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Blast Design Optimization Using Artificial Neural Network Approach and Langaford – Kihlstrom Model for Selected Rock Types in Nigeria

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ABSTRACT

Blasting is an important process in mining that affects loading, hauling, and crushing. A well-planned blast design helps to achieve good fragmentation, reduce energy use, and lower costs. This study develops an optimized blast design model by combining the Langaford-Kihlstrom method with an Artificial Neural Network (ANN) to improve blasting efficiency for selected rock types in Nigeria. The research examined the geomechanical and structural properties of limestone, granite, and marble from Lafarge Ewekoro Mines, Mercy Quarry, and Jakura Marble Obajana Mines. Parameters such as Uniaxial Compressive Strength (UCS), Rock Quality Designation (RQD), and Blastability Index (BI) were determined through laboratory and field tests. A comparison of ANN predictions with the Langaford-Kihlstrom model and quarry data showed that ANN provided more accurate estimates of explosive requirements and reduced the overestimation problems of empirical models. For limestone at Ewekoro Mines, ANN predicted explosive usage of 1,873.737 kg for Blast 1, closely matching the quarry data (1,900 kg), while the Langaford model overestimated at 2,316.5 kg. In granite blasting at Mercy Quarry, ANN estimated 1,628.187 kg for Blast 1, compared to quarry data (1,900 kg) and the Langaford model (2,316.5 kg). Similarly, for marble at Jakura Marble, ANN predicted 7,123.353 kg for Blast 1, closely matching the quarry data (7,025 kg), while the Langaford model significantly overestimated at 20,606.3 kg. The ANN model also reduced costs. For granite blasting, ANN lowered explosive costs by 39.7% compared to quarry estimates and 48.2% compared to the Langaford model. ANN optimization resulted in a 16.6% overall reduction in total explosive costs across all rock types. ANN predictions also improved fragmentation, producing sizes that reduced the need for secondary blasting. Performance evaluation showed that the ANN model achieved an R^2 score of 92.3% and an RMSE of 6.03, demonstrating its accuracy in blast design. The findings highlight the usefulness of ANN in improving blast planning, reducing costs, and improving efficiency in mining operations.

Key words: Blast Design, Artificial Neural Network, Langaford-Kilhstrom, Prediction and Models.

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1. Introduction

The mining process begins with drilling and blasting activities and these unit operations have a significant impact on downstream operating cost such as loading, hauling, crushing and milling. Drilling is the process of making a hole into a hard surface where the length of the hole is very large compared to the diameter (Gao *et al,* 2023). Surface mining requires drilling for different purposes that include: production drilling i.e. for making holes for placement of explosives for blasting, exploration drilling i.e. for sample collections to estimate the quality and quantity of a mineral reserve and technical drilling i.e. during development of a mine for drainage, slope stability and foundation testing purposes (Mosheni *et al,* 2023).

Blasting is the process of fracturing material by the use of a calculated amount of explosive so that a predetermined volume of material is broken (Nanda and Naik, 2023). Good blast design and execution are essential to successful mining operations. Many factors are taken into account when determining the type of blast design or Explosive to be used. This includes: rock type, density and rock strength are all important factors, as well as fracture condition of the rock (Bhadwakar *et al*, 2021).Drilling and blasting are seen as sub-systems of the size reducing operations in mining. In other to have better design parameters for economical mineral production and good fragmentation, the drilling and blasting operations needs to be optimized to improve fragmentation, reducing the time and energy to load. If blasting are not professionally designed, the use of explosive and safety of the mines environment are at risk (Saliu *et al,* 2017). Better blasting produces good fragmentation sizes, meaning, producing more fines will reduce the energy required to crush and grind the material hence increasing crusher and mill output. In nutshell, good blasting necessitates high productivity and safety (Fatima *et al, 2019;* Isa *et al,* 2020).

It is therefore important that much attention is given to drilling and blasting geometry using Langaford model for fragmentation prediction. There is need to develop drilling and blasting models for fragmentation optimization predictions in mines. Rock strength characteristics is a crucial factor in blast optimization and explosive efficiency (Albath and Sazid, 2021). The explosive energy level and distribution of explosives must correlate with the strength and structural conditions of the rock in order to obtain a successful rock fragmentation. Rocks exhibiting high uniaxial compressive strength after laboratory tests will require a larger quantity of explosives, an optimal design is therefore needed to obtain desirable rock size after blasting operation to avoid over-fragmentation or under-fragmentation, which consequently affects the cost of production. In terms of blasting parameters, bench height, the diameter of the hole, burden-to-spacing length, stemming length, powder factor etc. are considered in developing a suitable blast design that can be easily managed and implemented in the mine.

Geographical Region under Study

The Lafarge Cement limestone mine site is located approximately 50 km southwest of Abeokuta and 90 km northwest of Lagos, with coordinate of LatitudeN6°53' 36.53" and longitudeE3°12' 19.20". The second study area was Jakura Marble Industries Limited, Obajana with the coordinate Latitude N8°0' 31.82" and longitude E6°26' 50.496" located off Kaba-Lokoja road in Kogi State, Nigeria. The third site is Merciful Granite Quarry Limited, Ilara-mokin located off Akure-Ilesha Express road, Ondo State, Nigeria, with coordinate latitude; N7° 19' 39" and longitude, 5° 5' 29".

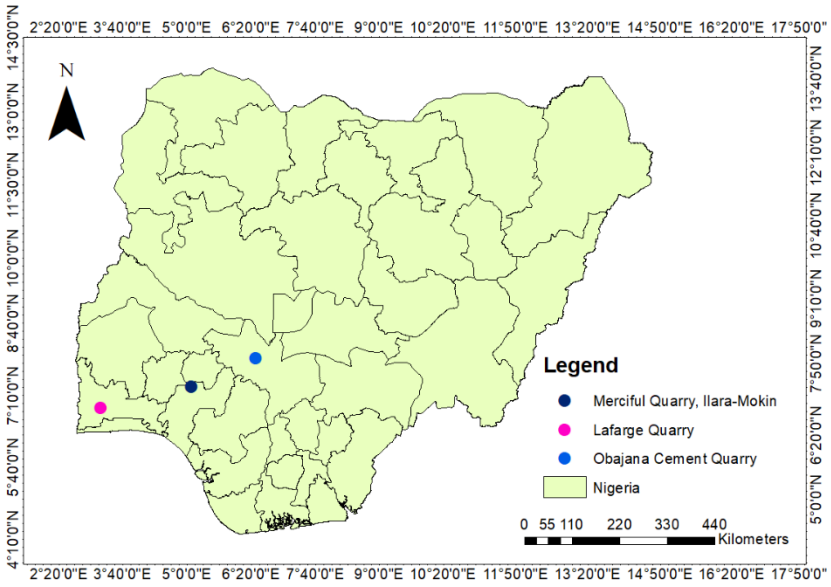


Figure 1: Geographical map of Nigeria showing Study Areas.

2. Material and Methods

Data Collection

The rock samples used in this research work were collected from Merciful granite quarry, Ilara- Mokin, Ondo State, Jakura Marble Industries Limited, Obajana, Kogi-State and Lafarge Cement Limestone mine site at Ewekoro, Ogun-State. They were characterized based on their rock strength and structural properties. The data collected from the blast experiments were used to evaluate the performance of the Langefors-Kihlstrom Model and ANN in predicting blast outcomes. The data include blast parameters such as hole diameter, bench height, burden, spacing, stemming height, blast pattern, sub-drill, rock strength (UCS), rock quality designation (RQD), blastability index (BI), total explosives used, and powder factor.

2.1 Direct Measurement on Field

Data collected based on rock structure and block size distribution in the field include;

a. Rock type: The rock type refers to the classification of the type of rock based on its mineral content, texture, and origin. Mercy granite rock is igneous rock in origin while Jakura Marble and Ewekoro limestones are sedimentary in origin. All the rock deposits consist of lateritic soil as the overburden, laminated black to dark grey soil overlain by the overburden. The texture are fine to medium grained, hard and compact in nature.

b. Uniaxial Compression Strength

The uniaxial compressive strength value of rock samples is the maximum stress that occurs in rock samples when the samples experience failure due to loading. The UCS of the specimen is calculated by dividing the maximum load (peak failure load) carried by the specimen during the test by the average original cross-sectional area.

where,

σ represents the uniaxial compression strength of the rock, MPa

F represents the magnitude of the force acting on the rock sample, N

A represents the cross-sectional area of rock samples tested, mm^2

$$\sigma_{ucs} = F/A \quad (1)$$

c. Joint spacing: Joint spacing refers to the measurement of distance between two parallel fractures or joints in a rock mass in mm or cm. It is an important factor that affects the stability of the rock mass and the design of rock support systems.

d. Joint Plane Orientation

The dip and dip direction has been found to play a significant role in the ease with which rock responds to blasting. In addition, the orientations of planes of weakness also affect the profile of the rock that remains on the periphery of the block that was blasted, that is, the high walls and floor.

e. Joint sets: Joint sets are groups of parallel or sub-parallel fractures or joints that occur in a rock mass. Joint sets are typically defined based on the orientation and spacing of the joints.

f. Joint volumetric count (Jv): Joint volumetric count is a measure of the amount of joint space in a rock mass. It is calculated by dividing the total volume of the joints by the total volume of the rock mass.

g. Rock Quality Designation (RQD): Rock Quality Designation is a measure of the quality of a rock mass. It is calculated as the percentage of the length of the core sample that consists of intact pieces of rock that are longer than specified size that is equal and greater than 10cm.

$$RQD = \frac{Length\ of\ Core\ Pieces > 10}{Total\ Length} \quad (2)$$

A high RQD indicates a good quality rock mass, while a low RQD indicates a poor quality rock mass.

Data collected during drilling and blasting operation in the studied sites (1, 2 and 3) include; hole diameter, burden, spacing, stemming, sub-drill, hole depth, number of holes, bench height, powder factor, amount of explosive used for both primer and column charge.

ANN Training and Testing

The development of the artificial neural network (ANN) model for blast design optimization was carried out using Python programming language in a Visual Studio (VS) Code environment. Firstly, data collected was preprocessed by scaling and normalization before being split into training, validation, and testing sets. The architecture of the ANN was then defined using Tensor Flow and Keras by specifying the number of layers, neurons, and activation functions. The ANN was trained using the training data by defining the loss function, optimizer (Stochastic Gradient Descent), and metrics, as well as specifying the number of epochs (300) and 2 batch size. The performance of the trained ANN was evaluated using the validation set by calculating metrics such as accuracy, and precision. The final model was tested on the testing set to evaluate its generalization performance. The model was deployed in a user-friendly interface to allow for easy use by blasting engineers.

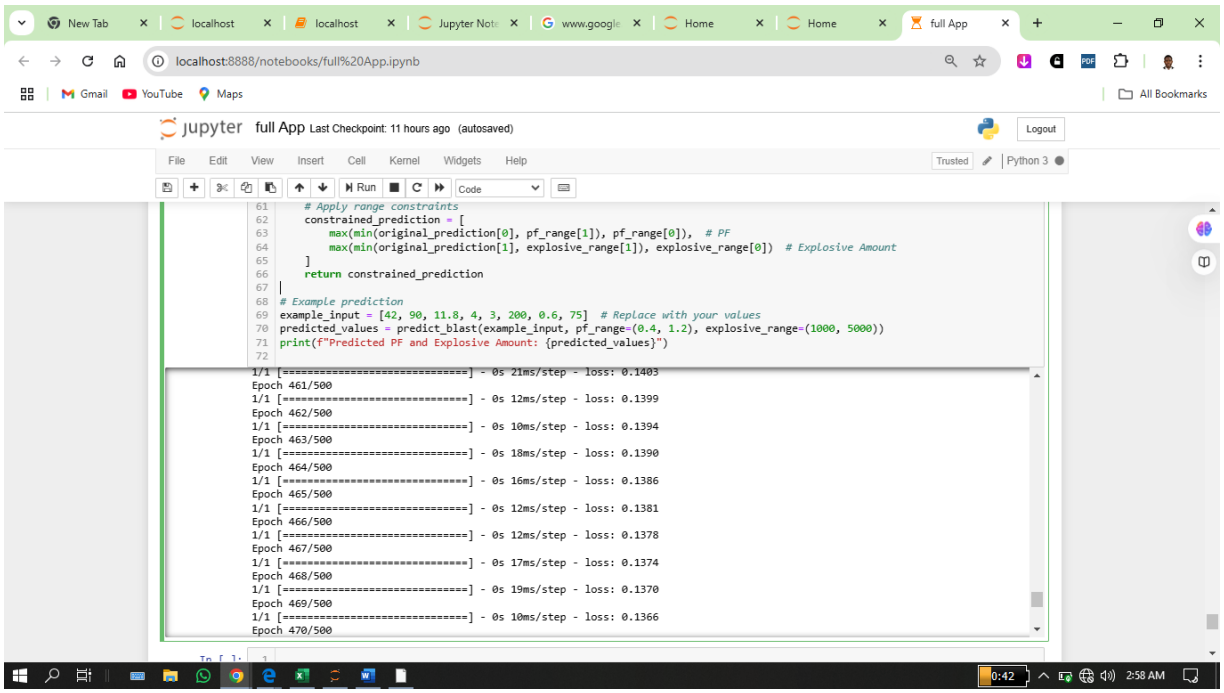


Figure 2 Blast dataset training process

2.2 Blast Parameters involved in Langaford-Kihlstrom Model

The Langaford-Kihlstrom model provides a systematic approach for designing blast parameters, ensuring effective fragmentation while minimizing adverse effects such as excessive vibration or flyrock. The following equations describe the relationships between key blast parameters:

1. **Maximum Burden ($Vmax$)**

$$Vmax = 45 \times D \tag{3}$$

This equation determines the maximum burden ($Vmax$), which represents the maximum distance from the blasthole to the free face where effective breakage occurs. It is directly proportional to the blasthole diameter (D).

2. **Subdrilling (U)**

$$U = 0.3 \times Vmax \tag{4}$$

The subdrilling depth (U) is the additional depth drilled below the intended bench level to ensure complete rock fragmentation. It is typically 30% of the maximum burden.

3. **Blasthole Depth (H)**

$$H = (K + U) \times 1.05 \tag{5}$$

The blasthole depth (H) accounts for the bench height (K) and subdrilling (U), with an additional 5% adjustment to compensate for any drilling inaccuracies.

4. **Drilling Error (F)**

$$F=0.05+0.003 \quad (6)$$

This parameter accounts for minor deviations in drilling precision, which can affect the burden calculation.

5. **Final Burden (V)**

$$V=Vmax-F \quad (7)$$

The final burden (V) is adjusted by subtracting the drilling error (F) from the maximum burden ($Vmax$).

6. **Blasthole Spacing for Rectangular Pattern ($E1$)**

$$E1=1.25\times V \quad (8)$$

This equation determines the spacing between holes in a rectangular blast pattern, which is typically 1.25 times the burden.

7. **Blasthole Spacing for Square Pattern ($E2$)**

$$E2=1.0\times V \quad (9)$$

The spacing between holes in a square blast pattern is equal to the burden (V).

8. **Stemming Length (ho)**

$$\mathrm{h}o=V \quad (10)$$

Stemming length (ho) is set equal to the burden to ensure proper confinement of explosives and efficient energy transfer.

Explosive Parameters involved in Langefors-Kihlstrom Model

Explosive parameters play a crucial role in determining the energy distribution within the roc23yj0k mass. The following equations define key explosive characteristics:

1. **Bottom Charge Length (hb)**

$$\mathrm{h}b=1.3\times V \quad (11)$$

The bottom charge length (hb) is generally set at 1.3 times the burden to ensure proper fragmentation of the toe region.

2. **Column Charge Length (hp)**

$$\mathrm{h}p=H-(\mathrm{h}b+\mathrm{h}o) \quad (12)$$

The column charge length (hp) is calculated by subtracting the bottom charge length (hb) and stemming length (ho) from the total blasthole depth (H).

3. **Quantity of Bottom Charge (Qb)**

$$Qb=\mathrm{h}b\times Qbk \tag{13}$$

The bottom charge quantity (Qb) is determined by multiplying the bottom charge length (hb) by the concentration of bottom charge (Qbk).

4. **Bottom Charge Concentration (Qbk)**

$$Qbk=\frac{D2}{100} \tag{14}$$

This equation calculates the concentration of bottom charge (Qbk) based on the blasthole diameter (D).

5. **Quantity of Column Charge (Qp)**

$$Qp=\mathrm{h}p\times Qpk \tag{15}$$

The column charge quantity (Qp) is obtained by multiplying the column charge length (hp) by the column charge concentration (Qpk).

6. **Column Charge Concentration (Qpk)**

$$Qpk=Range(\%40–\%50)ofQbk \tag{16}$$

The column charge concentration (Qpk) is typically 40–50% of the bottom charge concentration.

7. **Total Explosive Quantity per Hole (Qt)**

$$Qt=Qp+Qb \tag{17}$$

The total quantity of explosives (Qt) in a single blast hole is the sum of the column charge (Qp) and bottom charge (Qb).

8. **Total Explosive per Blast (Qe)**

$$Qe=\mathrm{No}\times Qt\times\exp Q \tag{18}$$

The total explosives used in a blast (Qe) are calculated based on the number of holes (No), the total charge per hole (Qt), and an expansion factor (exp).

Estimation of Mean Fragmentation Size

Mean fragment size were theoretically evaluated using Kuz-Ram model to estimate mean fragmentation size and compare to the actual Langeford-Kihlstrom model to determine the accuracy of the prediction.

$$X_m = A(K)^{-0.8} \times Q_e^{\frac{1}{6}} \left(\frac{115}{S_{anfo}}\right)^{\frac{19}{30}} \quad (19)$$

Where:
Xm is the mean fragment size (cm)
A is the rock factor = 7, assuming a middle hard rock.
K is the powder factor (kg/m^3)
Q_e is the mass of explosive being used (kg),
S_{anfo} is the relative weight strength of the explosive to ANFO (A Primer emulsion = 121)

3. Results and Discussion

This section presents the results and analysis of the performance of the Artificial Neural Network (ANN) model in optimizing blast parameters in mining operations. This will provide a comprehensive evaluation of the model's ability to predict the outcomes of blast parameters, including the extent of fragmentation, blast energy consumption, and production costs. The analysis will be based on the results obtained from the experiments conducted using the ANN model and a comparison with existing models.

3.1 Structural Properties of Blasted Area

The structural properties of the rock mass for the blast operation were obtained through a combination of field and laboratory tests. The UCS (Uniaxial Compressive Strength) of the rock mass was determined by conducting laboratory tests on samples of the rock mass at FUTA Rock mechanics laboratory. The RQD (Rock Quality Designation) of the rock mass was determined by measuring the joint spacing of the rock mass in the field. The Blastibility Index (BI) of the rock mass was determined using Lilly's (1986), by analyzing the blocks sizes in the field.

Comparison of Results for Limestone

Table 1 shows Comparison between existing model and ANN based on total explosive used for blasting limestone

Table 1: Comparison between existing model and ANN based on total explosive used for blasting limestone

Blast	Quarry data (kg)	Langaford data (kg)	ANN data (kg)
Blast 1	1900	2316.5	1873.737
Blast 2	1125	4336.8	1051.454
Blast 3	250	1306.9	754.5184
Blast 4	600	1602.6	650.1735
Blast 5	800	1323.7	835.2408
Blast 6	1400	4254.2	2503.633
Blast 7	400	1808.1	424.8441
Blast 8	675	2074	1132.158
Blast 9	1125	1378.8	1131.794

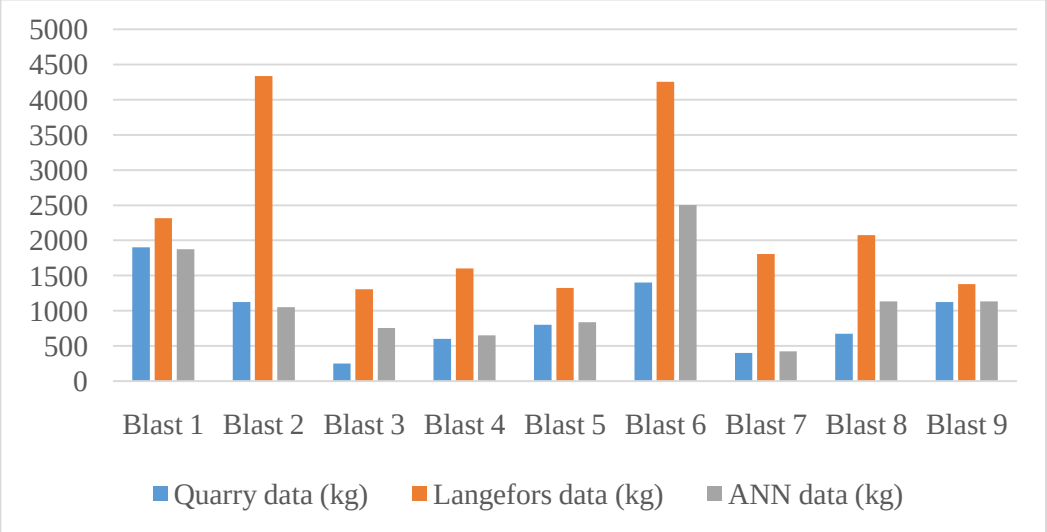


Figure 3: Comparison between existing model and ANN based on total explosive used forblasting limestone

Table 2: Cost evaluation for limestone using blast 1 data.

Cost	Existing data	Langaford data	ANN data
Drilling cost (₦/m)	9240000	9867816	9240000
Explosive cost (₦/kg)	47289600	28111160.3	32524978
DTH cost	400000	400000	400000
TLD cost	320000	320000	320000

Comparison of Results for Granite

Table 3: Comparison between existing model and ANN based on total explosive used for blasting granite

Blast	Quarry data (kg)	Langaford data (kg)	ANN data (kg)
Blast 1	1900	2316.5	1628.187
Blast 2	800	1323.7	1168.634
Blast 3	1125	1378.8	1238.733
Blast 4	875	1323.7	1216.508
Blast 5	900	1378.8	1141.832
Blast 6	875	1434	700.6083
Blast 7	1775	2537.1	2546.048
Blast 8	2535.5	3309.2	2372.208
Blast 9	1535.5	2757.7	978.9213

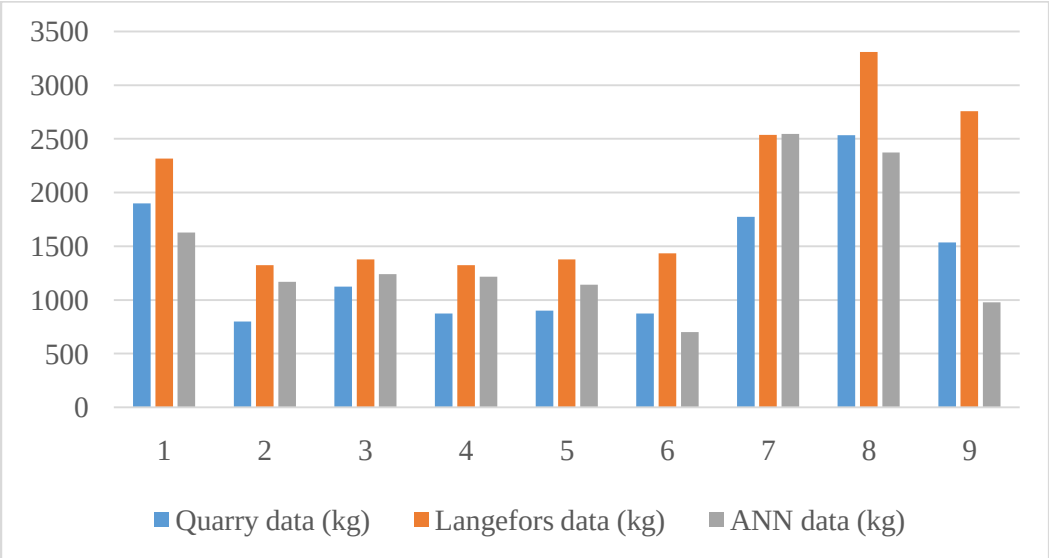


Figure 4 Comparison between existing model and ANN based on total explosive used

Table *4*: Cost evaluation for Granite using blast 1 data.

Cost	Existing data	Langaford data	ANN data
Drilling cost (₦/m)	9240000	9867816	9817500
Explosive cost (₦/kg)	58753200	28111160.3	40157392
DTH cost	400000	400000	425000
TLD cost	320000	320000	340000

Comparison of Results for Marble

Table 5: Comparison between existing model and ANN based on total explosive used for marble

Blast	Quarry data (kg)	Langaford data (kg)	ANN data (kg)
Blast 1	7025	20606.3	7123.353
Blast 2	5150	12607.2	4983.493
Blast 3	4050	12085.6	4693.243
Blast 4	3475	8694.6	3439.659
Blast 5	2775	8259.9	2855.89
Blast 6	2525	6260.1	2980.46
Blast 7	2592.5	6086.3	2592.5
Blast 8	2415	5825.4	2582.791
Blast 9	2115	5651.5	2394.475

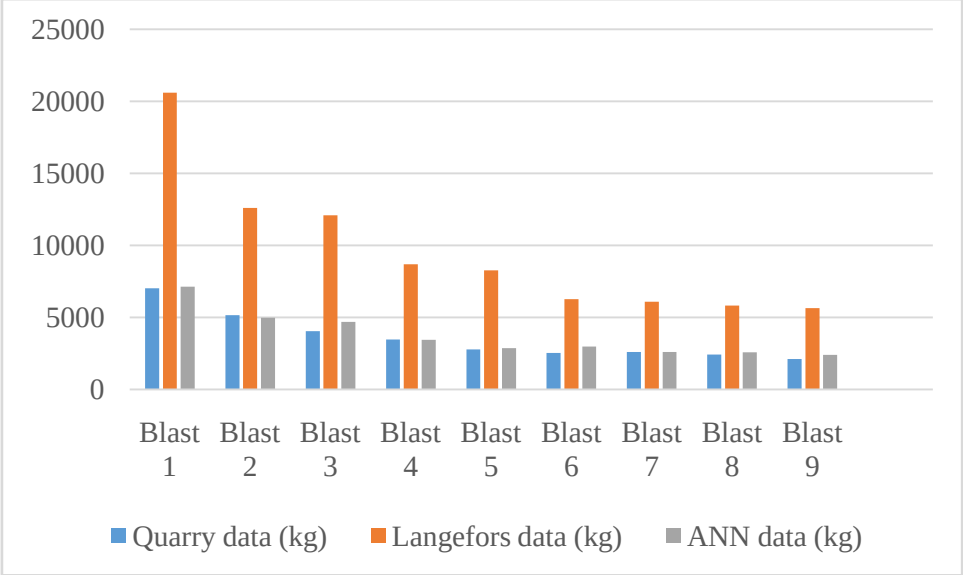


Figure 5: Comparison between existing model and ANN based on total explosive used for blasting marble

Table 6: Cost evaluation for Granite using blast 1 data

Cost	Existing data	Langaford data	ANN data
Drilling cost (₦/m)	7350000	8195985	8400000
Explosive cost (₦/kg)	50813200	59145027.24	30653158
DTH cost	350000	350000	400000
TLD cost	280000	280000	320000

Fragmentation of Limestone

Table 7: Kuz-Ram Fragmentation Model for Limestone

	Blast 1	Blast 2	Blast 3	Blast 4	Blast 5	Blast 6	Blast 7	Blast 8	Blast 9
Existing data (cm)	92.08	92.23	97.72	100.95	100.73	97.59	100.73	99.62	99.98
Langaford-Kihlstrom data (cm)	83.82	83.82	85.95	87.47	87.6	85.84	87.45	86.18	86.67
ANN data (cm)	95.63	97.1	55.65	73.04	78.83	93.14	54.16	84.67	97.12

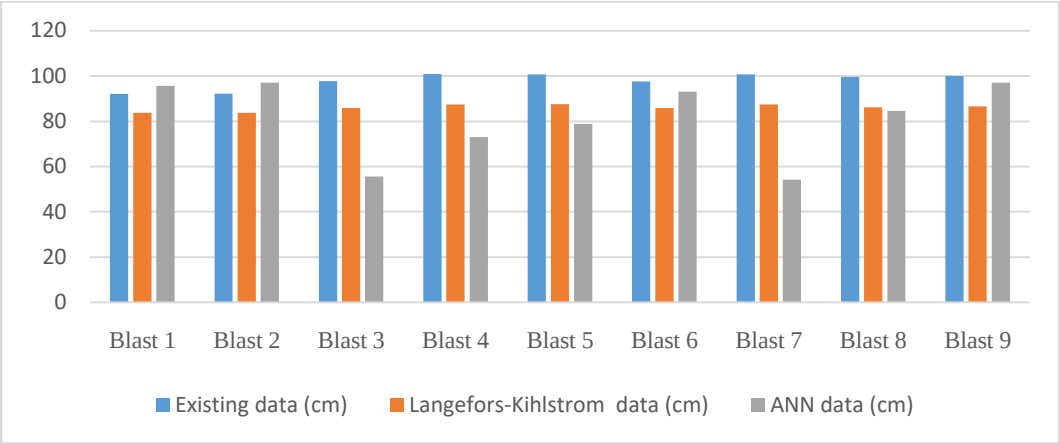


Figure 6. Kuz-Ram fragmentation model for limestone

Fragmentation of Granite

Table 8: Kuz-Ram fragmentation model for granite

	Blast 1	Blast 2	Blast 3	Blast 4	Blast 5	Blast 6	Blast 7	Blast 8	Blast 9
Existing data (cm)	73.46	73.46	73.49	75.5	75.19	73.73	74.56	74.15	73.9
Langaford-Kihlstrom data (cm)	64.45	64.45	64.9	66.89	66.55	65.66	66.64	66.26	66.54
ANN data (cm)	66.57	78.28	69.63	64.93	53.89	57.19	57.19	71.07	68.21

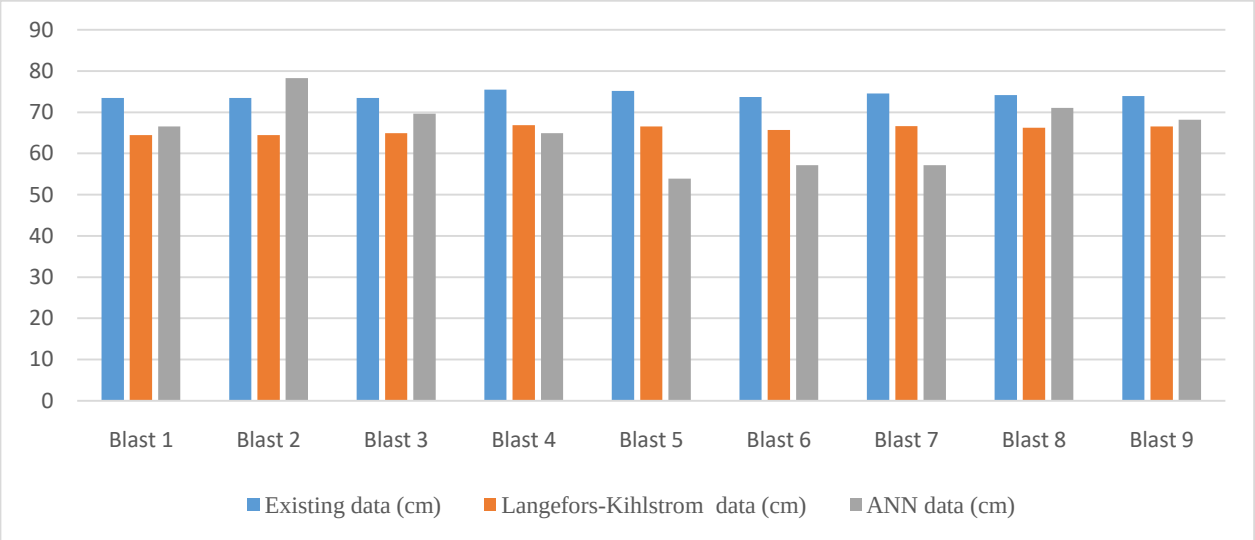


Figure 7: Kuz-Ram fragmentation model for granite

Fragmentation of Marble

Table 9: Kuz-Ram fragmentation model for marble

	Blast 1	Blast 2	Blast 3	Blast 4	Blast 5	Blast 6	Blast 7	Blast 8	Blast 9
Existing data (cm)	93.18	93.13	93.88	95.22	94.03	93.53	94.03	93.41	93.66
Langaford-Kihlstrom data (cm)	95.3	95.3	97.45	101.14	100.45	98.44	100.28	98.82	99.38
ANN data (cm)	82.21	82.21	84.33	84.8	89.73	82.21	84.8	84.8	90.95

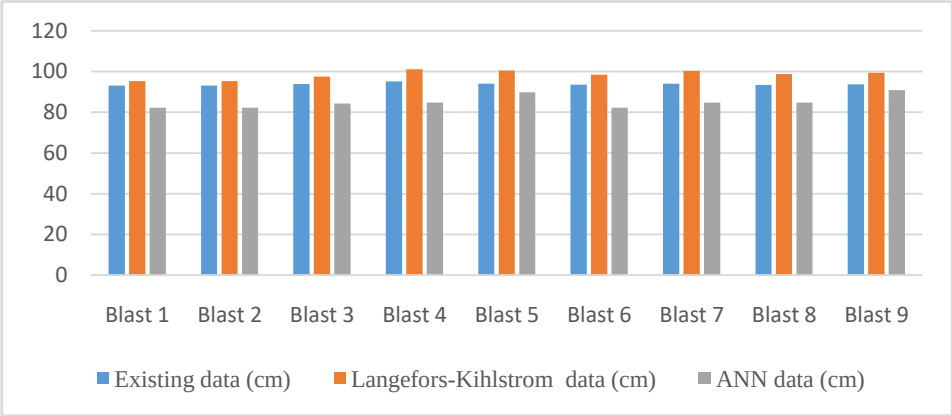


Figure 8. Kuz-Ram fragmentation model for marble

Optimized ANN Trained Application

The blast software designed using the data dependencies:

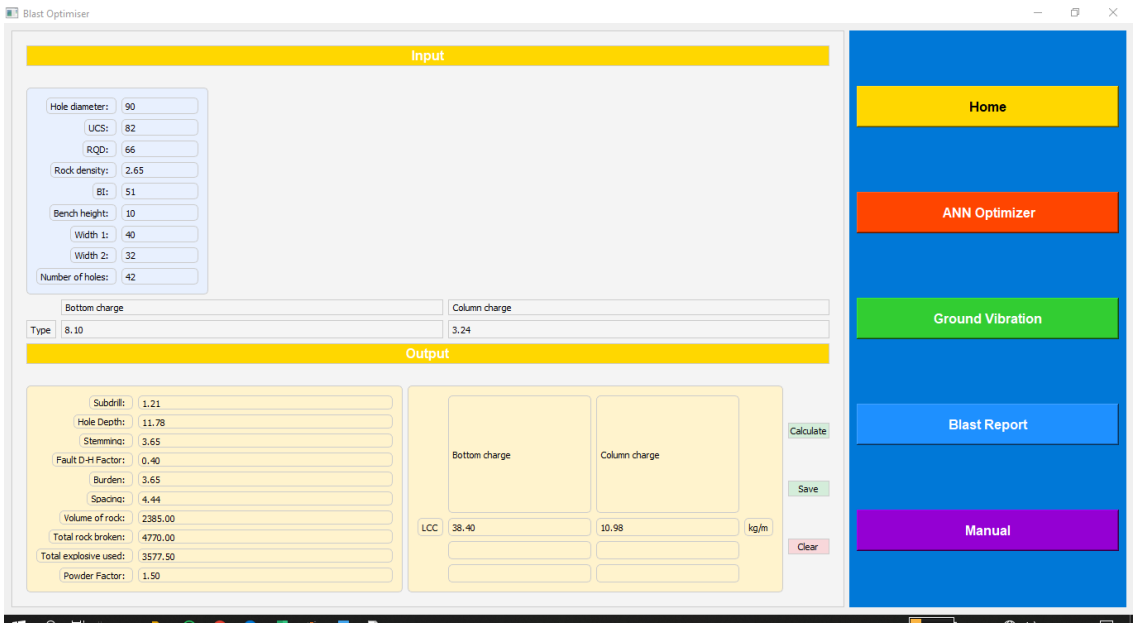


Figure 9. ANN optimizer page of the created App

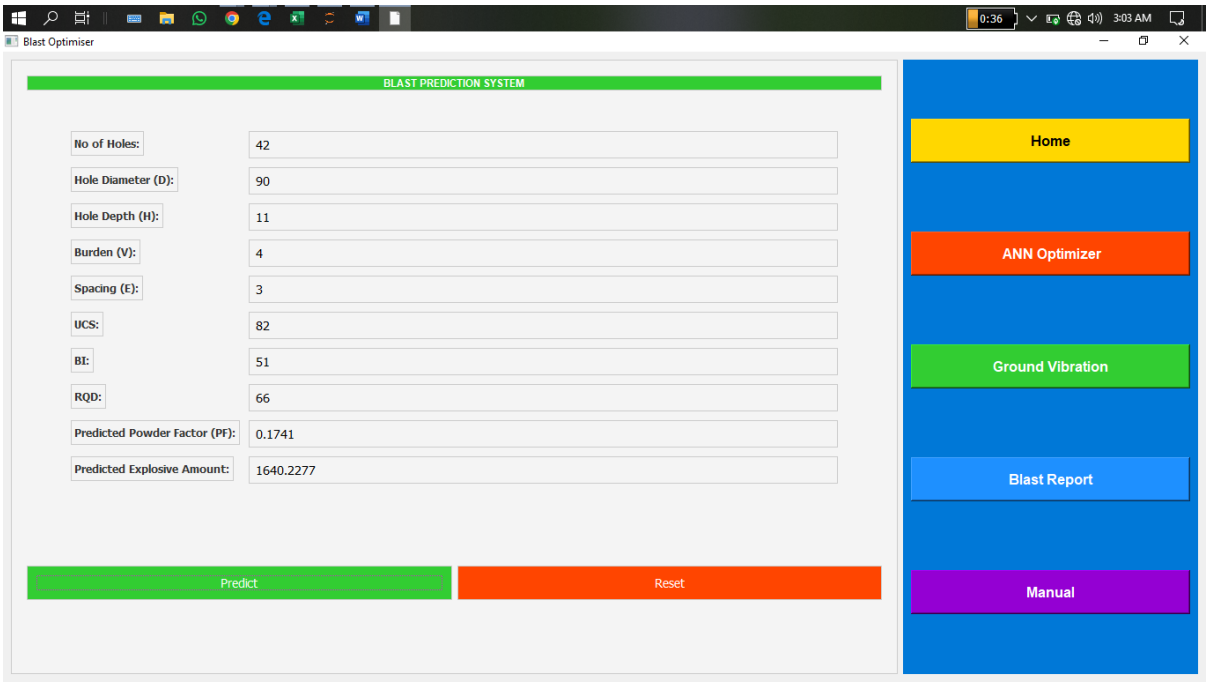


Figure 10. Home Interface of the App created

4. Conclusion

The study has demonstrated the effectiveness of using the Langaford-Kihlstrom model and artificial neural network (ANN) in optimizing blast design at Ewekoro Limestone, Jakura Marble and Merciful quarry, Ibule, while considering rock strength and structural properties. The findings of the study show that incorporating the ANN model improves the accuracy of the blast design process, leading to better fragmentation results.

The ANN data was able to save an average of 16.6% in total explosives costs compared to the existing data and Langaford-Kihlstrom data. This demonstrates the cost-effectiveness of the ANN blast prediction model and its ability to reduce costs while still providing accurate predictions. The cost savings achieved by using the ANN blast prediction model makes it a highly recommended tool for blasting operations.

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