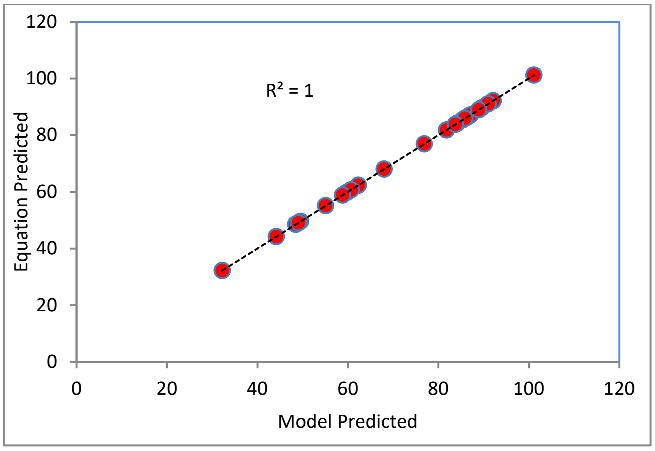


Fig. 8 Comparison between the model prediction and mathematical equation prediction

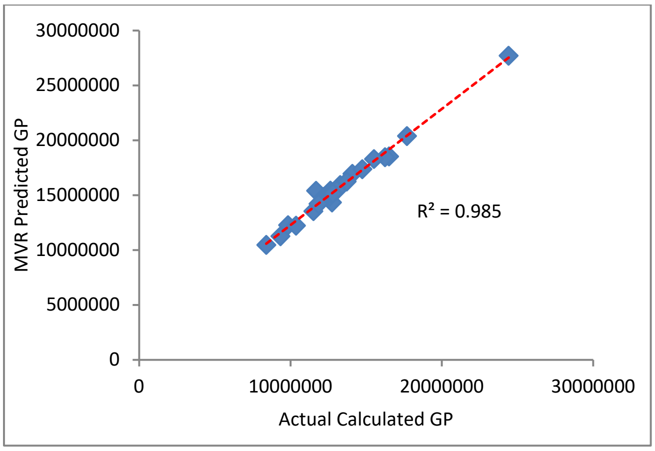


Fig. 9 MVR Model Prediction Performance Curve

F. Comparison between the MVR and ANN Developed Model Prediction Performance

Table II and Fig. 10 show the predicted Generated Profit and the actual calculated value for the two models. Fig. 10 depicts the similarity of ANN predicted values to GP calculated values. Both models overestimated blast efficiency in the same way. Three model prediction checkers were used to compare the performance of the two models. Table III contains the evaluation result from the three model performance indices adopted in this study.

TABLE II
PREDICTED GENERATED PROFIT FROM THE TWO MODELS

Calculated Generated Profit (GP) ₦	MVR Predicted GP (₦)	ANN Predicted GP (₦)
24409500	27708150	24409500
11689500	15399026	11689500
12739500	14327693	12739501
11519500	13535452	11519503
12629500	15337761	12629502
17703500	20393503	17703504
12201878.4	14851135	12201880
14092278.4	16947468	14092279
12597878.4	14870263	12597884
13288918.4	15917627	13288915
12474374.4	15141286	12474376
13060630.4	15441371	13060633
16521193.6	18523845	16521192
12642080	15406100	12642084
13717280	16252395	13717276
14752480	17370664	14752470
12664240	15160552	12664240
12803680	15174127	12803683
16246880	18457568	16246880
15514240	18292286	15514234
9343840	11253219	9343837
9846880	12264288	9846872
11846880	14199688	12846880
8398720	10464842	8398725
10363200	12225091	10363196

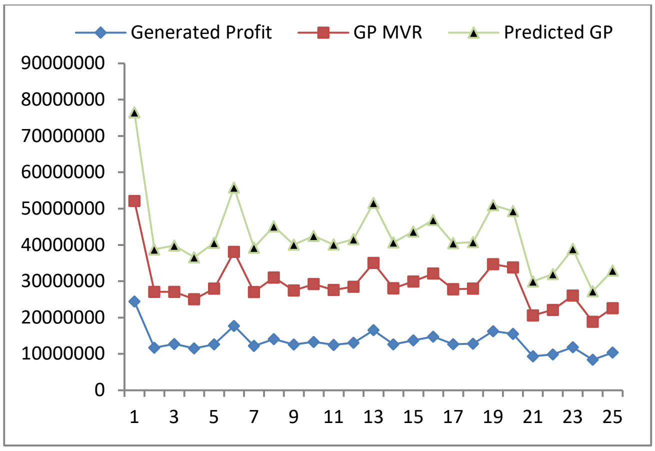


Fig. 10 Prediction performance comparison for MVR, ANN models and the Actual GP values for year

TABLE III
RESULT OF THE MODEL EVALUATORS

Model Evaluators	ANN Model	MVR Model
R^2	0.998	0.985
RSME	4.355	1.58E+14
MSE	474.0668	1.58E+14

Table III indicated that the model prediction result for generated profit closely correlates with that calculated profit as also indicated by the evaluation indices (RSME and R^2 values). 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.

IV. Conclusion

The study developed artificial intelligent empirical prediction models for determining the profitability of Granite aggregate production. The study's specific objectives included: investigating the operation characteristics of the selected granite aggregate quarries in the case study area; 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 both ANN and MVR models using three model performance indicators. The data for this study were 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 study areas.

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

1. 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.
2. 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.
3. 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.
4. 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.
5. 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.
6. 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.

V. Recommendations

Based on the results, the discussion and the conclusion presented in this study the following recommendations are made:

1. More quarries from Nigeria's southwest region and other geopolitical zones should be considered to improve the ANN prediction accuracy.
2. The government and private sector should promote processing by making financing facilities available to encourage private sector investment in processing activities.
3. The government should develop standard measures to prevent middlemen from exploiting end users.

Declaration of Conflict of Interests

The authors declare that there is no conflict of interest and No funds, grants, or other support was received for the completion of this work.

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