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Optimization of Blast Fragmentation Efficiency in a Small-Scale Underground Gold Mine Using Neuro-Fuzzy Approach

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ABSTRACT

Poor blast fragmentation has direct effects not only on blasting costs but also on the efficiency of downstream processes. Toronto mine has recently encountered significant challenges in optimizing its blasting and fragmentation processes with an average fragmentation efficiency of 60%. The main goal of this research was to optimize blast fragmentation efficiency from an average of 60% to above 80%. The methodological approach proposes the development of a hybrid Artificial Intelligence model, Adaptive Neuro-Fuzzy Inference System (ANFIS). The proposed ANFIS model performance has been compared with Artificial Neural Network (ANN) and Multivariate Regression (MVRA) models after training. The model performance in prediction was tested using 5 statistical indices, Coefficient of Regression, Mean Square Error, Root Mean Square Error, Mean Absolute Error and Value Accounted For. Based on statistical indices, it was found that the ANFIS model performs better than the ANN and the MVRA models, achieving a coefficient of determination of 0.9955 compared to 0.9249 (ANN) and 0.9005 (MVRA). Additionally, Root Mean Square Error improved from 0.8305 (ANN) and 2.0738 (MVRA) to 0.2087 for ANFIS, demonstrating significant prediction accuracy gains. The sensitivity analysis shows that the burden and uniaxial compressive strength have the most effect on the blast fragmentation efficiency. The ANFIS model optimized by Particle Swarm Optimization algorithm (PSO) provided optimized input parameters to achieve a blast fragmentation efficiency of 84%. These optimized input parameters were used in the trial blast. WipFrag software was used to analyze and evaluate blast fragmentation performance based on images of blasted muck piles from the trial blast. From the WipFrag analysis a targeted particle size distribution of P80 at 15 cm by 15 cm was achieved and this demonstrated that the proposed methodology offers a practical framework for achieving the objectives. Finally, the results of this research provide strong evidence for the ongoing use of Artificial Intelligence and metaheuristics algorithms in mining operations to maximize efficiency, lower operating costs, and enhance general mine's profitability.

1. INTRODUCTION

The direct impacts of blast fragmentation to downstream operations have resulted in the quest for solutions to fragmentation efficiency in mining operations. The prediction and control of the particle size distribution of fragmented rock is important to reduce costs in mining. This also enhance operational safety and improve the overall productivity of mining activities. The complexity of the rock masses and the highly dynamic nature of blasting have been a challenge to obtaining consistently accurate prediction. Several techniques have been developed to improve fragmentation outcomes, but each of these has certain limitations, which has driven the need for more advanced approaches.[1][2][3].

The earliest methods for blast fragmentation prediction and optimization were largely empirical. The most widely used model is the Kuz-Ram model, developed in the 1970s. This model combines Kuznetsov's equation for predicting the mean fragment size with a Rosin-Rammler distribution to

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describe the spread of fragment sizes [4][5]. These empirical models have served well to provide a first-order approximation of fragmentation outcomes [6]. Empirical models, on the other hand, are more relied on predefined parameters that may not be applicable in all rock conditions or for all blasting configurations [7].

The methods are highly dependent on assumptions regarding rock mass characteristics, explosive energy and blast design parameters [8]. As a result, these models often fail to provide accurate predictions when conditions deviate from their underlying assumptions. This makes them not suitable for more complex and heterogeneous rock masses. Empirical models also lack flexibility in adapting to varying conditions. [9][10].

Recently, AI techniques have been increasingly applied to overcome the limitations of empirical models in underground mining environments. Studies have demonstrated the efficiency of these AI models. Reference [11] utilized metaheuristic algorithms to predict overbreak area, maximum linear overbreak, crown settlement, and maximum fragment size in a hard rock underground mine. Similarly, Reference [12] focused on predicting peak particle velocity in underground mine blasting operations using two machine learning models, Support Vector Regression (SVR) and Random Forest (RF), which were optimized using the Particle Swarm Optimization (PSO) algorithm, achieving an R^2 of 0.9645 for the PSO-SVR model and R^2 of 0.8048 for the PSO-RF model. However, the models failed to capture the complexity of the correlation between the input and output parameters in the test data, and exhibited poor performance for datasets with fewer measured observations. Implementing an ANFIS-PSO model is essential to address these limitations by effectively capturing nonlinear interactions and uncertainties in blast design parameters for relatively small datasets.

Figure 1 shows the geological location of Toronto mine.

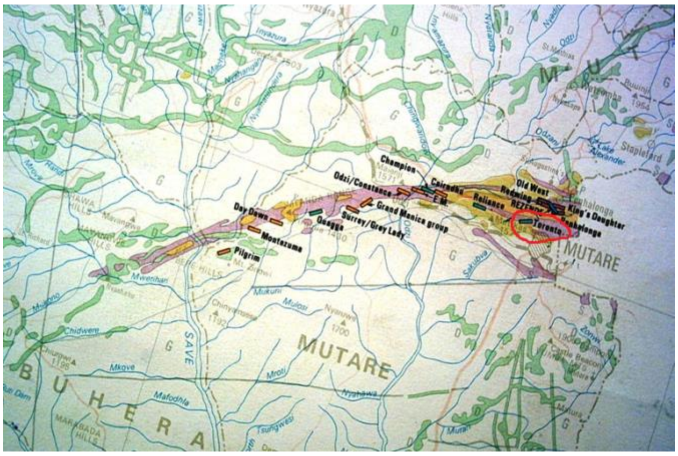

Fig. 1. Geological location of Toronto mine

The focus of this research is to develop a hybrid Artificial Intelligence model for predicting blast fragmentation efficiency at Toronto mine. The mine is located in the Odzi-Mutare-Manica greenstone belt, in Penhalonga. The Odzi-Mutare Manica greenstone belt is located in the eastern part of the Zimbabwe craton, and is an east-west trending synclinorium of ultramafic, mafic and banded-iron formations (BIF) corresponding to the Bulawayan Group. Overlying this succession and occupying the core of this structure are metasediments of the Shamvaian Group. Both the northern and southern margins are intruded by granites. The northern limb of the synclinorium is intruded by quartz-dolerites and felsite. The rock mass classification is characterized by a Rock Mass Rating (RMR) in the range of 40–60, indicating fair to poor quality ground. Uniaxial compressive strength (UCS) of intact rock varies between 120 and 195 MPa. Several discontinuity sets are present, with steep dips and joint spacings of 0.2–0.6 m. Foliation and shear planes act as planes of weakness, promoting preferential crack propagation during blasting. The mapping of the local area established the succession of the metasediments most of which were derived by erosion of the older greenstones. At the base is a well-developed basal conglomerate composed of angular to subrounded pebbles of actinolite schist, banded iron formation (BIF), metabasalt, serpentinite and quartz within a greywacke matrix. There are also outcrops of chlorite schist. The orebody strikes east-west and dipping at locally variable but shallow angle of about 85 degrees to the north.[13][14][15]

The mine is a small-scale underground gold mining operation that has recently encountered significant challenges in optimizing its blasting and ore handling processes. Double-handling of fragmented rock by secondary blasting is the main problem which has resulted in a considerable loss of production time and increased operational costs. The oversized boulders in the muck piles are exceeding 35 cm by 35 cm and the processing plant is designed to handle boulders that are below size of 22 cm. The research proposes a targeted particle size distribution of P80 at 15 cm by 15 cm for high processing plant efficiency, reducing primary crusher choke feeding and clogging risks.

2. Artificial Intelligence in Fragmentation Prediction and Optimization

Artificial Intelligence (A.I.) is one of the available methods which offers best solutions to challenging mining engineering problems. AI has emerged as a powerful tool in mining, capable of addressing limitations traditional empirical models [16]. It has various tools, which include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy Logic (FL), Machine Learning (ML), Swarm Intelligence, Expert Systems and others. They can be applied in optimization and can analyze large datasets, identifying patterns that may not be evident through conventional methods. [17][18][19].

2.1 *Artificial Neural Network*

ANNs. have been particularly effective in blast fragmentation optimization. A.N.Ns mimic the human brain's functioning by processing input data through layers of interconnected neurons to produce output predictions. In blasting, ANN can analyze multiple input variables, such as rock properties, blast design parameters and explosive characteristics and use this information to predict fragmentation outcomes. Studies have demonstrated the superior predictive capability of ANNs over traditional models. Reference [20] developed an ANN model to predict blast fragmentation, achieving improved accuracy in comparison to empirical methods like the Kuz-Ram model. Reference [21] developed a control model using a double hidden layer BP (Back Propagation) neural network to effectively manage oversized rock proportions in shaft blasting.

ANN is very important in mining due to its capacity to model non-linear systems. ANNs, on the other hand, have several limitations that make them less ideal for this task [22][23]. They require large amounts of training data to achieve accurate predictions and gathering such data can be costly and time consuming in mining operations [24]. Figure 2 shows the architecture of Artificial Neural Network.

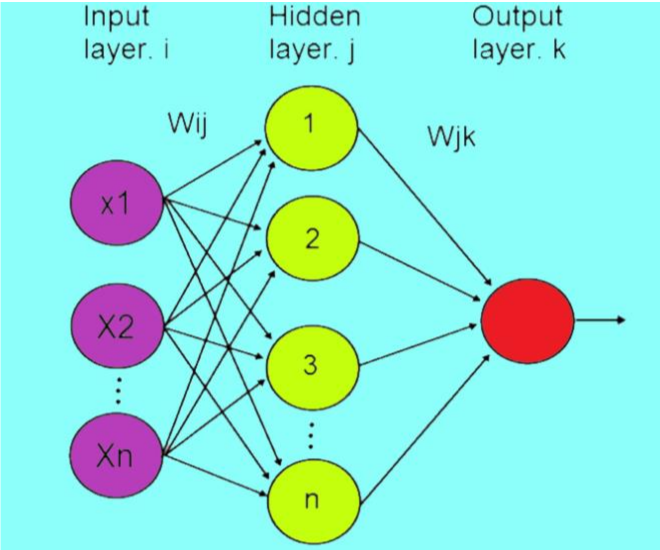

Fig. 2. Artificial Neural Network architecture

2.2 Fuzzy Logic

Fuzzy logic is a soft computing technique that has been applied to blast fragmentation optimization. Unlike traditional logic systems that operate with binary true/false values, fuzzy logic allows for degrees of truth. This makes it well-suited for handling the inherent uncertainty and variability in mining environments. Fuzzy logic can be used to model the complex relationships between rock properties, blasting parameters and fragmentation outcomes by using linguistic rules to describe these relationships [25].

The weakness of fuzzy logic is that it requires expert knowledge to define the rules and membership functions that govern the model. In complex systems like blast fragmentation, defining these rules can be difficult and time-consuming process. Fuzzy Logic systems alone may not be sufficient to capture the full complexity of the fragmentation process [26].

2.3 Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is an adaptive system that combines Fuzzy Logic's rule-based structure with the learning ability of Artificial Neural Networks (ANN). It is a hybrid algorithm artificial intelligence modelling that features together, to learn on experimental or actual measured supplied dataset and develop an optimized prediction model [27]. Studies comparing ANN and fuzzy logic confirm that neither alone sufficiently addresses all fragmentation complexities. Hence, the hybrid ANFIS approach integrates ANN's learning with fuzzy logic's uncertainty handling, producing superior performance in blasting predictions as supported by enhanced accuracy in hybrid models [23][28][29][30][31][32][33]. ANFIS can model intricate dependencies between input parameters such as burden, spacing, rock properties and output variables such as fragmentation efficiency. Reference [34] showed that ANFIS can handle multi-dimensional input data effectively, resulting in the improved prediction accuracy. The modelling technique as in [35] was explained to adopt linguistic information based on a fuzzy logic inference system and learning algorithm approach and the training process of an artificial neural networks to adjust the membership function. ANFIS as a hybrid system was also described in [36], to utilize the least square method and back-propagation learning algorithm during the training process.

Reference [37] explored the impact of geological discontinuities on blast fragmentation, demonstrating that understanding rock mass characteristics is essential for optimizing blasting operations. This highlights the necessity of integrating the AI techniques, ANN and Fuzzy Logic to optimize blast fragmentation, which is the focus of this research.

Reference [38] explained ANFIS as the modelling that uses the Fuzzy "if-then" rules from Tagaki and Sugeno fuzzy model and as a hybrid system that adopts the Tagaki-Sugeno-Kang (TSK) fuzzy inference system to estimate the optimal relationship between membership functions. There are two types of fuzzy inference systems which are the Mamdani and the Sugeno type system. Reference [39] explained Mamdani as Fuzzy Inference System that demands the adoption of fuzzy rules to connect fuzzy sets to the target outputs dataset. They further explain that there is defuzzification of the connected fuzzy set and output sets to obtain scalar variables. The Sugeno type system does not require inclusion of output membership function and output distribution during learning. The output function is obtained by multiplying the input membership function by a constant and sums up the generated results.

Figure 3 shows the five layers used to develop ANFIS architecture of the first-order Sugeno-type inference system. It also shows the working operation of a typical ANFIS with two input x and y and one output, f, adopting two fuzzy "If-Then" rules. The fixed node and an adaptive node are represented with circles and squares respectively. The back-working function of each rule for a typical first-order Sugeno-type inference system is denoted by equation (1) and (2) as in [40]:

Rule 1: If x is A1 and y is B1, then $f1 = p1x + q1y + r1$

Rule 2: If x is A2 and y is B2, then $f2 = p2x + q2y + r2$

Where x and y are inputs, f is the output and A1, B1, A2, B2 are fuzzy sets, p1, q1, p2, q2, r1 and r2 are the coefficients of the output function that are determined during the training.

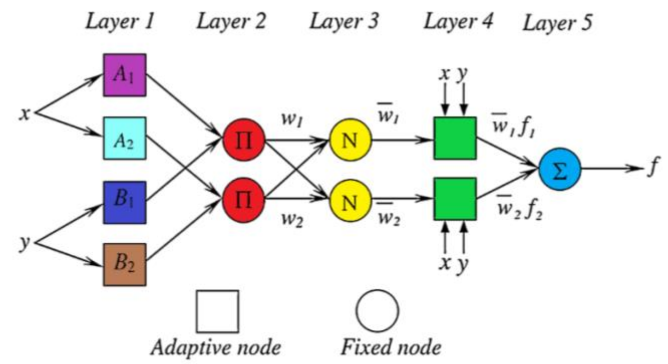

Fig. 3. Adaptive Neuro-Fuzzy Inference System architecture

2.4 Metaheuristics algorithms in blast fragmentation optimization

Metaheuristics algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are used for optimization. The algorithms have been applied to optimize blast fragmentation by handling the uncertainty and variability inherent in mining operations [41][42][43]. Multi-Objective Particle Swarm Optimization (MOPSO) was utilized to enhance blast design parameters, demonstrating the effectiveness of intelligent algorithms in minimizing ground vibrations and improving fragmentation [44]. These techniques are particularly useful in situations where input data is not precise or incomplete. This makes them well-suited for the highly variable conditions encountered in underground mines.

3. METHODOLOGY

The methodological approach for this research seeks to develop and implement a hybrid model that leverages Artificial Intelligence models and optimization algorithms to optimize blast design parameters and fragmentation outcome.

The methodology followed five sequential stages. In the data collection stage, blast design parameters were gathered and rock mass properties, specifically uniaxial compressive strength (UCS), were measured. In the modelling stage, Multivariate Regression (MVR), Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models were developed, validated, and their performance tested and fine-tuned. In the selection of blasting parameters stage, the ANFIS model was integrated with an optimization algorithm to simulate different blasting scenarios. In the sensitivity analysis stage, a sensitivity analysis was conducted on the input variables. Finally, in the implementation stage, trial blasts were run, the blasted muck pile was monitored and analyzed, and the model was continuously updated.

3.1 Data collection

The blast design parameters for each blast were recorded. The dataset included critical parameters such as burden, spacing, blast hole depth, charge weight, powder factor and uniaxial compressive strength (UCS). Literature have demonstrated that uniaxial compressive strength, two cost impact blast design factors which are powder factor and charge weight, three blast controllable factors which are burden, spacing and blast hole depth have a significant effect on blast fragmentation efficiency. Uniaxial compressive strength from each blast was measured using point load tests.

Photogrammetric analysis for particle size distribution of fragmented rock was done using WipFrag 3.3 software. Images taken from the blasted muck pile were analyzed separately with WipFrag 3.3 software. The fragmentation efficiency was measured by comparing the WipFrag particle size distribution curve to the corresponding mine primary crusher feed size. Figure 4 shows photogrammetric analysis and particle size distribution chart.

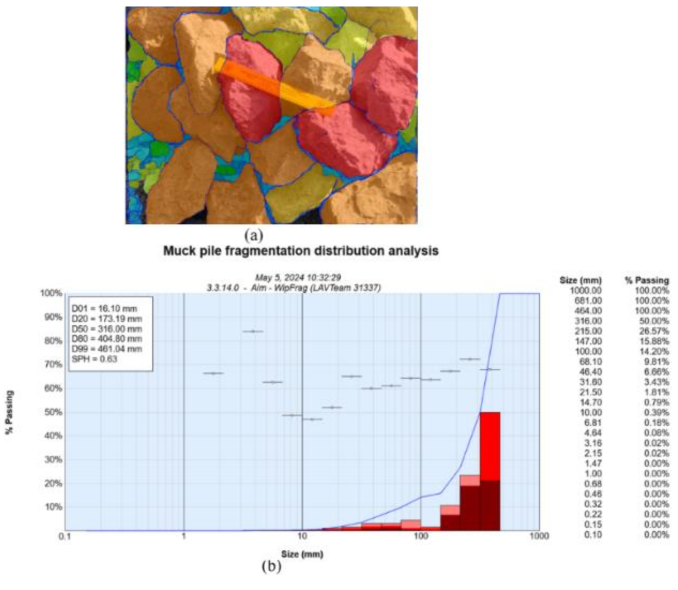

Fig. 4. (a) Photogrammetric analysis (b) A graph showing fragmentation size distribution

The input blast design parameters and their corresponding fragmentation efficiencies were compiled into a dataset which is summarized as shown in Table 1.

Table 1. Parameter ranges from the blast dataset

Input Parameter	Symbol	Range
Burden (m)	B	0.42 – 0.62
Spacing (m)	S	0.47 – 0.70
Blast hole depth (m)	HD	1.50 – 2.01
Charge weight (kg)	CW	0.40 – 0.52
Powder factor (kg/m^3)	PF	0.55 – 1.28
Uniaxial compressive strength (MPa)	UCS	140.67 – 195.31
Output Parameter	**Symbol**	**Range**
Fragmentation Efficiency (%)	FE	40.11 – 65.44

In this study, A total of 100 blasting observations was recorded, compiling six input parameters and corresponding fragmentation efficiency outputs. The dataset was randomly divided into parts, 80% for a training set and 20% for a testing set. This split ratio is a standard convention in machine learning model development [45][46][47]. This provides a sufficient volume of data for the model to learn the underlying patterns while retaining an adequate and independent subset for unbiased evaluation of the model's generalization capability to new, unseen data.

3.2 Multivariate model development

Multivariate Regression (MVR) analysis is a statistical method used to establish a mathematical relationship between multiple independent variables (inputs) and the dependent variable (output). The MVR model development process for predicting blast fragmentation efficiency was done in Microsoft Excel.

The input and output data were selected separately. After running the analysis, the MS Excel will generate a table on the spreadsheet. The data that will be displayed include R^2 (Coefficient of regression) and the ANOVA table. The mathematical regression equation was developed.

3.3 ANN model development

The ANN model was constructed with three different neuron architectures: *6:4:1*, *6:5:1* and *6:10:1*. These structures represent the number of inputs, hidden and output layers, respectively. The dataset was randomly divided into two parts: 80% for training and 20% for testing. The Levenberg-Marquardt (LM) and the Bayesian Regularization (BR) algorithms were applied to train the ANN modes. The training was contacted in MATLAB R2018a and the trained models were validated using the test dataset and assess the prediction accuracy. Figure 5 shows the *6:10:1* neuron architecture.

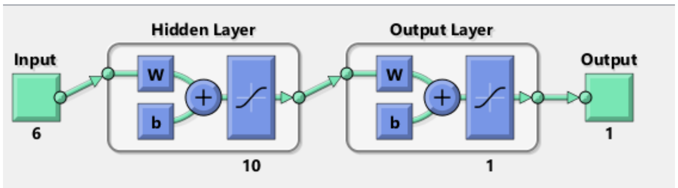

Fig. 5. The ANN model with the 6:10:1 architecture

3.4 ANFIS model development

In this study, a Sugeno-type fuzzy inference system was selected for model development, which allows the system to process small datasets and still maintain a high degree of prediction accuracy. Six blast design parameters, burden, spacing, blast hole depth, powder factor, charge weight and uniaxial compressive strength were used as inputs to predict the blast fragmentation efficiency. The ANFIS model was developed in MATLAB R2018a, with Gaussian membership functions applied to classify input data. The Gaussian membership functions were used for all inputs due to their smoothness and ability to represent uncertainty effectively. The model used 729 fuzzy rules. The number of fuzzy rules is derived from the number of input parameters and membership functions (in this case number of fuzzy rules = 3^6). This high number of fuzzy rules raises the risk of overfitting. Early stopping can be implemented during training to prevent overfitting to training data. Reference [48] explains early stopping in neural and neuro-fuzzy networks as a way to control excessive fitting by monitoring validation error and stopping training once error stops improving to prevent overfitting. Another strategy to reduce overfitting is utilizing Gaussian membership functions when generating FIS, for their smoothness and generalizability. Reference [40] originally noted that Gaussian membership functions provide smooth and continuous coverage of the input space. This contributes to better generalization in an ANFIS model. Recent works confirm that Gaussian membership functions are widely preferred for their smoothness and practical performance in ANFIS model implementations [49]. Several studies were done to address rule-based dimensionality and clustering for rule reduction [50][51][52][53].

The suggested ANFIS structure is shown in Figure 6.

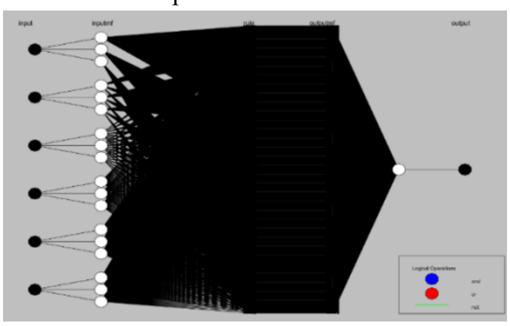

Fig. 6. ANFIS structure with six input parameters and one output parameter (729 rules)

The linguistic values for input parameters are assigned as Low (L), Medium (M) and High (H). These membership functions were assigned before the ANFIS training stage. A linear type of membership function was used for the output, Blast Fragmentation Efficiency(FE).

All the 729 fuzzy rules were trained using two methods, the Least Square Method (LSM) for parameter optimization and Backpropagation for minimizing prediction errors. These hybrid learning algorithms are often referred to as the forward pass and the backward pass respectively.

In forward pass, the hybrid learning algorithm, functional signals go forward till Layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent or back propagation.

The testing set was used to evaluate the performance of the ANFIS model during the training phase. This set was to monitor how well the model generalizes to unseen data. It helps in adjusting hyperparameters such as the number of membership functions, the number of fuzzy rules or the learning rate. It also plays a crucial role in early stopping to prevent overfitting. The trained ANFIS model was validated using the original dataset and its performance was evaluated using metrics such as Root Mean Square Error (RMSE), Mean Square Error (MSE) and coefficient of determination (R^2). Figure 7 shows the ANFIS workflow.

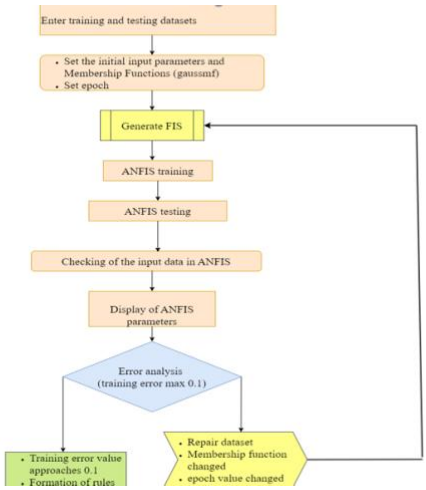

Fig. 7. ANFIS workflow

3.5 *Integration of ANFIS with Particle Swarm Optimization (PSO) algorithm*

PSO is an optimization technique inspired by the social behaviour of birds and fish. It optimizes a problem by iteratively improving a candidate solution based on the particle's own best-known position and the best know positions of the swarm.

Each blast parameter was treated as a particle in the swarm, with random initial values assigned. As the particles moved through the solution space, their velocities and positions were updated based on the best positions identified by the swarm and the individual particle's best performance. The fitness function was based on minimizing the error from the ANFIS model's predictions. In the proposed ANFIS-PSO method, Particle Swarm Optimization approach was used to adjust Gaussian membership functions parameters. This method is more flexible and less computationally expensive in comparison with classical ANFIS structure.

The objective was to find the optimal combination of input parameters (controllable parameters) that achieves the desired target fragmentation efficiency. The fitness function was defined as the difference between the predicted and target blast fragmentation efficiency values.

Additionally, PSO is considered as the population-based search method. The population consists of potential solutions, named particles. PSO algorithm consists of the following steps:

Step 1: Initialization. Randomly setting of position and velocity of all particles.

Step 2: updating velocities of all particles by the following equation:

$$V_{i(a)} = V_i + c_1 r_1 \left(P_{i,best} - P_i\right) + c_2 r_2 \left(G_{i,best} - P_i\right) \quad (1)$$

Where for a particle i, P_i , $V_{i(a)}$, V_i , $P_{i,best}$ and $G_{i,best}$, are the position, updated velocity, velocity, position of the best objective value found so far (Personal/local best position of particle) and the entire population (Global best position of swarm), respectively. c_1 and c_2 are controlling factors (cognitive and social factors), r_1 and r_2 are random variables.

Step 3: updating positions of all particles by the following equation:

$$P_{i(a)} = P_i + V_{i(a)} \quad (2)$$

Where $P_{i(a)}$ is updated position of a particle.

Step 4: updating $P_{i,best}$ and $G_{i,best}$ by the following equations:

$$P_{i(best)} = P_{i(a)} \quad \text{if } F(P_{i(a)}) > F(P_{i,best}) \quad (3)$$

$$G_{i,best} = G_{i(a)} \quad \text{if } G(P_{i(a)}) > G(P_{i,best}) \quad (4)$$

Where $F(x)$ is the objective function.

These steps are repeated until certain stopping conditions are met. The PSO algorithm was terminated when the fitness value was below a predefined threshold (0.0005) and also when the maximum number of iterations was reached. The algorithm was run for a maximum of 100 iterations.

In this research, the PSO algorithm implemented the following hyperparameters: a population size (n) of 30 particles, an inertia weight (w) of 0.7, a cognitive coefficient (c_1) of 1.5, and a social coefficient (c_2) of 1.5. These hyperparameters balance exploration and exploitation in the PSO algorithm's search, as recommended in metaheuristic optimization literature [54][55][56].

Fitness function was defined and the purpose was to evaluate the performance of a given set of parameters for the ANFIS model. In this research, Mean Absolute Error (MAE) was used as the fitness function. It measures the average absolute difference between predicted and actual outputs, ensuring the parameters lead to accurate predictions. The equation for fitness function:

$$MAE = \frac{1}{N}\sum_{i=1}^{n} |\, x_{i(actual)} - x_{i(predicted)}| \qquad (5)$$

Where $x_{i(actual)}$ and $x_{i(predicted)}$ are actual data or experimental data and predicted values, respectively. N is the number of observations. Figure 8 shows a conceptual ANFIS-PSO model workflow.

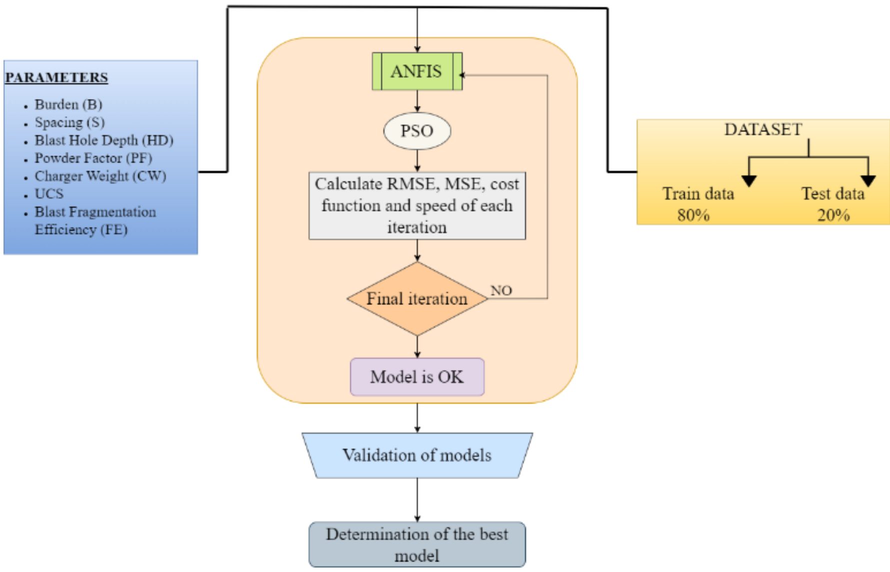

Fig. 8. Conceptual ANFIS-PSO model workflow

3.6 Sensitivity analysis of input parameters

Cosine Amplitude Method was used to calculate the strength of the relationship of each input parameter with blast fragmentation efficiency. The Cosine Amplitude Method measures the similarity or strength of the relationship between the input variables and the output variables in a multi-dimensional space. It uses the cosine of the angle between two vectors representing the input and output variables. The strength of the relationship, r_{io} between input X_i (for example Burden) and output X_o (for example Blast Fragmentation Efficiency) is calculated as:

$$r_{io} = \frac{\sum_{k=1}^{n}(X_{ik}.X_{ok})}{\sqrt{\sum_{k=1}^{n} X_{ik}^{2}.\sqrt{\sum_{k=1}^{n} X_{ok}^{2}}}} \qquad (6)$$

Where:

- X_{ik}: Value of the input variable, i for the k-th observation.
- X_{ok}: Value of the output variable, o for the k-th observation.
- n: Number of observations (data points).

4. Results

Findings included in this research are from a comparative analysis of the results obtained from multiple models, to evaluate performance and accuracy. A comprehensive sensitivity analysis of all input parameters using the Cosine Amplitude Method (CAM) was conducted. Cosine Amplitude Method highlights the influence of each input parameter on blast fragmentation efficiency as well as offering a deeper understanding of the underlying relationships within the dataset. Trial blasts were conducted using the optimized blast design parameters from PSO algorithm. Pictures from the respective blasted muck piles were taken and analyzed using WipFrag software.

4.1 Developed ANN model results

The Artificial Neural Network models with architectures of *6:4:1*, *6:5:1* and *6:10:1* were developed using two distinct training algorithms, Levenberg-Marquardt (trainlm) and Bayesian Regularization (trainbr). The prediction regression results for these models are shown in Figure 9. Among these models, the *6:10:1* Bayesian Regularization ANN demonstrated the highest regression coefficient (R^2 = 0.94812). A hybrid training approach was implemented by combining the two training algorithms to refine and simplify mathematical complexity of the model.

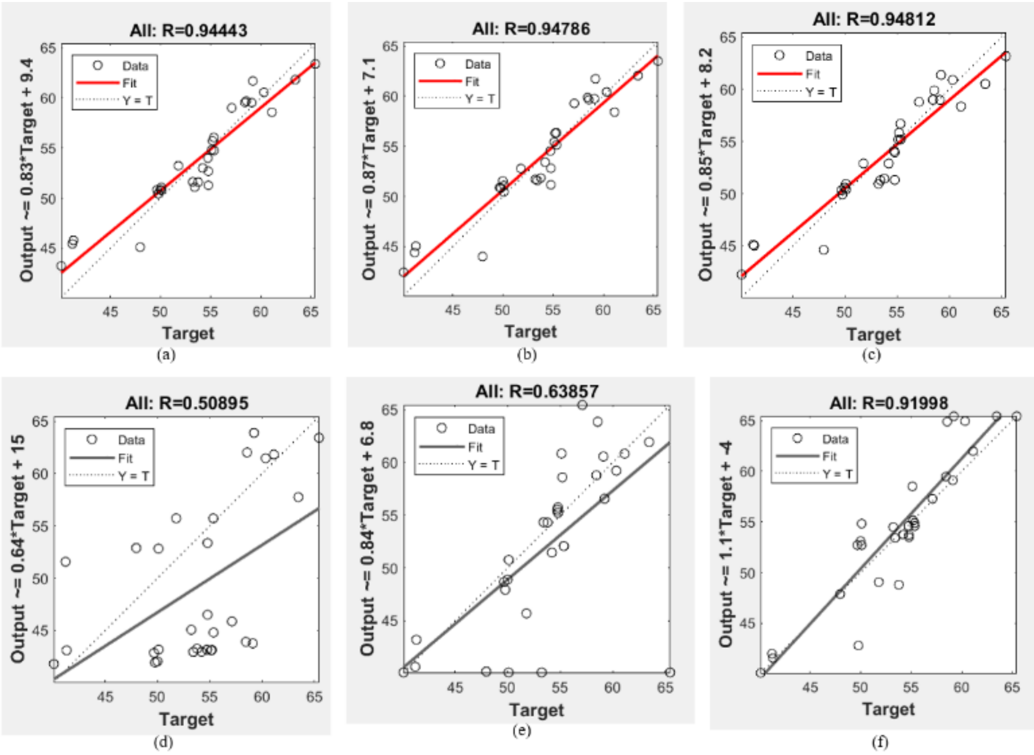

Fig. 9. ANN model regression performance; (a) BR 6:4:1 model, (b) BR 6:5:1 model, (c) BR 6:10:1 model, (d) LM 6:4:1 model, (e) LM 6:5:1 model and (f) LM 6:10:1 model

The hybrid approach began with training the ANN model using the *trainlm* algorithm, which offers fast convergence for smaller datasets. After completing this initial training, the model was retrained using *trainbr* algorithm. The *trainbr* algorithm introduced regularization to prevent overfitting and improve generalization. This hybrid training process optimized the model, achieving an R^2 value of 0.96631 and low mean square error (MSE) of 3.556 at epoch 80, as presented in Figure 10.

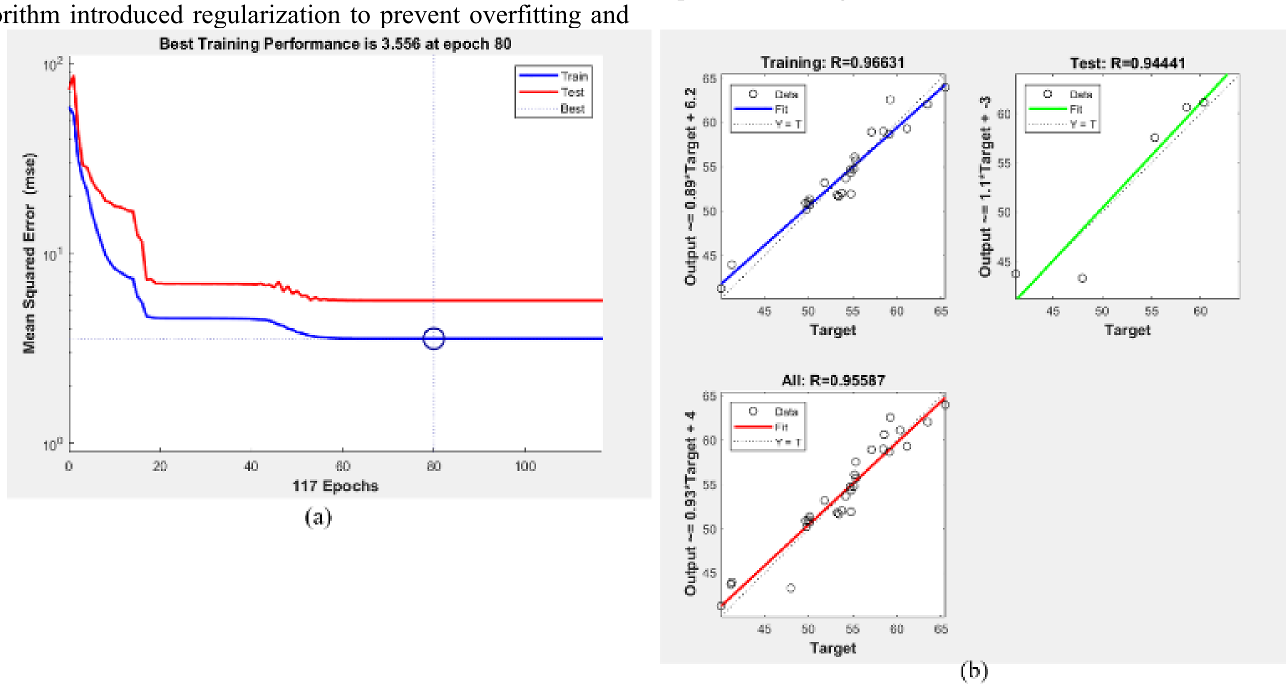

Fig. 10. The hybrid approach (Levenberg-Marquardt and Bayesian Regularization): (a) Best Training Performance, (b) Regression Results

4.2 Developed Multivariate model results

The relationship between input blast parameters and the resulting blast fragmentation efficiency was shown using Multivariate Regression model. A statistical analysis was performed to derive a predictive equation. This regression model captures the linear relationship between input parameters and the output. The adjusted correlation coefficient, R^2 value for Multivariate Regression Analysis was 0.8844. The derived MVR equation is expressed as:

$$FE\% = -39.613B - 121.156S - 26.708HD - 25.162PF + 108.944CW + 0.255UCS + 123.367$$

4.3 Developed Adaptive Neuro-Fuzzy Inference System model results

The ANFIS model was developed by employing Gaussian membership in conjunction with the grid partition method for the classification of input datasets. The Gaussian membership function was specifically chosen due to its ability to effectively handle uncertainties, smooth transitions between membership grades and nonlinear relationships among the variables. The grid partition method systematically divided the input data space into multiple fuzzy regions, ensuring that all potential input-output interactions were captured.

The model was developed with high correlation coefficient for training, testing and validation ranging from 0.934 to 0.998. The Average Error Value was found as 0.00055425 for both training and testing with 100 epochs as shown in Figure 11.

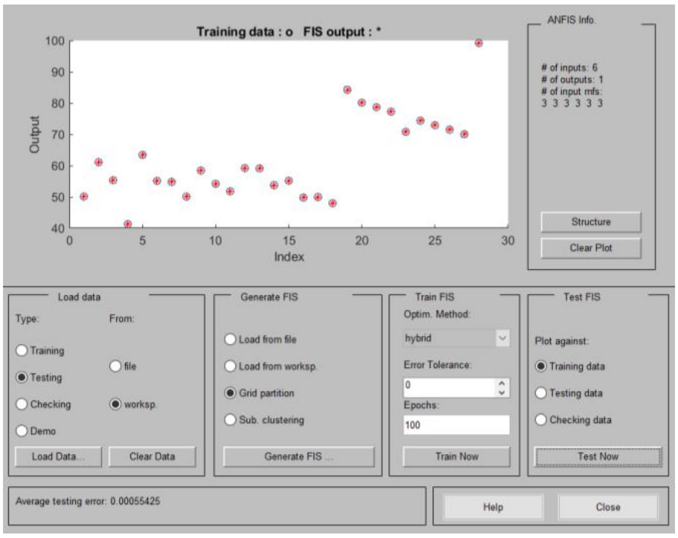

Fig. 11. ANFIS data training and testing plot

Figure 12 shows the Rule Viewer which simulates input conditions by applying fuzzy logic rules and inference mechanisms to predict the corresponding output. The rules correspond to all possible combinations of the input variables. They enable the model to comprehensively represent the relationships between the parameters influencing blast fragmentation efficiency. During the training process, the model achieved a lower training error performance value, reflecting the accuracy of the model in mapping the input-output relationships. The model attained a prediction regression result (R^2) of 0.9955. The R^2 value signifies the model's ability to accurately predict the target output based on the input parameters.

Fig. 12. Rules of ANFIS model illustrating the relationships between input and output variables

Figure 13 shows the Surface Viewer. This graph represents the relationship between two input variables (for example burden and spacing) and one output variable fragmentation efficiency. The purpose of this visualization is to help in understanding how the output, fragmentation efficiency changes with the variations in the input parameters (in this case burden and spacing). As both burden and spacing decreases, the surface gradually rises, indicating that lower values of burden and spacing lead to an increase in fragmentation efficiency. At the peak (yellow region), fragmentation efficiency reaches its maximum value. This suggest that there exist an optimal range of burden and spacing that maximizes the output variable.

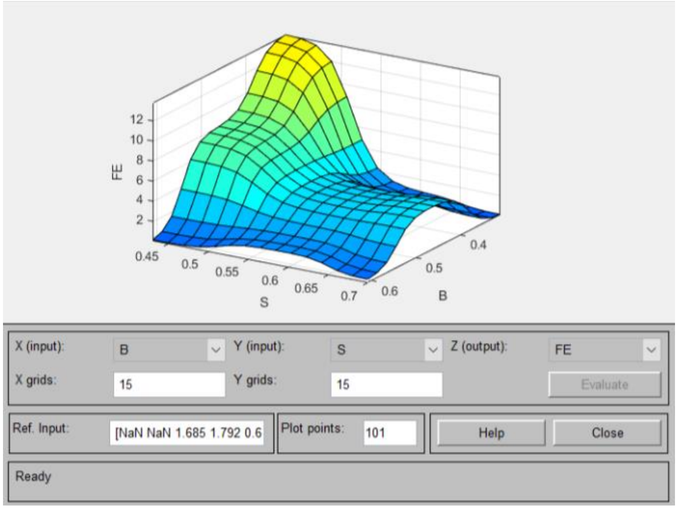

Fig. 13. Surface Viewer; Fragmentation Efficiency(FE) in relation to changes in Burden(B) and Spacing(S)

After generating output predictions using developed models, the performance of these models was evaluated by comparing predicted values (output from model) against actual measured values (data from field measurements). Table 2 and Figure 14 present the results of the error analysis performed for three models in this study. The error analysis indices used were Coefficient of Regression (R^2), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Value Accounted For (VAF).

Table 2. Results of the Error analysis for each proposed model

Models	R^2	MSE	RMSE	MAE	VAF(%)
ANFIS	0.9955	0.04356	0.2087	0.1665	99.56
ANN	0.9249	0.68969	0.8305	0.6624	92.48
MVRA	0.9005	4.3005	2.0738	1.6548	89.57

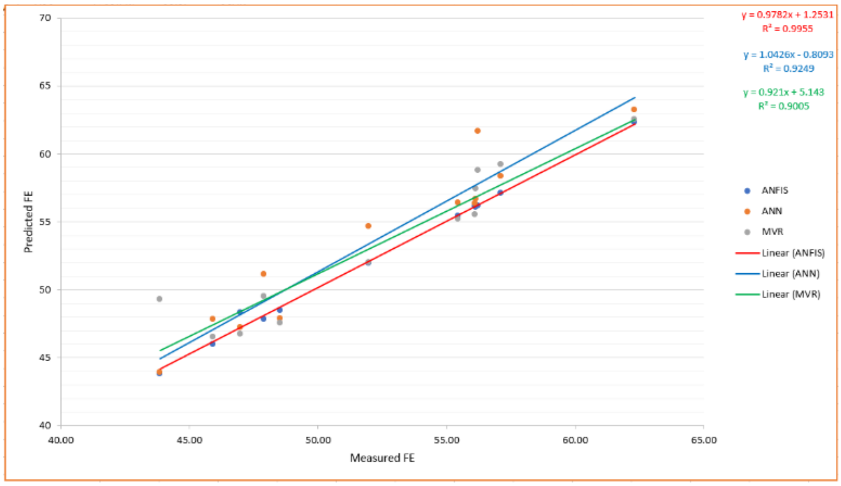

Fig. 14. Comparison of measured and predicted blast fragmentation efficiency for ANFIS, ANN and MVRA.

4.4 Integration of the ANFIS model and PSO algorithm

The graph in Figure 15 represents the fitness performance of a Particle Swarm Optimization algorithm over a series of iterations. The algorithm is used to find optimum values of input parameters that gives the desired blast fragmentation efficiency. In this graph, fitness represents the objective function value being maximized, while iterations represent the number of steps the PSO algorithm has taken to refine its solution. The goal of PSO is to reduce the fitness value to an optimal minimum, which indicates that the best possible solution has been found for the given optimization problem. The final fitness value was 0.0004193 at an iteration 100. This suggested that the PSO algorithm was successfully converged to an optimal solution with very low error.

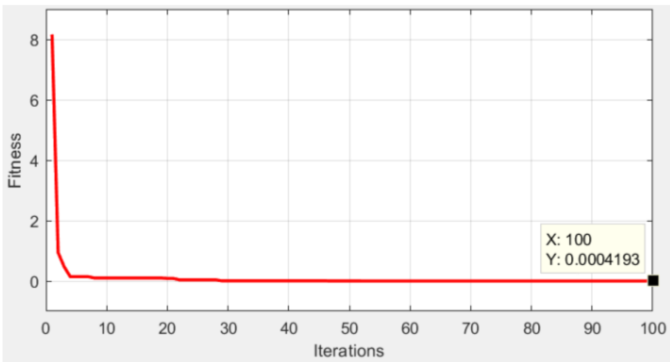

Fig. 15. Fitness function of PSO algorithm

Particle Swarm Optimization algorithm optimized input parameters to achieve a blast fragmentation efficiency of 84%. Suggested optimal input parameters were:

For rock mass with UCS of 175 MPa, the following are the optimum parameters from the PSO algorithm: Burden = 0.35 m; Spacing = 0.47 m; Hole Depth = 2.00 m; Powder Factor = 1.8 kg/m^3; Charge Weight = 0.6 kg.

4.5 Sensitivity analysis

In this research, sensitivity analysis was used to determine the influence of input variable on blast fragmentation efficiency. The Cosine Amplitude Method (CAM) for sensitivity analysis was used. The CAM equation was used to calculate the strength or weight of the relationship (r_{io}) between the datasets, X_i (input) and X_o (output) with n data points. Figure 16 shows the outcome of the sensitivity analysis performed in this study.

The results in Figure 16 were based on the cosine amplitude approach in (6). The equation demonstrated the strength of the relationship between each input variable and blast fragmentation efficiency

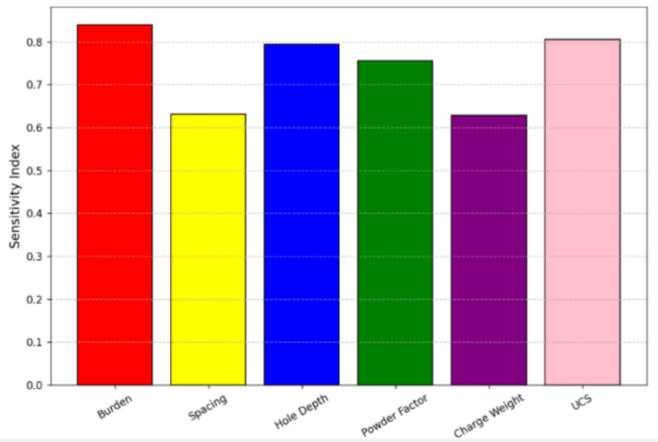

Fig. 16. Sensitivity analysis of input variables

Burden has the greatest influence on fragmentation efficiency, followed by uniaxial compressive strength, hole depth, powder factor, charge weight and lastly spacing. The sensitivity indexes of these input parameters were: Burden = 0.839; Spacing = 0.632; Hole Depth = 0.793; Powder Factor = 0.755; Charge Weight = 0.628; UCS = 0.805. Sensitivity analysis results from the Cosine Amplitude Method indicate that burden and UCS have high sensitivity to blast fragmentation efficiency. The findings align strongly with the blasting theory. Fragment size is directly affected by explosive energy concentration per unit volume of rock, hence explaining the influence of burden in blast fragmentation. The high sensitivity of UCS is explained by the rock's resistance to fracture. Higher UCS values demand correspondingly optimized blast designs for effective fragmentation. The importance of energy distribution and the specific energy applied per volume of rock is explained by the subsequent influence of blasthole depth and powder factor. The effect of spacing is often optimized in relation to the burden due to its strong coupling with burden in the blast design, hence showing a relatively lower impact. These findings are supported by recent field and modeling studies in blasting literature, which confirm that both parameters are the most sensitive factors affecting fragmentation outcomes, and validate the theoretical basis for their influence [26][57][58][59].

4.6 Trial blasts and performance evaluation of optimized input parameters

Trial blasts were conducted using the optimized blast design parameters from the PSO algorithm. The optimized blast design model resulted in improved blast fragmentation efficiency (from 40.11%-65.44% to 68.43%-85.23%). To statistically validate that this improvement was due to the optimized parameters and not due to uncontrollable variables or to random chance, a paired t-test was conducted on the fragmentation efficiency values from 10 blasts before and after optimization. Statistical validation (paired t-test, $p<0.01$) was carried out following established practices in recent PSO and engineering optimization literature, confirming that observed improvements are significant and unlikely to result from random variation or uncontrolled factors [60][61][62][63][64]. Table 3 shows 10 blasts before and after optimization.

Table 3. Blast fragmentation efficiency before and after optimization

Blast	Pre-optimization efficiency	Post-optimization efficiency	Difference (*d*)
1	41.2	68.8	27.6
2	44.5	74.5	30.0
3	50.7	81.4	30.7
4	62.3	82.9	20.6
5	54.0	77.6	23.6
6	63.9	83.7	19.8
7	57.8	71.2	13.4
8	46.2	79.5	33.3
9	60.1	85.1	25.0
10	65.4	80.3	14.9

From Table 3, the mean of the differences, $\bar{d}$, is 23.89. The standard deviation of the differences, the standard error, the t-statistic and the degrees of freedom are then obtained from Eqs. (7) to (10), respectively.

Standard deviation of the differences,

$$s_d = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(d_i - \bar{d})^2} \quad (7)$$

Standard error,

$$SE = \frac{s_d}{\sqrt{n}} \quad (8)$$

t-statistic,

$$t = \frac{\bar{d}}{SE} \quad (9)$$

Degrees of freedom,

$$df = \mathrm{n} - 1 \quad (10)$$

Substituting the values from Table 3 gives a standard deviation of 6.71 and a standard error of 2.12, yielding a t-statistic of 11.25 at 9 degrees of freedom. The corresponding two-tailed p-value is 1.33×10^{-6}, which is well below 0.01 and therefore indicates a statistically significant improvement. The 95% confidence interval for the mean difference, (19.09, 28.69), lies entirely above zero, confirming that the observed gains in blast fragmentation are not attributable to chance.

Pictures from the respective blasted muck piles were taken and analyzed using WipFrag software. Figure 17, Figure 18 and Figure 19 show combined particle size distribution curves for pre-optimization and post-optimization blasts.

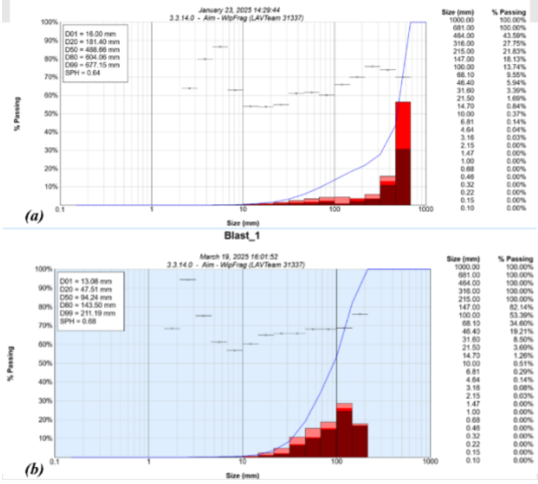

Fig. 17. Results from WipFrag analysis of particle size distribution for first blasted muck pile; (a) pre-optimization curve, (b) post-optimization curve.

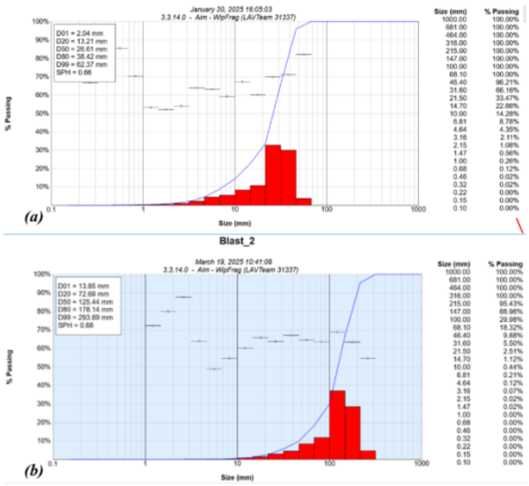

Fig. 18. Results from WipFrag analysis of particle size distribution for second blasted muck pile; (a) pre-optimization curve, (b) post-optimization curve.

As illustrated in Figure 17, Figure 18 and Figure 19, the blast fragmentation efficiency shows an improvement after implementing the optimized blast design parameters. Prior to optimization, the fragmentation efficiency ranged between 40.11% and 65.44%. After implementing the optimized blast design, the fragmentation efficiency increased significantly, achieving a range of blast fragmentation efficiency between 68.43% and 85.23%. This notable improvement demonstrates the effectiveness of ANFIS-PSO model which leads to better fragmentation control and improved operational efficiency. Two among the key elements in WipFrag analysis are histogram and sphericity lines on the PSD chart. By analyzing the histogram, it shows the frequency of particle sizes within specific bins, helping to visualize fragmentation trends. The histogram shape in post-optimization curves is a normal distribution, which suggest a well-balanced fragmentation. The shape of the histogram is also more like a right-skewed distribution which indicates less boulders and small particles sizes dominance. Sphericity represents the ratio of particle length to width, indicating shape uniformity. WipFrag incorporates sphericity lines on the PSD chart to provide insight into particle geometry. From these PSD charts, the sphericity ranges from 60% to 90%, which represents well-shaped, near-uniform particles, ideal for crushing and handling.

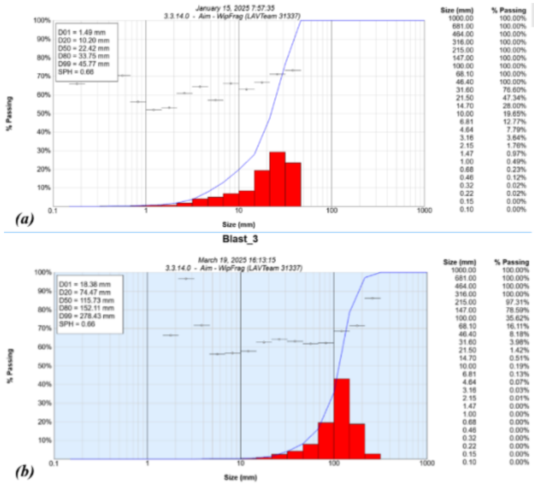

Fig. 19. Results from WipFrag analysis of particle size distribution for third blasted muck pile; (a) pre-optimization curve, (b) post-optimization curve

5. DISCUSSIONS

The use of AI models in mining operations is improving efficiency and yielding positive impacts. Previously, empirical techniques were used in the prediction of blast fragmentation outcomes, but were not capable for producing higher accuracy predictions. This is because of their inability to adapt to the varying and complex geological conditions across different mining zones, as well as the non-linearity between input and output variables. Artificial Intelligence has emerged as a powerful tool in the mining industry, capable of addressing these limitations of empirical models. In this study, an Adaptive Neuro-Fuzzy Inference System coupled with a Particle Swarm Optimization algorithm, Multivariate Regression Algorithm, and Artificial Neural Network models was utilized to solve the blast fragmentation problem. The ANFIS-PSO model has demonstrated superiority over ANN and MVRA in prediction performance, indicating its strong suitability in predicting blast design variables. This highlights the need for hybrid AI models. This is because the ANFIS model's hybrid architecture leverages Fuzzy Logic's capability to handle uncertainty and imprecision alongside ANN's adaptive learning capacity. ANFIS can model the highly non-linear and complex interactions between blasting parameters, whereas MVRA is limited to capturing linear relationships. The ANN model effectively learns nonlinear relations in the dataset. However, the model may struggle with noise and lack interpretability. Fuzzy Logic, on the other hand, captures vagueness but lacks data-driven learning. The strengths of ANN and Fuzzy Logic are integrated in an ANFIS model, enabling it to capture complex nonlinear and uncertain relationships intrinsic to blasting parameters in variable geological settings. Similar findings have also been shown by [65][66][67][68].

The proposed ANFIS model has problems with dimensionality. The model's training complexity grows exponentially with the increase in the number of input variables usually above 5. The exponential rule is derived from the number of membership grades and the number of input variables. This will result in an increase in memory and training time. The training time for the ANFIS model on the dataset was approximately 45 minutes using MATLAB R2018a on a standard workstation (Intel i5 processor, 16GB RAM). This training time was compared with that of Artificial Neural Network (ANN) model with a 6:10:1 architecture and hybrid Bayesian Regularization algorithm which required only about 2 minutes on the same hardware. This difference in training time for the ANFIS model with the ANN model highlights the computational overhead introduced by the comprehensive fuzzy rule base. Recent studies have shown this challenge, noting the computational expense of the ANFIS model, despite its high interpretability and accuracy, implying that as a limiting factor for real-time applications.[69][70][71][72].

As a result, it is crucial for future research to explore the use of clustering techniques that reduce rule explosion by grouping input data before generating fuzzy rules.

The model is usually trained on static datasets and cannot react dynamically to real-time changes. This results in the model's inability to adapt to unexpected field conditions such as moisture content. It is recommended that future researchers should consider implementing real-time data collection with diverse input parameters, considering dynamic changes in blasting conditions. This approach will allow real-time adjustments of blast parameters in an adaptive system.

In this research, 6 input parameters have been utilized: burden, spacing, blast hole depth, charge weight, powder factor and UCS. Future research should focus on considering advanced geotechnical parameters like Rock Quality Designation. This will enable predictive models to better account for geological variability and improve their adaptability across diverse mining conditions, leading to more precise blast designs.

6. CONCLUSION

The findings of this study show that in mining operations, Artificial Intelligence-driven blast optimization is revolutionary. Significant gains in fragmentation efficiency, cost savings, and operational performance were obtained by combining hybrid Artificial Intelligence and metaheuristics optimization algorithms. Predicting fragmentation using the ANFIS model was most successful. In all statistical tests the hybrid model outperformed ANN and MVR. The optimized blast design model resulted in;

- Improve blast fragmentation efficiency (from 40.11%-65.44% to 84% and above).
- Reduced secondary blasting costs.
- Lower energy consumption (material rehandling and crushing in plant).
- Higher production output.

The results of this study provide strong evidence for the ongoing use of Artificial Intelligence, soft computing and optimizing algorithms in mining operations to maximize efficiency, lower operating costs, and enhance general mine's profitability. The revenue lost during 6 months prior to optimization, from October to March, was $66130.10 and total explosives cost due to secondary blasting in 6 months was $3052.50. Electrical energy consumption, mainly from compressor and other costs were $80 811. This gives the total cost before optimization of $149993.60. The cost incurred in implementing predictive models and conducting trial blasts was $50150, constituting energy costs for drilling and explosive costs.

The benefits after optimization represent the economic recovery of the mining operations. Revenue recovered after optimization is 85% of the previously lost revenue. The recovery resulted from increased monthly output and reduced operational costs. This implies that anticipated recovered revenue is $56210.59. The results from WipFrag shows a positive impact of the optimized blast model with a predicted 79% cost reduction in secondary blasting and this is translated to about $2411.48. The blast design saves energy up to approximately 50% of the previous energy cost. This is because the optimized design reduces energy usage in material rehandling and crushing in plant. Increased throughput is realized and also equipment life and maintenance costs are reduced.

Overall, the optimized blast design yielded a return on investment estimated at 199%, with a payback period slightly exceeding three months. These figures assume the continuation of projected savings and highlight the significant financial and operational advantages of implementing AI-driven blast optimization.

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