



Measurement and Prediction of Blast-Induced Flyrock Distance Using Unmanned Aerial Vehicles and Metaheuristic-Optimized ANFIS Neural Networks

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Flyrock from blasting in open-pit mining is one of the most dangerous occurrences that can cause accidents to workers, damage to machinery and equipment and even fatalities. Therefore, quick and reliable prediction of blast-induced flyrock distance (BIFRD) in open-pit mines is very crucial to ensure the safety of the surrounding environment. In this study, unmanned aerial vehicle (UAV) technology combined with advanced artificial intelligence techniques was used to predict BIFRD in open-pit mines and improve safety. UAV was used to record blasting operations and the resulting flyrock. The distance of the flyrock was then measured from the recorded video footage and was analyzed using the ProAnalyst software. Then, various metaheuristics-optimized ANFIS (adaptive neuro-fuzzy inference system) was developed to predict BIFRD. These networks were optimized using adaptive differential evolution with optional external archive (JADE), genetic algorithm (GA), fireworks algorithm (FWA), and artificial bee colony (ABC) algorithms and resulted to JADE-ANFIS, GA-ANFIS, FWA-ANFIS, and ABC-ANFIS models. A dataset with 204 blasting events was gathered and analyzed, and finally, only four input variables were used for developing these models, including spacing, weight charge, stemming, and powder factor. The results showed that JADE-ANFIS is the best with high accuracy (97.8%), good generalizability (MAPE of 1.1%), and reasonable training time for predicting BIFRD in this study. The other models performed poorly with accuracy ranging from 88.7 to 96.5% and MAPE ranging from 1.4 to 3.0%. Sensitivity analysis also showed that the length of stemming is the most affecting factor to flyrock distance in blasting and thus careful consideration should be given in designing blast patterns to control flyrock distance in open-pit mines.

KEY WORDS: Mine blasting, Flyrock safety, Monitoring flyrock, Flyrock prediction, Unmanned aerial vehicle, ANFIS, Metaheuristic algorithms.

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INTRODUCTION

Blasting is a critical operation in open-pit mining, as it affects the performance of the next activities, such as excavation/loading, hauling/transporting, crushing, and dumping. Too small rock mass after blasting may fulfill the requirements of the next activities; however, it is costly and requires high explosive energy for frag-

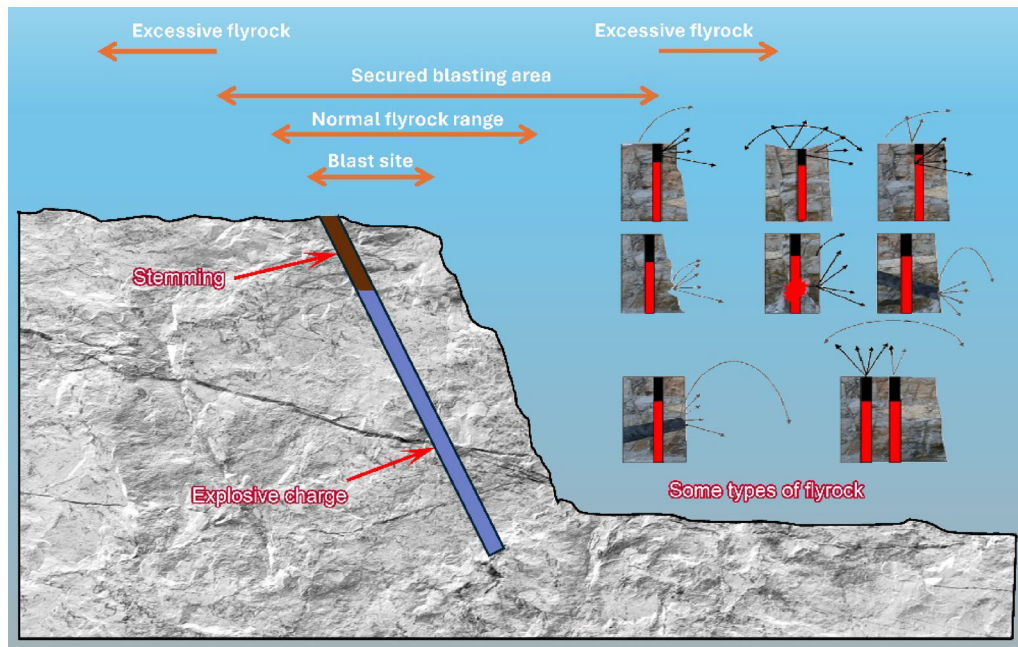


Figure 1. Classification of flyrock zones induced by mine blasting.

menting rock as such small sizes. In contrast, over-size rock might reduce the efficiency of the next technological processes. Therefore, the effective utilization of explosive energy is a crucial issue in open-pit mines.

Based on earlier studies, a portion of the energy from the explosive material is not fully utilized in fragmenting rock. Only 20–30% of the explosive energy is utilized for this purpose, with the rest being wasted, and released with negative effects on the surrounding environment, such as blast-induced flyrock distance (BIFRD), ground vibration, back-break, air over-pressure, toxic, and gases (Monjezi et al., 2014; Persson, 2020; Nguyen & Bui, 2022). While considerable attention has been given in recent years to BIFRD, ground vibration, and air over-pressure (Stojadinović et al., 2015; Zhu et al., 2022; Yardimci & Erkayaoglu, 2023), they are also known as the most concerning that can damage the surrounding, particularly humans (Bajpayee et al., 2004; Armaghani et al., 2014; Roy et al., 2022). While ground vibration and air overpressure can also cause damage, flyrock presents an immediate and unpredictable threat to human life and property (Sevelka, 2022, 2023). Unlike ground vibrations, which tend to affect structures over time, and air overpressure, which is primarily a concern for

nearby buildings and equipment, flyrock involves physical debris ejected from the blast site at high velocities, which can travel beyond predicted distances. This makes it more dangerous because it can cause sudden, catastrophic injuries to workers or fatalities, damage to machinery, and destruction of infrastructure.

Investigated by Fletcher and D'Andrea (1987), flyrock was divided into different zones, including normal flyrock range, secured blasting area, and excessive flyrock (Fig. 1). However, these zones are only suitable for throw-rock and excessive throw-rock, as the danger zones are not uniform and flyrock tends to fly toward the front of blast face (Fig. 1) (Fletcher & D'Andrea, 1987). Adjusting the direction of detonator of blast can mitigate the flyrock toward the front of blast face; however, it may make the blast-induced ground vibration and back-break increase in the benches and damage to the structures that need to be protected (Fig. 2).

Based on the significance of blasting, its use of explosive energy, the mechanism of flyrock, and its adverse effects on the surrounding environment (e.g., humans, structures), a rapid and highly reliable computation/prediction system for BIFRD is critical to ensuring safety in open-pit mines. Many researchers have proposed and applied various tech-

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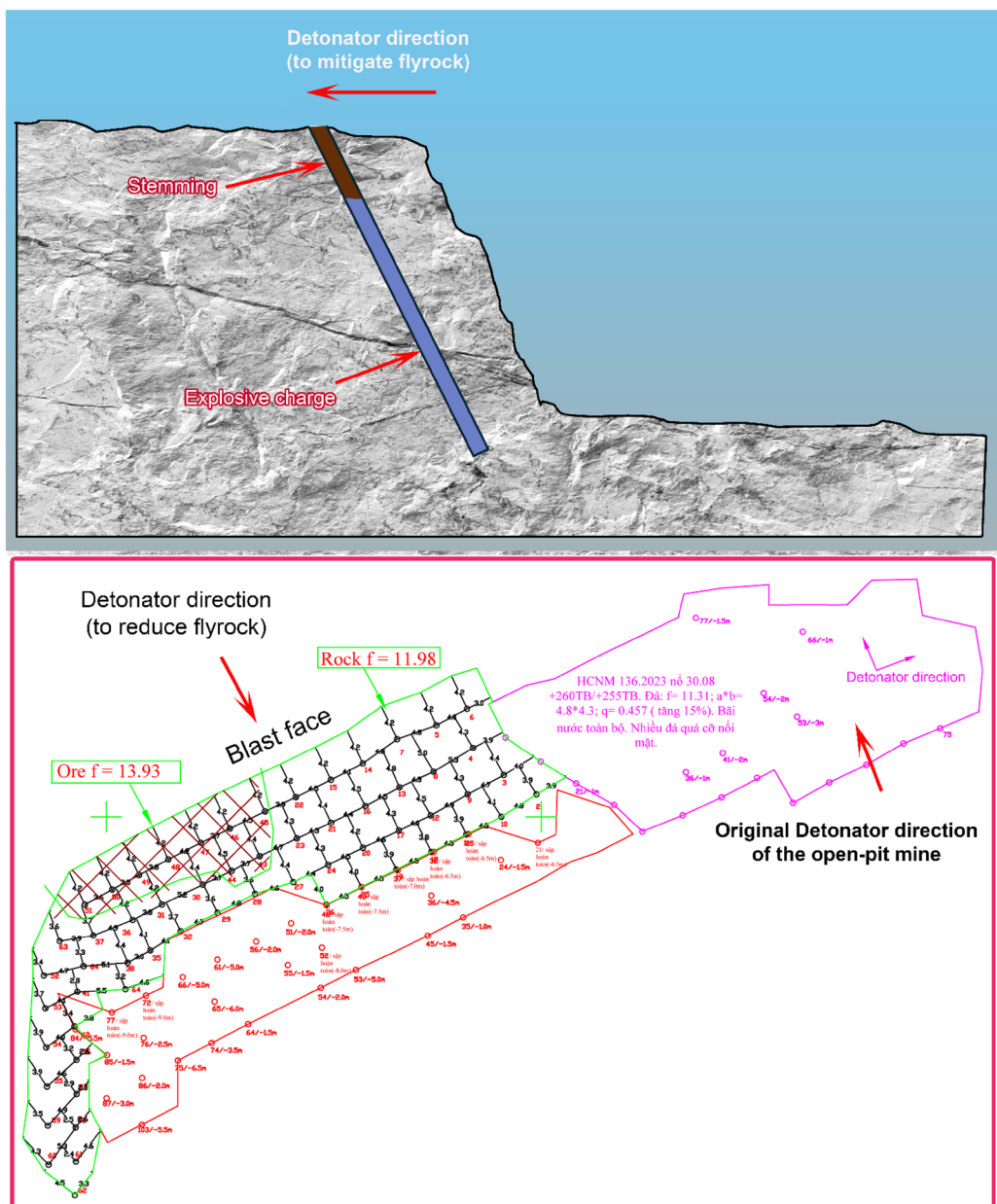


Figure 2. Orientation of the detonator for explosions intended to minimize flyrock directed toward the front of the blast face.

niques, such as empirical equations, artificial intelligence-based models, and simulations, to predict BIFRD. Among these techniques, machine learning-based models are recommended as superior ones, providing better accuracy in predicting BIFRD in open-pit mines, as reviewed in Table 1.

As summarized in Table 1, several machine learning-based models have been proposed between

2015 and 2024 to estimate BIFRD produced by mine blasting. Remarkably, Stojadinović et al. (2015) and Mishra et al. (2023) developed several machine learning-based models for predicting flyrock launch velocity (v_f) instead of BIFRD, and then BIFRD is also calculated based on this parameter. These models primarily utilize SVR, ANN (specifically MLP), ANFIS, GEP, and ELM. Some models are

Table 1. Summary of the machine learning-based models, flyrock distance measurement methods, and performances for predicting BIFRD

Models	Input parameters	BIFRD measure- ment method	Performance	Reference	Published year
ANFIS	MC, PF	GPS	$R^2 = 0.979$; RMSE = 0.029; VAF = 97.925	Armaghani et al. (2015)	2015
ANN	D_b , TD _h , β , S_s , S_f , S, Trbw, PF, τ , N_R , B, H_b/B , I_s/I_{bh} , B/d, MC, N_b , R_n	GPS	Accuracy: 94% $\pm$ 10% error margin	Stojadinović et al. (2015)	2015
PSO-based power equa- tion	B, S, ST, PF, RD	GPS	RMSE = 12.01; NS = 0.97; $R^2 = 0.96$	Hasanipanah et al. (2016)	2016
ORELM	B, S, ST, PF, RD	GPS	RMSE = 12.753; MAE = 10.144	Lu et al. (2019)	2019
BN	D_b , D_h , B/S, ST, MC, PF	GPS	Probability = 100%	Han et al. (2019)	2019
DNN	B, S, ST, PF, MC	GPS	$R^2 = 0.978$; RMSE = 9.112	Guo et al. (2019)	2019
GA-based	B, S, ST, D_h , RMR, D_b , PF, H_b	GPS	$R^2 = 0.984$; RMSE = 5.237; VAF = 98.420; MAE = 4.719	Hasanipanah and Bakhtshandeh Amnieh (2020)	2020
ELM-BBO	B/S, D_b , PF, ST, MC, D_h	GPS	RMSE = 18.84; MAE = 13.43; $R^2 = 0.94$	Murlidhar et al. (2020)	2020
SVR	D_b , D_h , B/S, ST, MC, PF	GPS	$R^2 = 0.905$; RMSE = 18.794	Armaghani et al. (2020)	2020
KELM	B, S, ST, PF	GPS	$R = 0.971$; RMSE = 13.046; MAPE = 5.097; KGE = 0.958; Theil ₁ = 0.028; Theil ₂ = 0.055.	Jamei et al. (2021)	2021
HHO-MLP	D_b , GSI, D_h , WI, RQD, ST/B, PF, CPM	GPS	$R^2 = 0.996$; RMSE = 7.205; MAPE = 0.026; VAF = 99.636; RSE = 0.0051	Murlidhar et al. (2021)	2021
GEP	B, S, ST, PF	GPS	$R^2 = 0.91$; RMSE = 10.81	Monjezi et al. (2021)	2021
GEP	S, B, ST, PF, L_c	GPS	$R^2 = 0.914$	Dehghani et al. (2021)	2021
ANFIS-GOA	S, B, ST, PF, RD	GPS	MSE = 0.003; $R^2 = 0.974$	Fattahi & Hasanipanah (2021)	2021
SSM bagging	D_b , D_h , B/S, ST, MC, PF	GPS	MSE = 0.0059; $R^2 = 0.974$	Barkhordari et al. (2022)	2022
ANFIS	B, S, H_b , D_b , ST, D_{sub} , T_c , C_s , X_{bbs} , M_f	GPS	MAE = 5.4; MAPE = 7.84; $R = 0.986$; NSE = 0.970	Hudaverdi (2022)	2022
ANN	ST, MC, PF	UAV	$R = 0.998$	Lawal et al. (2022)	2022
MSHMO-SVR	D_b , D_h , B/S, ST, MC, PF	GPS	RMSE = 12.282; $R^2 = 0.966$; MAE = 8.503; VAF = 96.616	Li et al. (2023)	2023
ERTR-BO	B, H_b/B , I_s/I_{bh} , B/d, W, ρ_r	GPS	$R^2 = 0.988$; RMSE = 0.866; MAE = 0.517; MAPE = 2.126	Mishra et al. (2023)	2023
PSO-MRA	D_b , D_h , PF, ST, MC, B	GPS	$R = 0.918$	Chen et al. (2024)	2024
Boosted SD-MKL	D_h , PF, ST, S, D_s , B	GPS	RMSE = 1.73; MAE = 0.78; VAF = 99.24	R. Zhang et al. (2024)	2024

B burden, TD_h total drilling length, GSI geological strength index, RQD rock quality designation, ST stemming, T_c total explosive used, S spacing, T_p total of primer, Nb number of blast holes, Trbw total rock blasted volume, PF powder factor, D_s specific drilling, D_h borehole depth, L_c length of charge, RD rock density, H_b bench height, MC maximum explosive charge per delay, C_s specific charge, D_b borehole diameter, X_{bbs} average in-place block size, RMR rock mass rating, M_f quantity of material in front of the surface, B/S burden-to-spacing ratio, W energy factor, CPM explosive charge per meter, V_f flyrock launch velocity, WI weathering index, ρ bulk density of rock, D_{sub} sub-drilling, β blasthole dip, S_s specific stemming, SF stemming factor, τ hole-to-hole delay, NR number of reliefs, R_n number of rows, ANFIS adaptive neuro-fuzzy inference system, ANN artificial neural network, PSO particle swarm optimization, ORELM outlier robust extreme learning machine, BN Bayesian network, DNN deep neural network, GA genetic algorithm, ELM-BBO extreme learning machine-biogeography-based optimization, SVR support vector regression, KELM kernel extreme learning machine, HHO-MLP Harris hawks optimization-multi-layer perceptrons neural network, GEP gene expression programming, GOA grasshopper optimization algorithm, SSM bagging separate stacking ensemble-bagging, MSHMO Harris hawks optimization with multi-strategies, ERTR-BO extremely randomized trees regression-Bayesian optimization, MRA multiple regression analysis, Boosted SD-MKL stacked deep multi-kernel learning, RMSE root-mean-squared error, MAE mean absolute error, VAF variance accounted for, R^2 = determination coefficient; MAPE = mean absolute percentage error.

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further enhanced through optimization with metaheuristic algorithms, which, as indicated by reviews, generally outperform standalone machine learning-based models in predicting BIFRD. The prediction of flyrock distances has evolved from simpler models like PSO-based power equations (Hasanipanah et al., 2016) to more complex hybrid models such as HHO-MLP (Murlidhar et al., 2021) and Boosted SD-MKL (Zhang et al., 2024). The models incorporate metaheuristic algorithms such as Particle Swarm Optimization (PSO), Bat Algorithm (BA), and Genetic Algorithm (GA), demonstrating a shift toward optimization techniques to fine-tune model parameters and improve prediction accuracy.

Related to input parameters used, a wide range of input parameters is being utilized, such as burden (B), stemming (S), spacing (ST), and powder factor (PF), which have been constants throughout the years. However, more recent models incorporate additional factors like rock density (RD), moisture content (MC), and hole diameter (D_h). These new input variables reflect an attempt to capture more granular and varied aspects of the blasting environment that might affect flyrock distance.

Most studies in this area utilize the GPS method to measure BIFRD, with only one known instance using UAV (unmanned aerial vehicle) technology in conjunction with an ANN model for prediction, as outlined in Table 1. The GPS method involves high-speed cameras placed on the ground to record flyrock trajectories, with positions subsequently determined through video analysis. The GPS device is then used to measure the actual BIFRD. However, this method is laborious and time-consuming in data collection. In contrast, Lawal et al. (2022) demonstrated the convenience of measuring BIFRD using advanced techniques, especially through the use of UAV method. Nonetheless, this study only presented an ANN model without comparisons to elucidate the laws governing BIFRD in rock and ore blasting, which constitutes a limitation.

Based on the review, we see that the evolution of models for predicting BIFRD is rapid, from early stage to recent developments, and now hybrid models are dominant. Among the early models (2015–2016), classical approaches like ANFIS and power equations optimized using metaheuristics performed reasonably well, but their error margins were large, and their scope was limited by the rela-

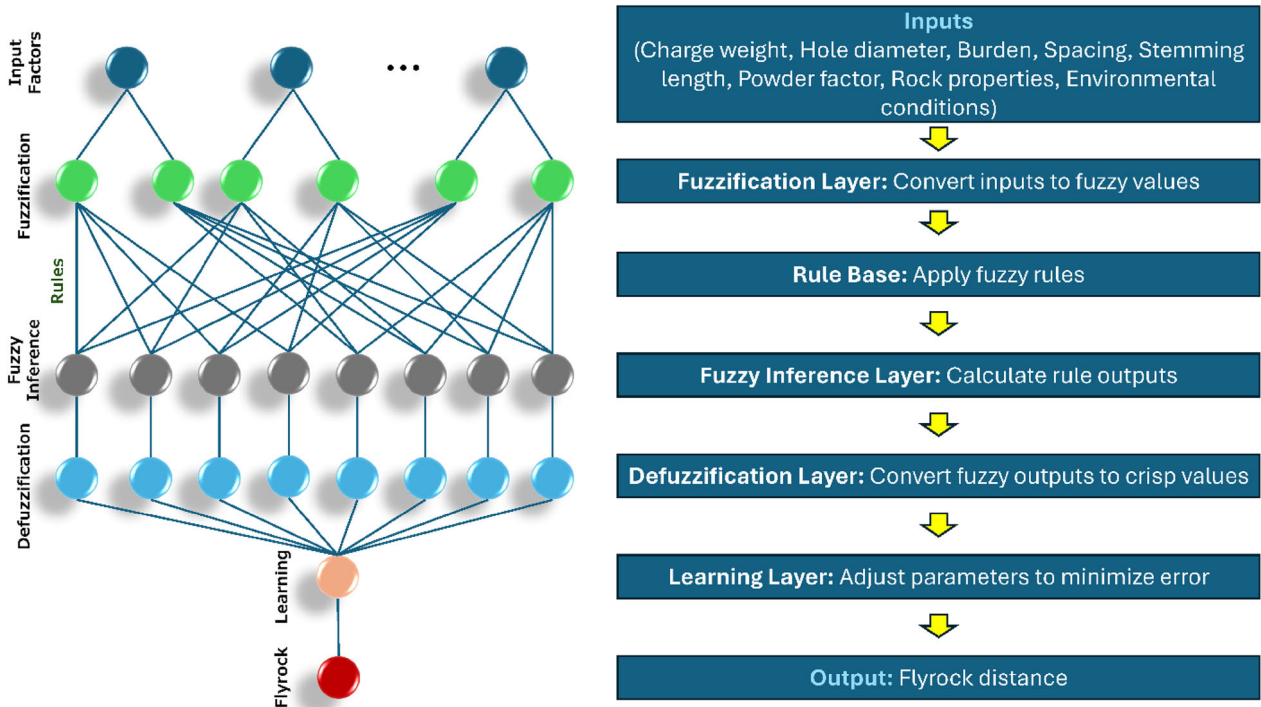


Figure 3. Key elements of an ANFIS model to predict BIFRD in mine blasting.

Pseudo-code of the Genetic Algorithm (GA)

Inputs :

- k : number of generations
- n : number of individuals in a population
- p_c : crossover probability
- p_m : mutation probability

Output: Best solution

```

1  $t \leftarrow 0$ ;
2 Let  $P^{(t)} = (I_1, I_2, \dots, I_n)$  be an initial population of  $n$ 
   individuals;
3 FitnessOperator( $P^{(t)}$ ) ;
4 repeat
5   Select a subset of individuals  $P^*$  such that  $P^* \subseteq P^{(t)}$  ;
6   CrossoverOperator( $P^*, p_c$ );
7   MutationOperator( $P^*, p_m$ );
8   FitnessOperator( $P^*$ ) ;
9    $P^{(t+1)} \leftarrow P^*$ ;
10   $t \leftarrow t + 1$ ;
11 until  $t > k$ ;
12 return the best individual in  $P^{(t)}$ ;

```

Figure 4. The GA algorithm's pseudo-code.

tively fewer input parameters. More recent models (2020–2024) incorporate deeper architectures like deep neural networks (DNN) and optimization-driven models like ELM–BBO (Murlidhar et al., 2020), leading to substantial improvements in performance. These models are more robust, leveraging a larger dataset with a wider range of input parameters. The latest researches focus on hybrid models combining neural networks (e.g., ANFIS, DNN) with optimization algorithms (e.g., GA, HHO, PSO). For instance, ANFIS–GOA (2021) and MSHHO–SVR (2023) are capable of reducing the error rates to previously unseen levels. Along with the rapid development of remote sensing technologies, like UAV, it is clear that the future trends of the mining industry are the incorporation of UAV combined with boosted algorithms.

Therefore, this paper proposes four new hybrid models for predicting BIFRD based on ANFIS and metaheuristic algorithms: adaptive differential evo-

lution with optional external archive (JADE)—ANFIS, GA—ANFIS, fireworks algorithm (FWA)—ANFIS, and artificial bee colony (ABC)—ANFIS. The study also integrated UAV technology for measuring BIFRD. The primary novelty and contribution of this work lie in the integration of UAV technology with new hybrid machine learning-based models for estimating BIFRD as a rapid and highly reliable computation model in open-pit mines.

METHODOLOGY

ANFIS Model for Predicting BIFRD

ANFIS is a powerful neural network that combines the capabilities of fuzzy logic systems and ANN to perform adaptive reasoning and decision-making. It was introduced first by Jang (1993) as a

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Pseudo-code of JADE with archive	
01	Begin
02	Set $\mu_{CR} = 0.5$; $\mu_F = 0.5$; $A = \emptyset$
03	Create a random initial population $\{\mathbf{x}_{i,0} i = 1, 2, \dots, NP\}$
04	For $g = 1$ to G
05	$S_F = \emptyset$; $S_{CR} = \emptyset$;
06	For $i = 1$ to NP
07	Generate $CR_i = \text{rand}_i(\mu_{CR}, 0.1)$, $F_i = \text{rand}_i(\mu_F, 0.1)$
08	Randomly choose $\mathbf{x}_{\text{best},g}^p$ as one of the 100p% best vectors
09	Randomly choose $\mathbf{x}_{r1,g} \neq \mathbf{x}_{i,g}$ from current population $\mathbf{P}$
10	Randomly choose $\tilde{\mathbf{x}}_{r2,g} \neq \mathbf{x}_{r1,g} \neq \mathbf{x}_{i,g}$ from $\mathbf{P} \cup \mathbf{A}$
11	$\mathbf{v}_{i,g} = \mathbf{x}_{i,g} + F_i \cdot (\mathbf{x}_{\text{best},g}^p - \mathbf{x}_{i,g}) + F_i \cdot (\mathbf{x}_{r1,g} - \tilde{\mathbf{x}}_{r2,g})$
12	Generate $j_{\text{rand}} = \text{randint}(1, D)$
13	For $j = 1$ to D
14	If $j = j_{\text{rand}}$ or $\text{rand}(0, 1) < CR_i$
15	$u_{j,i,g} = v_{j,i,g}$
16	Else
17	$u_{j,i,g} = x_{j,i,g}$
18	End If
19	End For
20	If $f(\mathbf{x}_{i,g}) \leq f(\mathbf{u}_{i,g})$
21	$\mathbf{x}_{i,g+1} = \mathbf{x}_{i,g}$
22	Else
23	$\mathbf{x}_{i,g+1} = \mathbf{u}_{i,g}$; $\mathbf{x}_{i,g} \rightarrow \mathbf{A}$; $CR_i \rightarrow S_{CR}$, $F_i \rightarrow S_F$
24	End If
25	End for
26	Randomly remove solutions from $\mathbf{A}$ so that $ \mathbf{A} \leq NP$
27	$\mu_{CR} = (1 - c) \cdot \mu_{CR} + c \cdot \text{mean}_A(S_{CR})$
28	$\mu_F = (1 - c) \cdot \mu_F + c \cdot \text{mean}_L(S_F)$
29	End for
30	End

Figure 5. Pseudo-code of the JADE algorithm.

way to cash-in on the strengths of both fuzzy systems and ANNs. The ANFIS architecture typically consists of five layers (Fig. 3).

In Figure 3, the fuzzification layer is a crucial part of fuzzy logic systems and fuzzy inference systems (FIS). It converts precise numerical input data into fuzzy sets to process uncertain or imprecise information. This layer is essential in bridging the gap between exact numerical inputs and the more flexible language used in fuzzy logic. Similarly, the rule base layer in ANFIS is fundamental to the decision-making process. It holds a set of fuzzy rules that define how the fuzzy input variables relate to the fuzzy output variables. This layer captures the expertise of human operators or domain specialists, organizing it into a structured form that the FIS can use. Next is the fuzzy inference layer, which turns fuzzy input information into meaningful fuzzy output. It applies the rules from the rule base to interpret the fuzzy sets from the fuzzification layer, processing them to generate fuzzy output values that

represent the system's decision or response. The defuzzification layer in ANFIS is responsible for converting this fuzzy output into a clear and actionable result. Defuzzification translates fuzzy sets and linguistic terms into a crisp output that is easy to interpret and use. Finally, the learning layer in ANFIS allows the system to adapt and fine-tune its parameters using training data. As a hybrid system, ANFIS combines the learning ability of neural networks with the reasoning power of fuzzy logic. This layer, closely tied to the neural network component, adjusts parameters to improve the system's ability to model complex relationships and make accurate predictions, such as in forecasting BIFRD in open-pit mines.

Optimization Algorithms Used for Training ANFIS Model

Principle of GA

The GA is a widely used metaheuristic algorithm for optimization problems due to its simplicity and effectiveness in finding near-optimal solutions within a reasonable time frame (Abdel-Basset et al., 2018; SS & HS, 2022). It imitates the processes of natural selection to develop a group of potential solutions, gradually moving them toward an optimal outcome (Alhijawi & Awajan, 2024). The algorithm starts by creating a random set of candidate solutions, each one representing a possible answer to the problem. It then assesses the effectiveness of each candidate solution by measuring how well it addresses the problem (Venkatraman & Yen, 2005). The selection process then picks the most suitable individuals from the population to become the parents of the next generation. This selection can be done using various methods, for instance, methods like roulette wheel selection or tournament selection, where the probability of being chosen is directly related to an individual's fitness (Cuevas et al., 2018). New offspring are created through genetic operators like crossover and mutation. Crossover mixes genetic material from two parents to create offspring that inherit characteristics from both parents, potentially improving the solution. Mutation introduces random changes to individual genes, adding diversity to the population. The offspring's fitness is evaluated, and either some or all of the members in the population are substituted with the new generation of offspring.

Pseudo-code of the ABC algorithm	
1	Initialize the population of solutions (food sources)
2	Evaluate the fitness of each food source
3	Repeat until termination criteria is met (e.g., max iterations or convergence):
4	// Employed Bee Phase
5	For each employed bee:
6	Select a food source randomly
7	Generate a new food source by modifying the selected one
8	Evaluate the new food source
9	If the new food source is better than the old one:
10	Replace the old food source with the new one
11	Else:
12	Increase the trial counter for the old food source
13	End if
14	End for
15	// Onlooker Bee Phase
16	Calculate the probability of selecting each food source
17	For each onlooker bee:
18	Select a food source based on the calculated probabilities
19	Generate a new food source by modifying the selected one
20	Evaluate the new food source
21	If the new food source is better than the old one:
22	Replace the old food source with the new one
23	Else:
24	Increase the trial counter for the old food source
25	End if
26	End for
27	// Scout Bee Phase
28	For each food source:
29	If the trial counter exceeds the limit (abandonment criteria):
30	Replace the food source with a new random one
31	Reset the trial counter for the new food source
32	End if
33	End for
34	Memorize the best food source found so far
35	End Repeat
36	Output the best solution found

Figure 6. The ABC algorithm's pseudo-code.

Genetic algorithms require careful parameter selection, including population size, mutation rate, and crossover rate, to ensure the quality of the final solution (Reeves, 2010). Solving large-scale problems can be difficult, often necessitating multiple iterations to reach a solution (Gallagher & Sambridge, 1994). Automatic tools, like IRACE, can help find optimal parameter combinations, but they

can be time-consuming (López-Ibáñez et al., 2016). Dynamic parameter adaptation during the algorithm's execution can also be used to adjust parameters based on the quality of solutions found, improving efficiency and effectiveness (Valdez et al., 2014). Figure 4 shows the pseudo-code of the GA algorithm.

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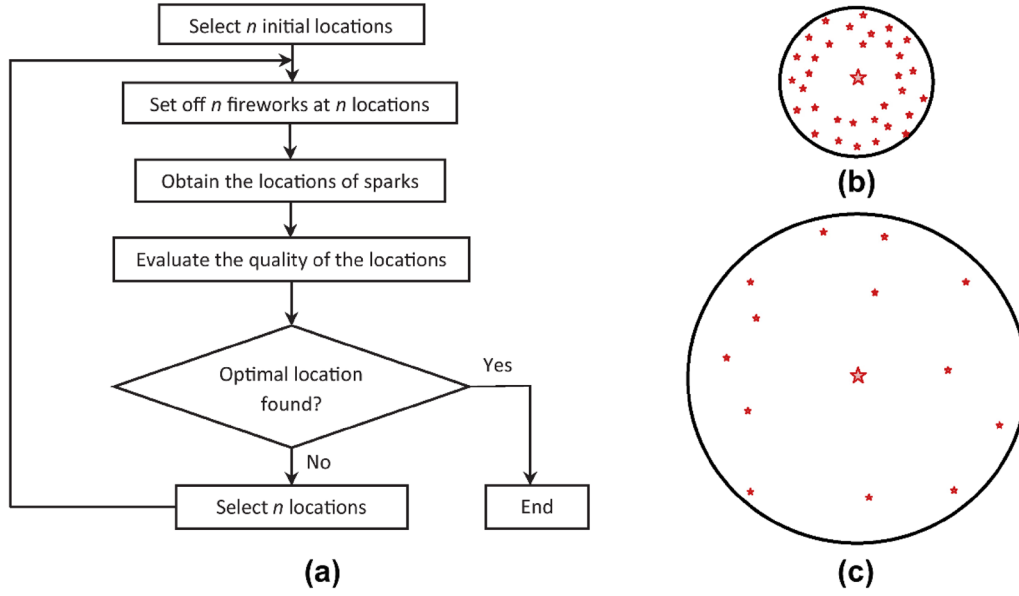


Figure 7. Visual representation of behaviors of “good” and “bad” explosions observed in fireworks displays (modified after Goswami & Chakraborty (2015)): (a) framework of FWA; (b) “good” explosion; (c) “bad” explosion.

Principle of JADE

Differential evolution (DE) is an evolutionary algorithm among the collection of metaheuristic algorithms, which are used to address optimization challenges. However, its performance depends heavily on setting control parameters, such as mutation factor (F), and crossover probability (CR) (Mohamed & Suganthan, 2018). While there are suggested parameter settings, the relationship between these settings and optimization performance remains complex and not fully understood (Pant et al., 2020). This is due to the lack of a universal parameter setting that works for different problems or for various stages of a single problem (Ahmad et al., 2022). To address this, self-adaptive and adaptive methods have been implemented to dynamically adjust control parameters based on feedback from the evolutionary search, improving the algorithm’s convergence performance. To do this, the control parameter is modified by predefined rules, without receiving any input from the evolutionary search process. This can be expressed with a simple formula, aiming to adjust the control parameter in iterations, thus:

$$\theta(t) = \theta_0 + \Delta\theta \cdot t \quad (1)$$

where $\theta(t)$ is the control parameter at iteration t , θ_0 denotes the initial value of the control parameter, and $\Delta\theta$ stands for the fixed change applied at each iteration. Next is adaptive parameter control task, where control parameters are dynamically adjusted based on feedback from the evolutionary search. This can be based on performance metrics such as fitness improvements, and it is presented as:

$$\theta(t) = \theta(t-1) + \alpha \cdot f(\Delta F) \quad (2)$$

where $\theta(t-1)$ is the control parameter at the previous iteration, α indicates the learning rate or scaling factor, and $f(\Delta F)$ stands for a function of the change in fitness (or another performance metric) between iterations. Finally, the self-adaptive parameter control, also referred to as “evolution of evolution,” where control parameters are closely linked to individuals and experience mutation and recombination. Superior parameter values generally produce individuals with a higher likelihood of survival, thus propagating these values to more offspring. This mechanism is performed through the initialization, mutation, recombination, and selection.

Initialization: Each individual i in the population has a control parameter θ_i associated with it:

$$\theta_i(0) \sim N(\mu, \sigma^2) \quad (3)$$

Pseudo-code of the Firework algorithm (FWA)

```

1  Randomly select n locations for fireworks
2  While stop criteria = false do
3      Set off n fireworks respectively at n locations
4      For each firework  $x_i$  do
5          Calculate the number of sparks that the firework yields,  $\hat{\delta}_i$ , as follows:
              
$$\hat{\delta}_i = \begin{cases} \text{round}(a \cdot m), & \text{if } \delta_i < am \\ \text{round}(b \cdot m), & \text{if } \delta_i > bm, a < b < 1 \\ \text{round}(\delta_i), & \text{otherwise} \end{cases}$$

              where  $\delta_i = m \cdot \frac{y_{\max} - f(x_i) + \xi}{\sum_{i=1}^n (y_{\max} - f(x_i)) + \xi}$ 
6          Obtain locations of  $\hat{\delta}_i$  sparks of the firework  $x_i$  using pseudo-code 1
7      End for
8      For  $k = 1 : m$  do
9          Randomly select a firework  $x_j$ 
10         Generate a specific spark for the firework using pseudo-code 2
11     End for
12     Select the best location and keep it for the next explosion generation
13     Randomly select (n-1) locations from the two types of sparks and the current fireworks
        according to the following probability:
            
$$p(x_i) = \frac{R(x_i)}{\sum_{j \in K} R(x_j)}$$

            where  $R(x_i) = \sum_{j \in K} \|x_i - x_j\|$ , and  $K$  is the set of all current locations of both fireworks and
            sparks.
14 End while
15 End

```

Pseudo-code 1: Obtain the location of a spark.

1. Initialize the location of the spark: $\tilde{x}_j = x_i$
 2. $z = \text{round}(d \cdot \text{rand}(0,1))$
 3. Randomly select z dimensions of $\tilde{x}_j$
 4. Calculate the displacement: $h = A_i \cdot \text{rand}(-1,1)$, where A_i is the amplitude of explosion of each firework
 5. **for** each dimension $\tilde{x}_k^j \in \{\text{pre-selected } z \text{ dimensions of } \tilde{x}_j\}$ **do**
 6. $\tilde{x}_k^j = \tilde{x}_k^j + h$
 7. **if** $\tilde{x}_k^j < x_k^{\min}$ or $\tilde{x}_k^j > x_k^{\max}$ **then**
 8. map $\tilde{x}_k^j$ to the potential space: $\tilde{x}_k^j = x_k^{\min} + \|\tilde{x}_k^j\| \% (x_k^{\max} - x_k^{\min})$
 9. **end if**
 10. **end for**
-

Pseudo-code 2: Obtain the location of a specific spark.

11. Initialize the location of the spark: $\hat{x}_j = x_i$
 12. $z = \text{round}(d \cdot \text{rand}(0,1))$;
 13. Randomly select z dimensions of $\hat{x}_j$
 14. Calculate the coefficient of the Gaussian explosion: $g = \text{Gaussian}(1,1)$
 15. **for** each dimension $\hat{x}_k^j \in \{\text{pre-selected } z \text{ dimensions of } \hat{x}_j\}$ **do**
 16. $\hat{x}_k^j = \hat{x}_k^j \cdot g$
 17. **if** $\hat{x}_k^j < x_k^{\min}$ or $\hat{x}_k^j > x_k^{\max}$ **then**
 18. map $\hat{x}_k^j$ to the potential space: $\hat{x}_k^j = x_k^{\min} + |\hat{x}_k^j| \% (x_k^{\max} - x_k^{\min})$
 19. **end if**
 20. **end for**
-

Figure 8. The FWA pseudo-code.

Measurement and Prediction of Blast-Induced Flyrock Distance

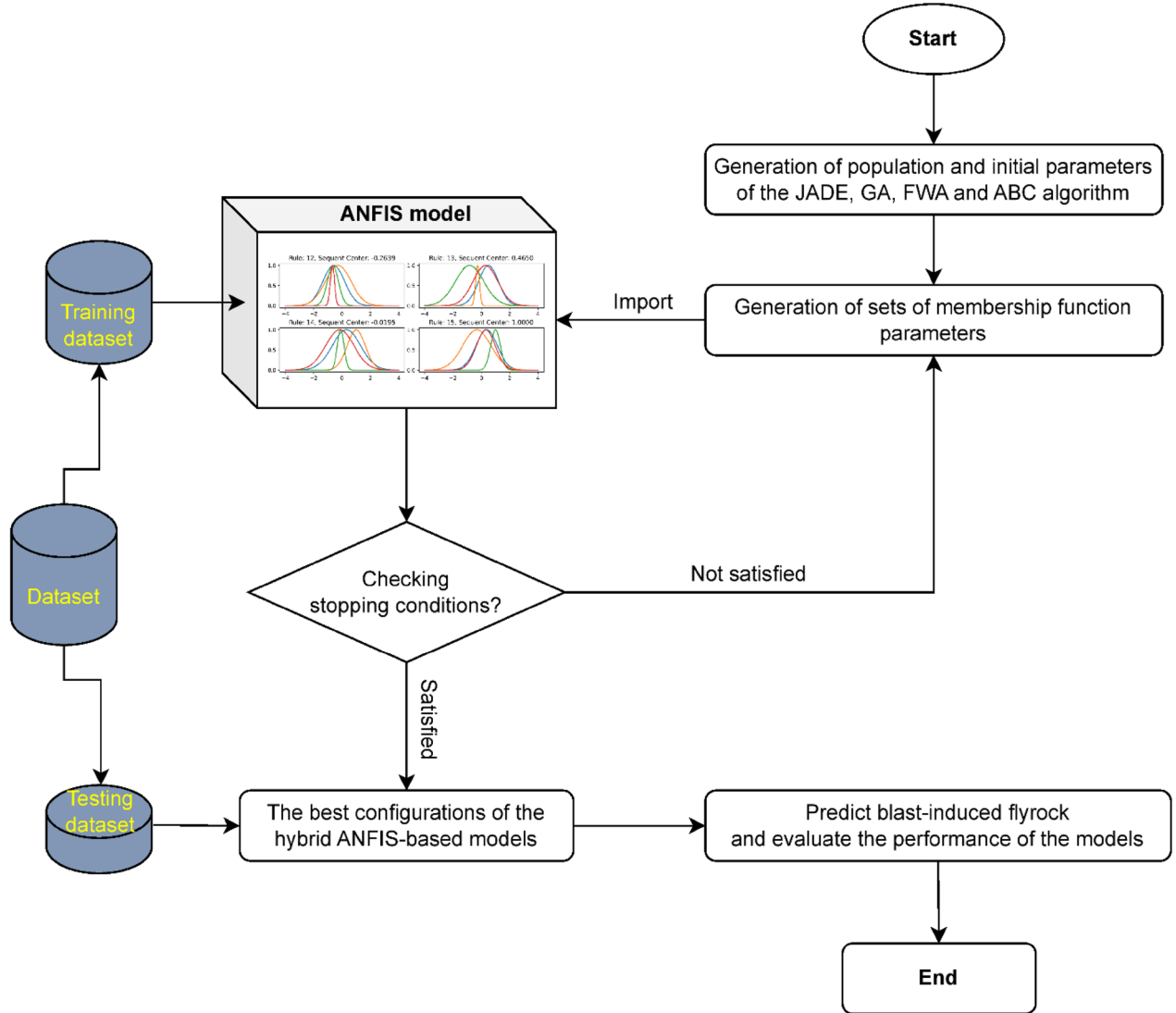


Figure 9. Framework of the new ANFIS-based hybrid models for predicting BIFRD in open-pit mines.

where $N(\mu, \sigma^2)$ is a normal distribution with mean μ and variance σ^2 .

Mutation: The control parameter undergoes mutation along with the individual:

$$\theta_i(t) = \theta_i(t-1) \cdot e^{\alpha_1 \cdot N(0,1)} \quad (4)$$

where α_1 is a learning rate specific to the parameter; $N(0, 1)$ stands for a random variable from a standard normal distribution.

Recombination:

$$\theta_{\text{offspring}} = \lambda \cdot \theta_i + (1 - \lambda) \cdot \theta_j \quad (5)$$

where $\theta_{\text{offspring}}$ is the control parameter of the offspring, θ_i and θ_j are the control parameters of the parent individuals, and λ stands for a recombination weight, typically $\lambda \in [0, 1]$.

Selection: Fitter offspring are more likely to survive and pass on their parameters to the next generation.

Self-adaptive parameter control makes an algorithm more robust by adapting parameters to different evolutionary environments. It is suitable for many optimization problems without trial and error and can speed up the convergence by adapting parameters to assign suitable values at different stages of the evolution of a problem.

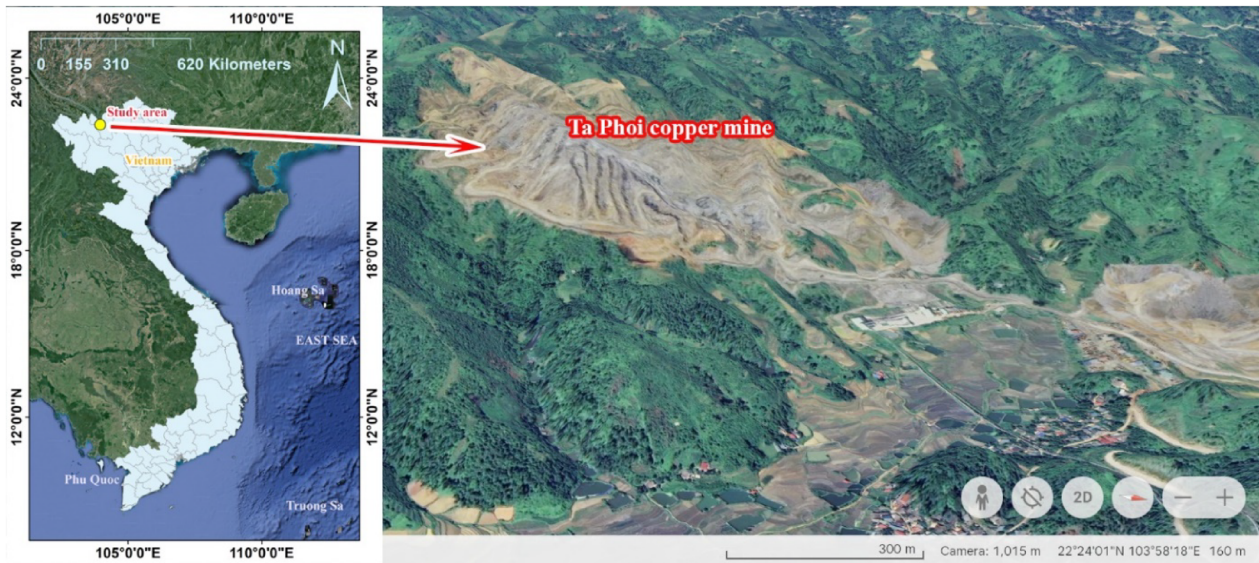


Figure 10. Location of the study area (Ta Phoi copper mine—Vietnam).

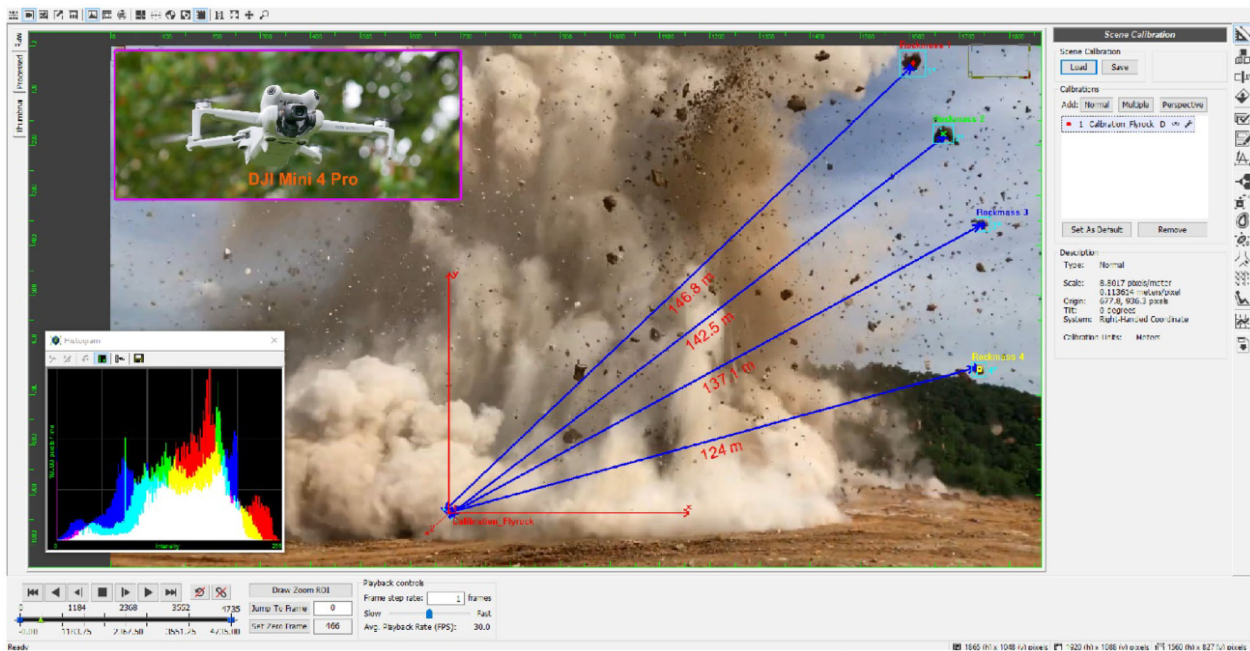


Figure 11. Unmanned aerial vehicle and analysis of BIFRD.

Adaptive and self-adaptive DE algorithms are faster and more reliable than traditional DE algorithms without parameter control on various benchmark problems. The JADE, a new version of DE algorithm, introduces a new mutation strategy “DE/

current-to-pbest” with an optional external archive which uses both the best and other good solutions’ information to guide the search (Zhang & Sander-son, 2009; Cui et al., 2016). This strategy along with self-adaptive parameter control makes the algorithm

Measurement and Prediction of Blast-Induced Flyrock Distance

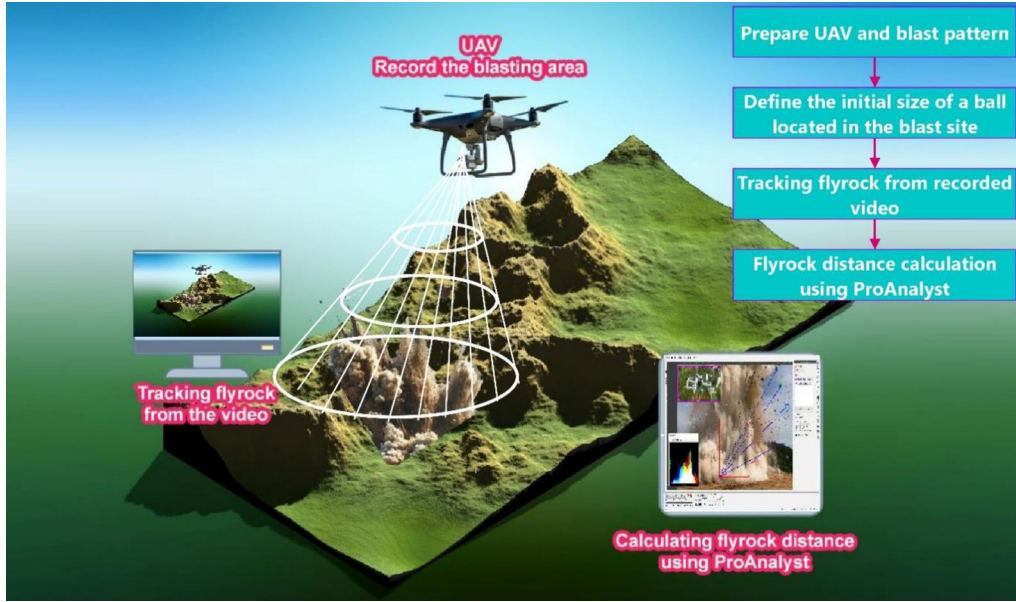


Figure 12. Scheme for measuring BIFRD using UAV and ProAnalyst.

more robust and faster. It is based on DE/current-to-best strategy but uses information from other good solutions not just the best solution. In DE/current-to-pbest strategy, a mutation vector is generated for each individual by combining its current position with a weighted sum of the best solution and another randomly selected solution (Islam et al., 2011). The weight for each solution is determined by the F of the individual. The algorithm also has an adaptive mechanism to control F and CR . F is generated for each individual according to a Cauchy distribution and then truncated to a certain range (Choi et al., 2020). The mean of the successful $F(s)$ is used to update the central tendency parameter of the Cauchy distribution. This adaptation mechanism helps to vary $F(s)$ to prevent early convergence. Similarly, CR is randomly generated for each individual from a normal distribution and then truncated to a certain range. The mean of the successful crossover probabilities is used to update the mean of the normal distribution. This adaptation mechanism helps to balance the exploration and exploitation during the search. Figure 5 shows the JADE's pseudo-code.

Principle of ABC

The ABC algorithm is an advanced optimization technique inspired by the foraging activities of

bees. It consists of four main components and simulates the honey harvesting process to solve optimization problems. (1) Food source: In this metaheuristic algorithm, the food source means the potential solutions to the optimization problem (optimization MFs of ANFIS) at hand. Each solution is encoded in a specific way. The quality of these solutions or food sources is evaluated based on a fitness function. (2) Employed bee stage: This stage has a number of employed bees equal to the number of food sources. These bees search and exploit the existing food sources and share the information with other bees. Through a selection process, employed bees send the promising food sources to follow bees. (3) Follow bee stage: These bees use the information provided by employed bees to search for new food sources near the current ones. They select the best food sources based on their quality and contribute to the optimization process. (4) Scout bee stage: Bees that diversify the search space are called scout bees. They go out from the nest to search for totally new food sources. If a food source is not replenished after multiple exploration, an employed bee becomes a scout bee to keep searching for good solutions.

Moreover, the ABC algorithm works because it can balance between exploration and exploitation, like the adaptive foraging behavior of bees in nature. By dynamically changing the roles employed, follow

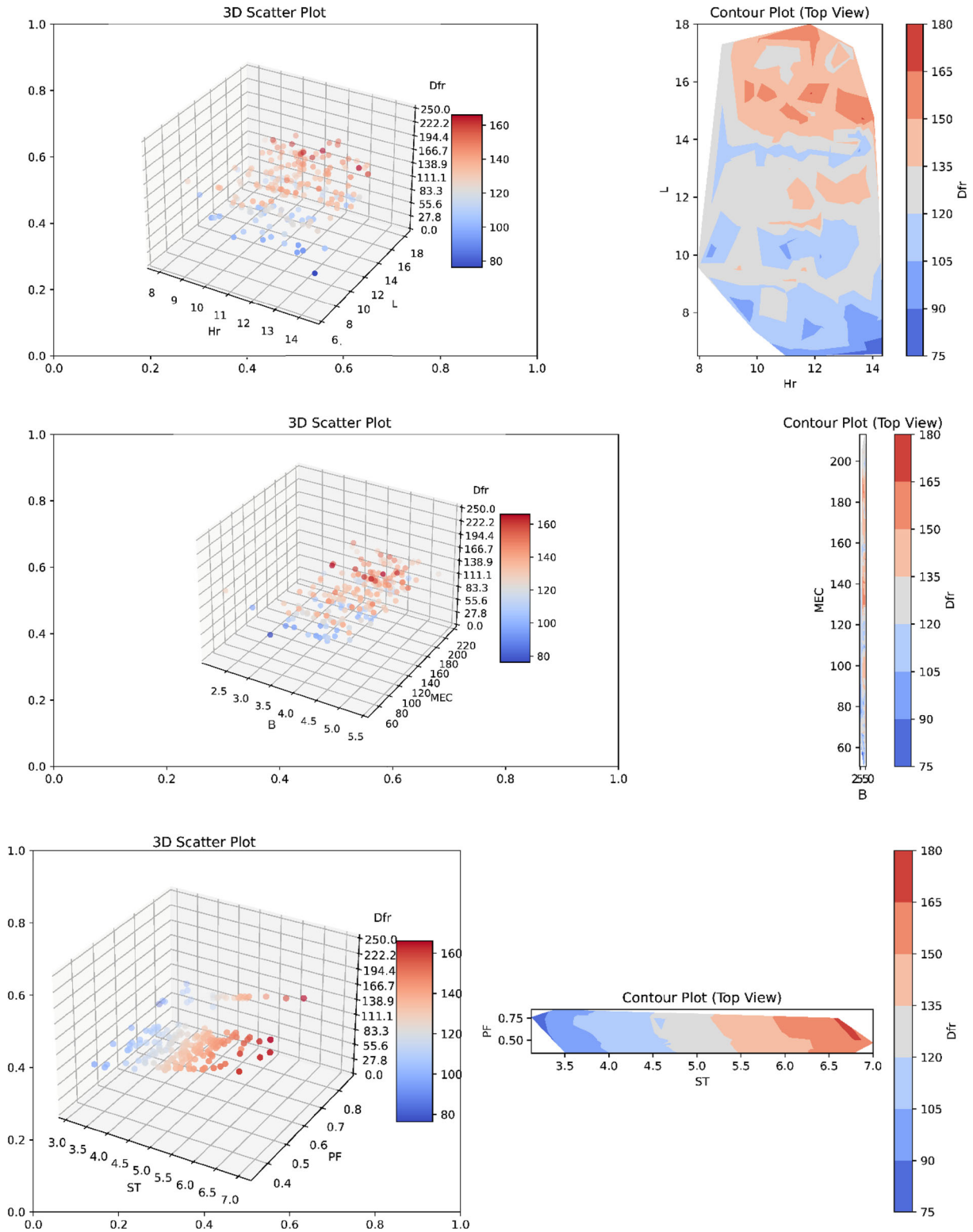


Figure 13. Distribution with contour plots of the BIFRD dataset collected in this study.

Measurement and Prediction of Blast-Induced Flyrock Distance

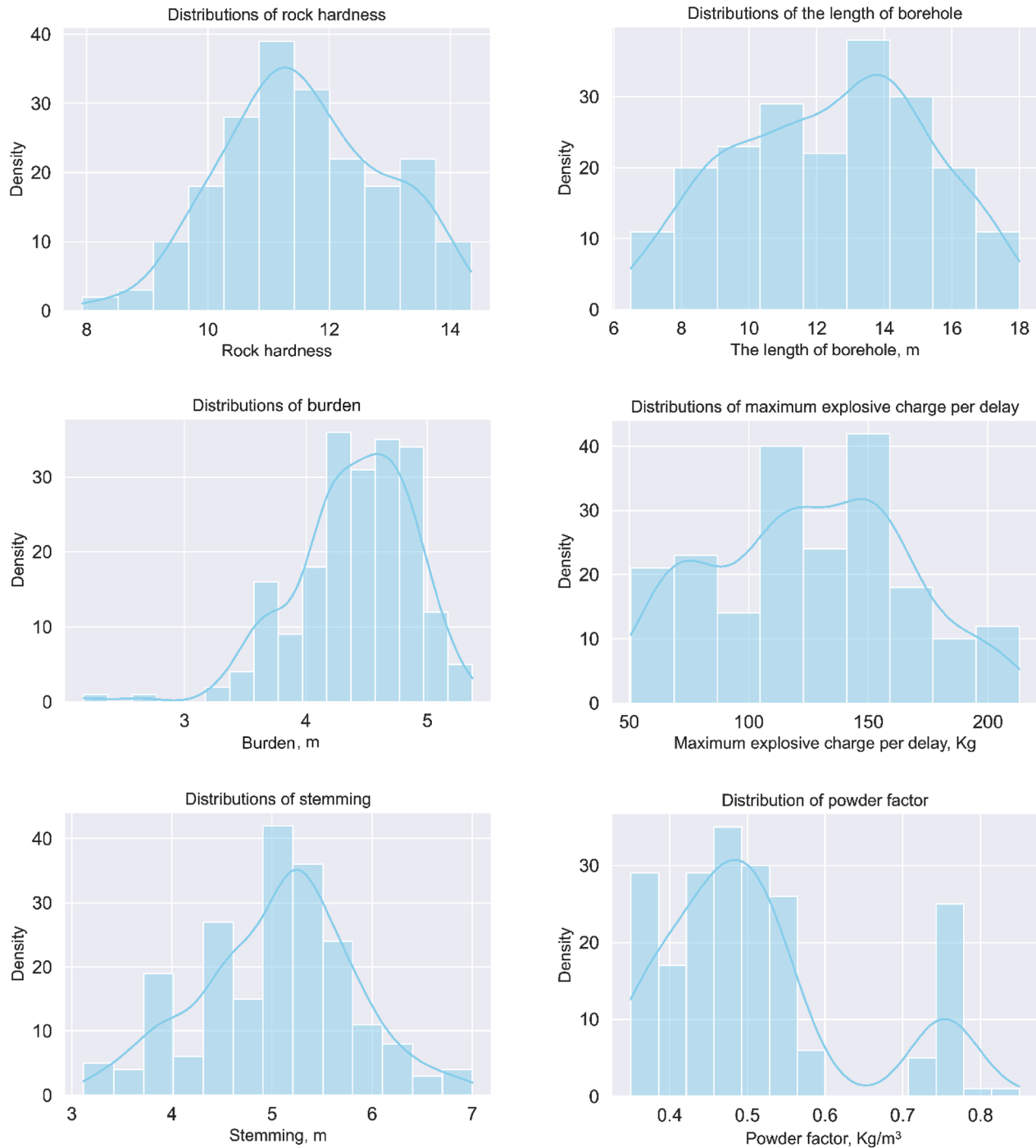


Figure 14. Histograms and density plots of the BIFRD dataset input attributes.

and scout bees, the algorithm can navigate complex optimization landscapes and reach optimal or near-optimal solutions. Figure 6 shows the pseudo-code of the ABC algorithm.

Principle of FWA

Over the past few years there has been a big increase in the use of algorithms inspired by swarm

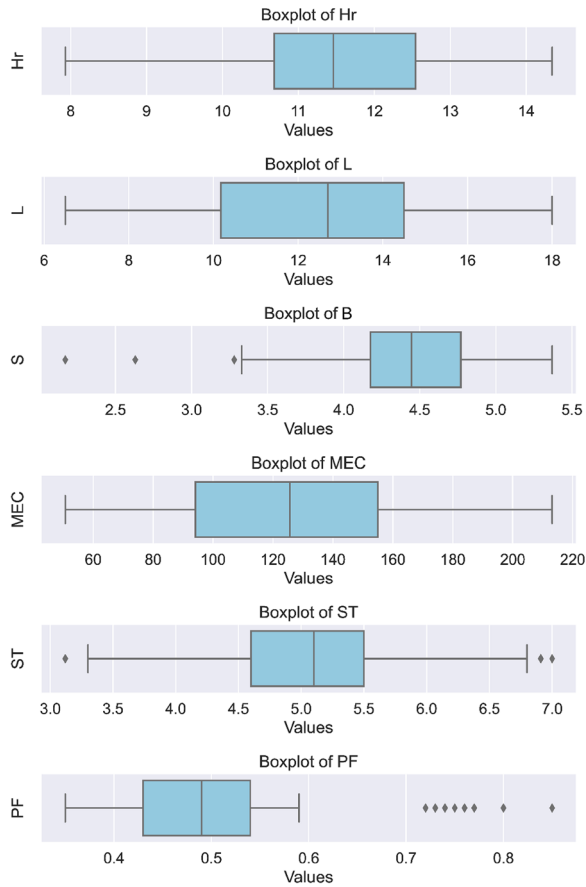


Figure 15. Box and Whisker plots of the BIFRD dataset input attributes.

intelligence as global optimization tools for multi-dimensional problems. These algorithms are based on mathematical models that mimic behaviors in biology, society, and other parts of nature. One such algorithm the FWA has been getting a lot of attention for its global optimization approach inspired by the beauty of fireworks exploding in the night sky (Tan, 2015).

The idea behind FWA is like a fireworks display (Tan, 2015). When a firework goes off it releases a shower of sparks that spread out in the surrounding space. This explosion is like a search in the local neighborhood of the firework's origin point, facilitated by the sparks that are released during the explosion. In optimization, FWA works by continuously igniting virtual "fireworks" in the solution space until a spark hits or gets close to the solution point.

The key to FWA is the ability to replicate a good explosion and a good selection of ignition

points (Jin et al., 2023). One of the insights from observing real fireworks is the difference between two types of behavior: a "good" explosion where many sparks converge to the explosion center and a "bad" explosion where only a few sparks are released and scattered randomly in space. These are shown in Figure 7. By leveraging these insights, FWA optimally balances the generation and distribution of sparks, enhancing its ability to efficiently explore and converge upon optimal solutions within complex problem spaces. This unique amalgamation of natural inspiration and algorithmic innovation positions FWA as a promising tool for tackling challenging optimization tasks across various domains.

Normally, FWA is designed to solve general optimization problems with the loss function, thus:

$$\text{Loss function : Minimize } f(x) \in \mathbb{R}, x_{\min} \leq x \leq x_{\max} \quad (6)$$

where $x = x_1 = x_2 = \dots = x_n$ denotes a location in the potential space; $x_{\min}, x_{\max}$ stand for the minimum and maximum of the potential space. The pseudo-code of the FWA is introduced in Figure 8.

Hybrid Metaheuristic-trained ANFIS Models for Predicting BIFRD

As mentioned before, this study used UAV to measure BIFRD and developed advanced hybrid ANFIS models to improve BIFRD prediction. The ANFIS model optimization for this purpose used JADE, GA, FWA, and ABC algorithms in open-pit mines.

ANFIS is a good solution for BIFRD prediction because of its ability to handle nonlinearity, interpretability, adaptability, expertise combination, and suitable for small data. However, challenges such as complexity, scalability, overfitting, computational cost, and limited data generation may arise. Designing ANFIS model requires expertise in both fuzzy logic and neural networks, making the rule structure complex and potentially dependent on domain knowledge or expert input.

To address these challenges, metaheuristic algorithms can be used as optimization techniques to improve the ANFIS model performance for BIFRD prediction. Parameters such as membership functions, rule antecedents, rule consequents, learning algorithms, and regularization are considered for

Measurement and Prediction of Blast-Induced Flyrock Distance

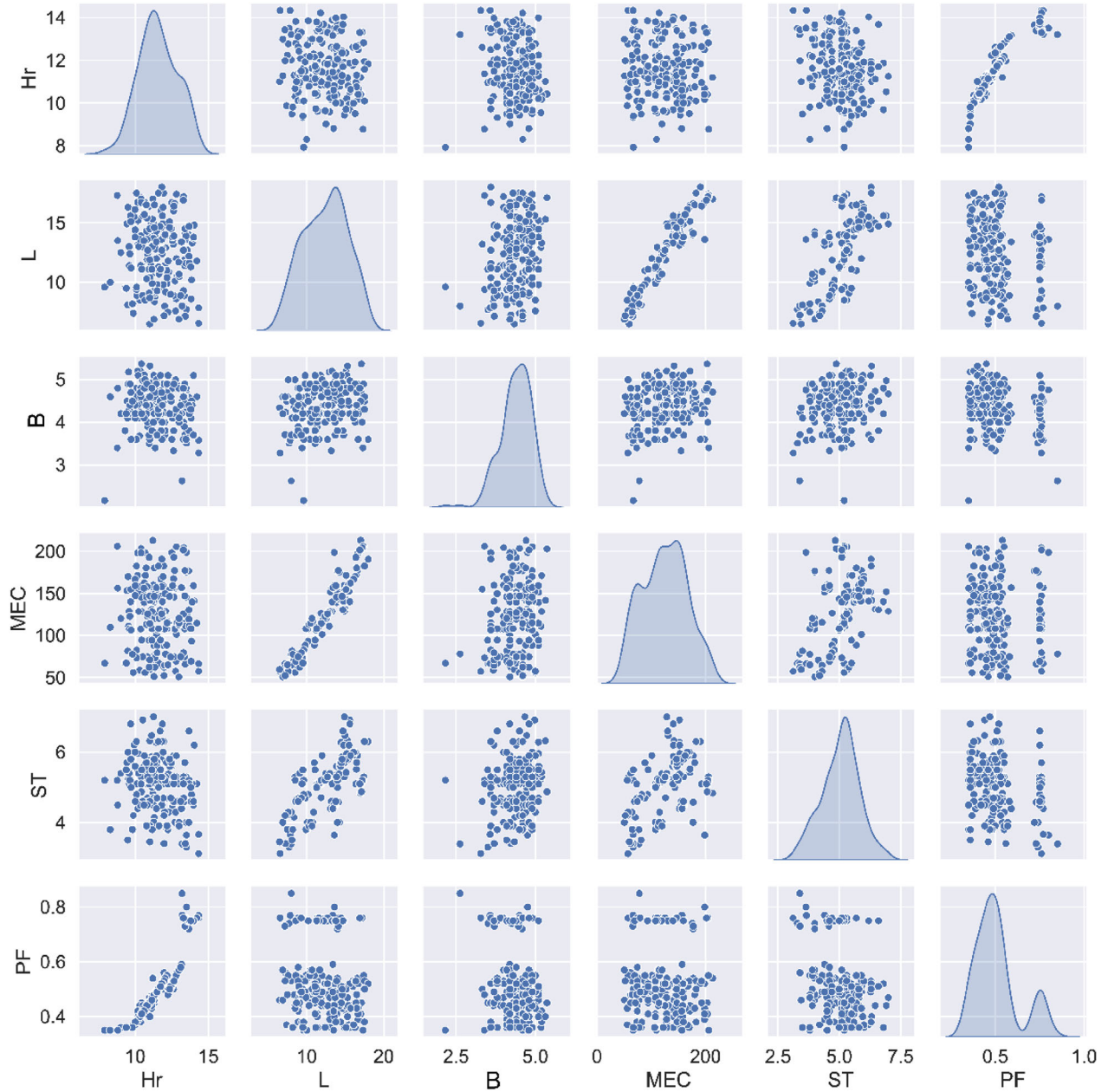


Figure 16. Scatter matrix of the BIFRD dataset input attributes.

optimization. In this study, JADE, GA, FWA, and ABC algorithms were used to optimize membership function parameters and improve the ANFIS model performance. The model uses fuzzy sets to represent input and output variables, and parameters such as shape and scale were optimized by the above algo-

ritms as shown in Figure 9, the framework of ANFIS hybrid models.

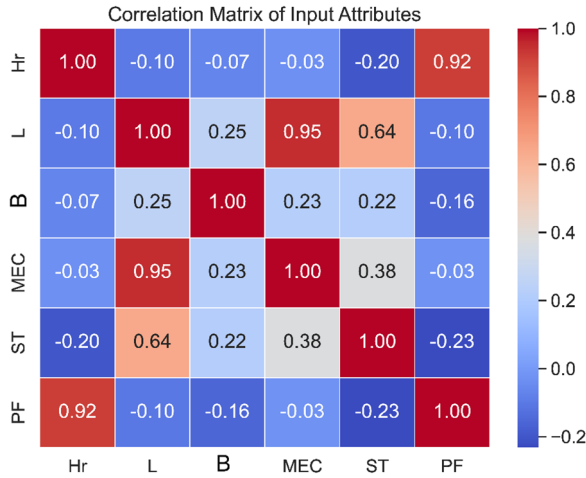


Figure 17. Correlation matrix of the BIFRD dataset input attributes.

APPLICATIONS

Study Area

We conducted blasting events and measured BIFRD at the Ta Phoi open-pit copper mine in Lao Cai, Vietnam. The mine, about 200 hectares, is located in Ta Phoi commune, Lao Cai, on the eastern slope of Cam Thang mountain (Fig. 10). The mine is on the right bank of Red River, 210–720 m in altitude. The terrain trends mostly NE–SW in the north, and nearly N–S in the south. The central part of the mine is over 700 m high and gradually decreases to the N and S. River and stream systems and small gully systems divide the terrain, mostly in E–W or sub-parallel directions. Geologically, the mine lies within the northeastern portion of the PoSen anticline, characterized by metamorphic sedimentary formations such as the Sin Quyen formation, along with features like Da Dinh and the Cam Duong formations, intersected by the Posen complex magma block.

The mine comprises four sections, with mining depths ranging from + 110 m to + 460 m. Despite a geological reserve of 11,325,000 tons, the mine's active mining reserve stands at 11,022,717 tons. The Ta Phoi open-pit copper mine boasts an impressive annual productivity exceeding 967,000 tons.

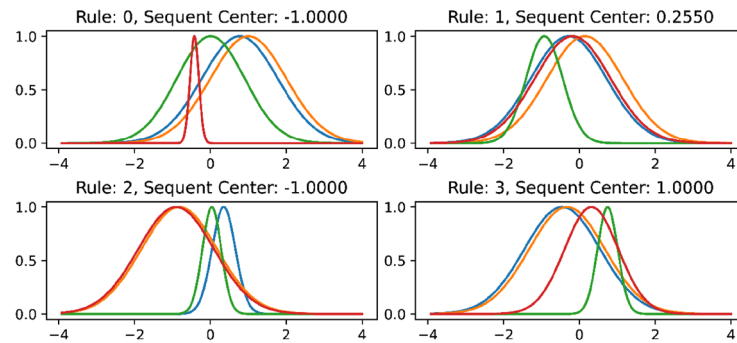
Data Collection

Because the primary objective of this mine is copper ore extraction, the hardness of the rock and ore is significant, with the unconfined compressive strength (UCS) ranging from 1100 to 1400 kg/cm². Thus, blasting is an effective method for rock and ore fragmentation. In this mine, ANFO is the primary explosive used due to its low cost and availability, making it the preferred choice for large-scale mining and construction projects. However, ANFO has poor water resistance because it absorbs water, which renders it ineffective in wet conditions. To address this, emulsion explosives are often used in wet environments, or ANFO is packaged in plastic sleeves. Nonetheless, given the terrain and hydraulic conditions of this mine, water issues are not significant, and ANFO remains the primary explosive for rock and ore fragmentation.

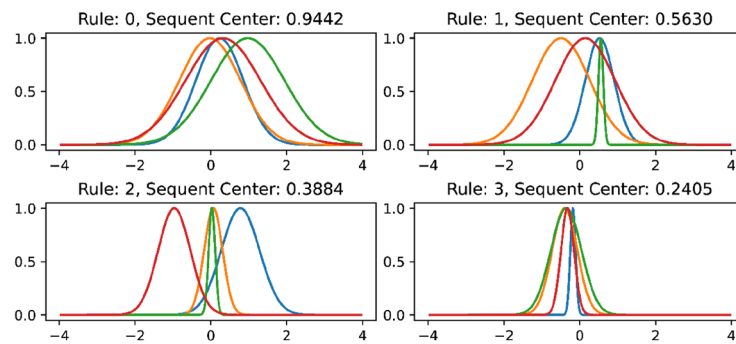
After the ore is fragmented, it is transported to the crushing stations for further mineral processing. To ensure efficient crushing (with maximum size of 0.7 m), the average ore size i typically around 250 mm. This requires designing blast patterns that meet these size requirements. However, achieving this can result in flyrock during blasting. Therefore, it is important to consider controllable factors, such as blasting parameters, to accurately predict BIFRD and optimize the blast design to minimize flyrock.

In this study, data collection started with preparing the blasting patterns and, then, extracting blasting parameters such as rock hardness (H_r), borehole length (L), burden (B), spacing (S), maximum explosive charge per delay (MEC), stemming (ST), and powder factor (PF). The selection of blast design variables in this study was based on their significant influence on flyrock and overall blasting outcomes. These variables were chosen after a thorough review of previous studies and field data, which consistently demonstrate that certain parameters play a critical role in controlling the effectiveness of a blast, as reviewed in Table 1. However, at this copper mine, S was assigned the same value as B ; therefore, only B was retained, and S was removed from the dataset, as B is a crucial parameter in evaluating the effect of flyrock (Ghasemi et al., 2012; Raina & Bhatawdekar, 2022). In addition, in this study, H_r was used as a parameter (i.e., a coefficient) instead of UCS, and it was calculated based on the method of Protodiakonov et al. (1964), specifically $H_r = \frac{UCS(\text{in kg/cm}^2)}{100}$. Finally, 204 blasting

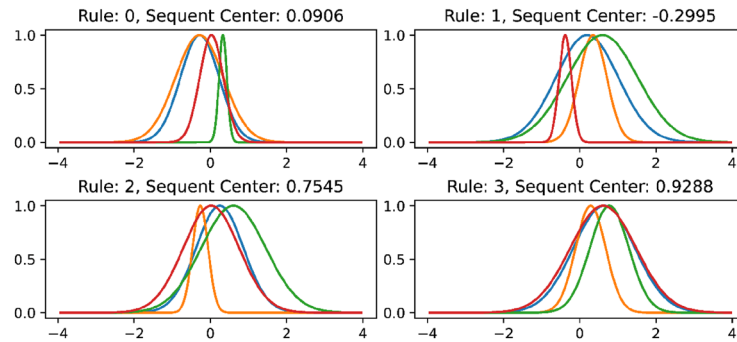
Measurement and Prediction of Blast-Induced Flyrock Distance



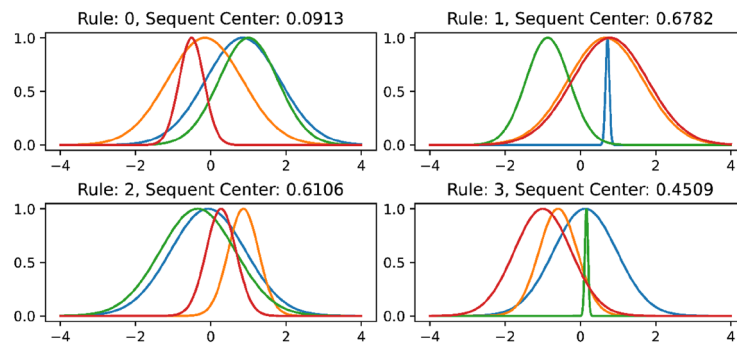
(a) Some JADE-ANFIS's membership functions



(b) Some GA-ANFIS's membership functions

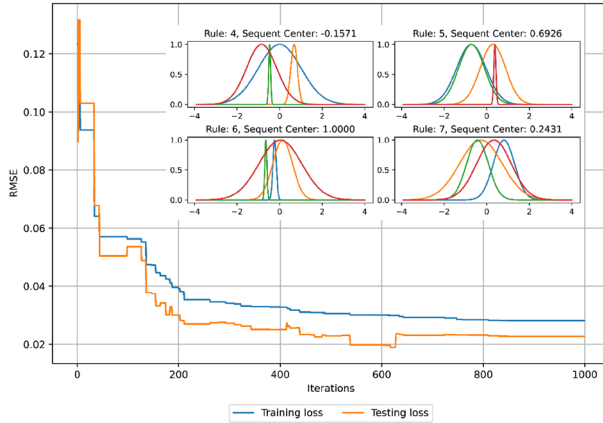


(c) Some FWA-ANFIS's membership functions

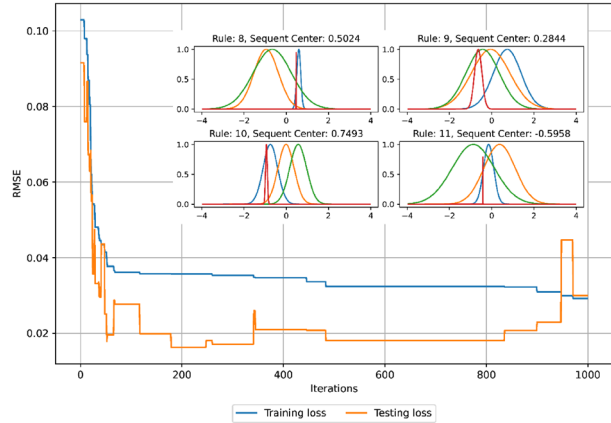


(d) Some ABC-ANFIS's membership functions

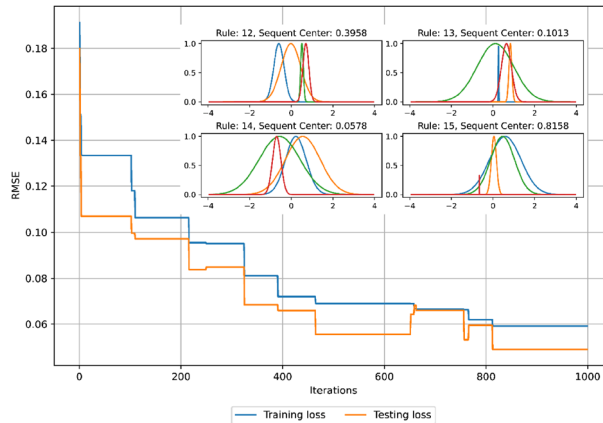
Figure 18. Membership functions of various developed hybrid models based on the Gaussian method.



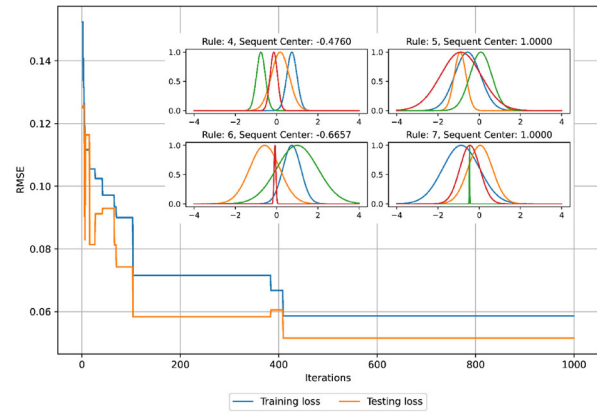
(a) JADE-ANFIS's convergence



(b) GA-ANFIS's convergence



(c) FWA-ANFIS's convergence



(d) ABC-ANFIS's convergence

Figure 19. Training and testing loss of the hybrid models with the designed membership functions.

events were collected and the corresponding variables were compiled into a dataset. In this copper mine, H_r was 11–14, L 13–15 m, B 3–5 m, MEC 50–100 kg, and PF of 0.40–0.85 kg/m³ was used.

To measure BIFRD, DJI Mini 4 Pro UAV recorded the entire blasting process and captured both the blast and BIFRD. This device can record a slow-motion video with a resolution of 4 K/100 fps, using a camera with 1/1.3-inch CMOS, effective pixels of 48 MP (DJI, 2024). The UAV was placed at a safe distance from the flyrock, ~ 300 –350 m in this study, and so the recorder had a wide range to observe BIFRD. Then, the recorded videos were imported to ProAnalyst[®] software to analyze BIFRD. Scene calibration was a critical step to ensure that the measurements are accurate and reflect real-world dimensions. Before calculating BIFRD, two points on the ground were established as reference points

to calibrate the distance and scale between pixels in the recorded videos. This scale was then used to calculate the actual BIFRD (Fig. 11). Here, a ball was used, and its diameter was determined prior to blasting. The scheme for measuring BIFRD using UAV and ProAnalyst is shown in Figure 12. The measured BIFRD in this copper mine ranged 50–168 m. Overall, 204 measurements were collected and used to predict BIFRD in mine blasting; the data and features are shown in Figure 13.

Data Analysis

After collecting 204 measurements, the dataset was analyzed before BIFRD models were developed. This analysis aimed to get insights into the dataset so that informed decisions can be made

Measurement and Prediction of Blast-Induced Flyrock Distance

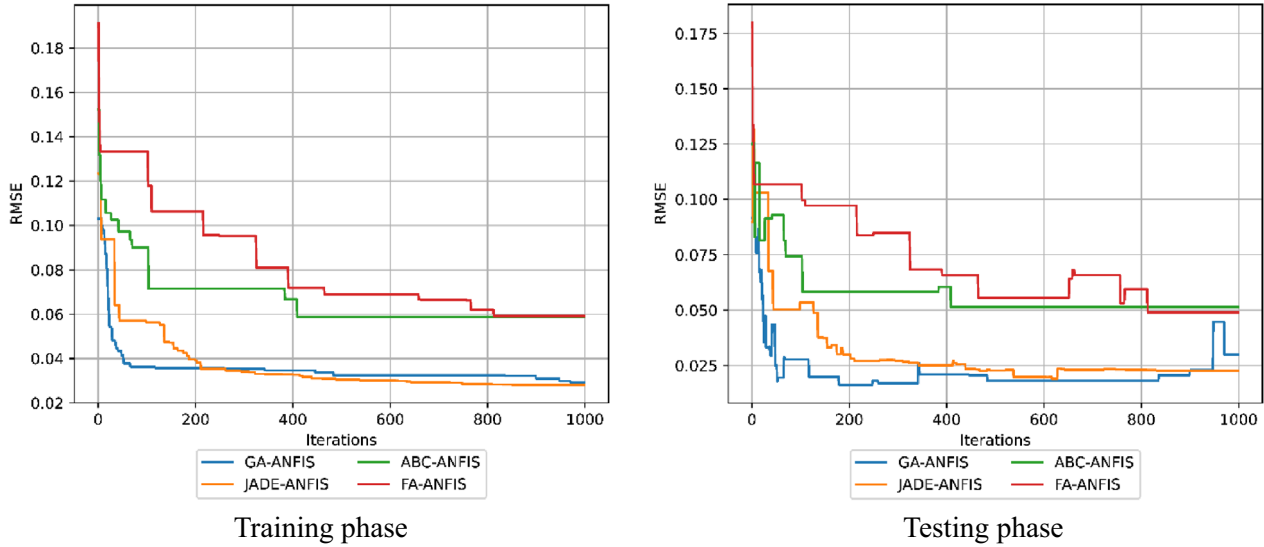


Figure 20. Comparison of various developed ANFIS-based hybrid models.

during model development and to improve overall reliability and performance. Figure 14 shows that the distributions of most input variables were skewed. This means that we needed to normalize these variables to understand the dataset and to improve the performance of the models. Figure 15 shows the box-and-whisker plots of the collected dataset. These help to identify skewness in the data, the presence of outliers, and a quick summary of the dataset's statistical measures. From Figure 15, we see that B, ST, and PF had some outliers. From a closer look at these variables, the outliers of these variables may be valid observations that provide important information in the data entry. These parameters were calculated in blast patterns and, due to the rock and ore hardness, were high in some cases; their PF must be increased and B must be decreased to ensure the fragmentation standard and rock/ore pile shape. Because the outliers were not due to data entry errors or mistakes, we handled them by applying data transformations to reduce their impact.

Besides the outliers, the structures of the data were looked into before applying more advanced statistics and building models. Thus, we did a scatter matrix to get an overall view of the data and to help decide what to do next or what kind of modeling to do (Fig. 16). As can be seen in Figure 16, Hr, L, and MEC had strong relationships and may have correlations. These also show the strengths and directions

of the linear relationships among these variables. Thus, we looked into how these variables are related and a correlation matrix was obtained (Fig. 17).

The correlation analyses in Figure 17 showcased a strong correlation between L and MEC. This, indeed, required consideration for the removal of one of them. However, due to the millisecond delay blasting method used in this copper mine to fragment rock and ore, and with only one blasthole detonated in each delay, a positive correlation between MEC and L is reasonable. Therefore, L was removed from the dataset. The correlation between H_r and PF was similar to the correlation between MEC and L, and with a high level of rock hardness, a high PF was used. Therefore, PF was retained and H_r was removed from the dataset. This choice was influenced by PF being the controllable parameter, while H_r is categorized as the uncontrollable parameter. This distinction may prove advantageous in the future if we need to optimize input parameters to minimize BIFRD. Finally, only four parameters were used to predict BIFRD, namely B, MEC, ST, and PF.

RESULTS AND DISCUSSION

Before building the ANFIS hybrid models (i.e., GA-ANFIS, JADE-ANFIS, ABC-ANFIS, FWA-ANFIS), the dataset was divided into two parts, 70%

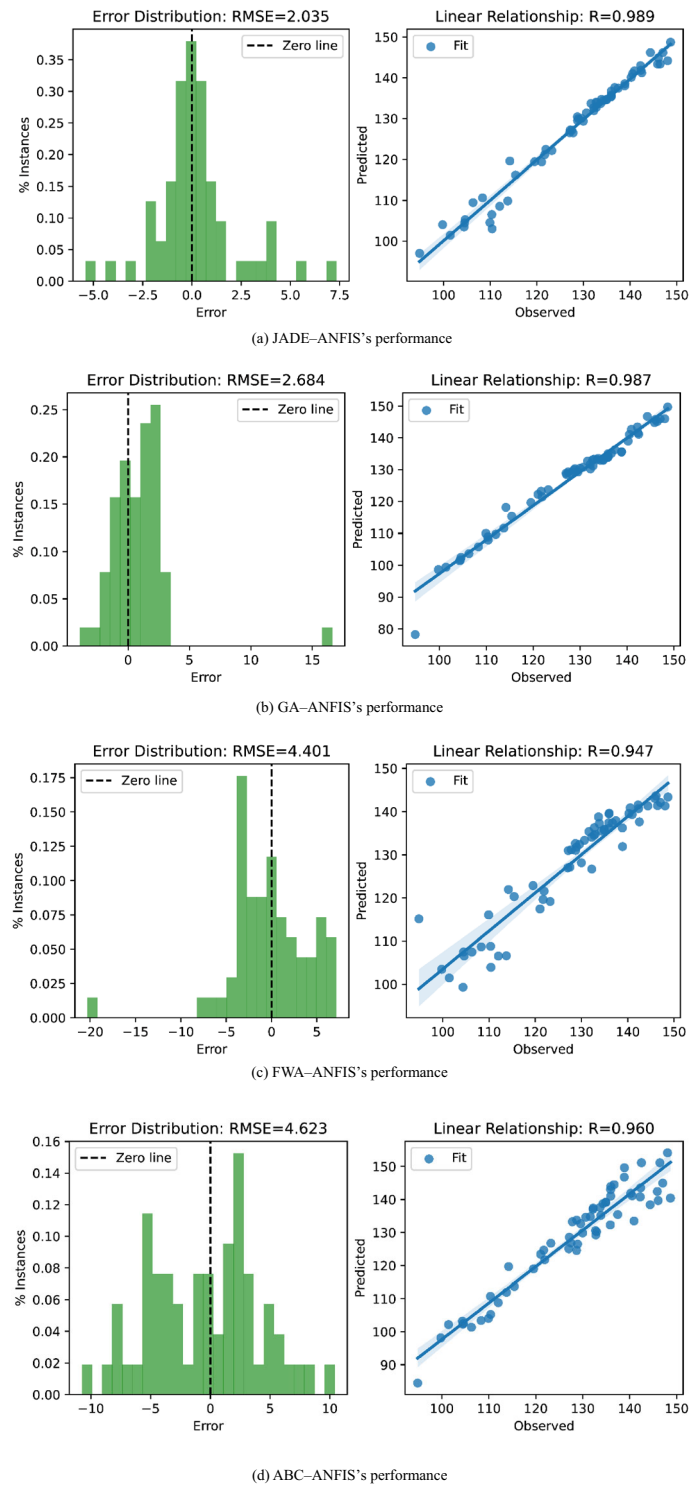


Figure 21. Error distribution and correlation between observed and predicted BIFRD by various developed hybrid models.

Measurement and Prediction of Blast-Induced Flyrock Distance

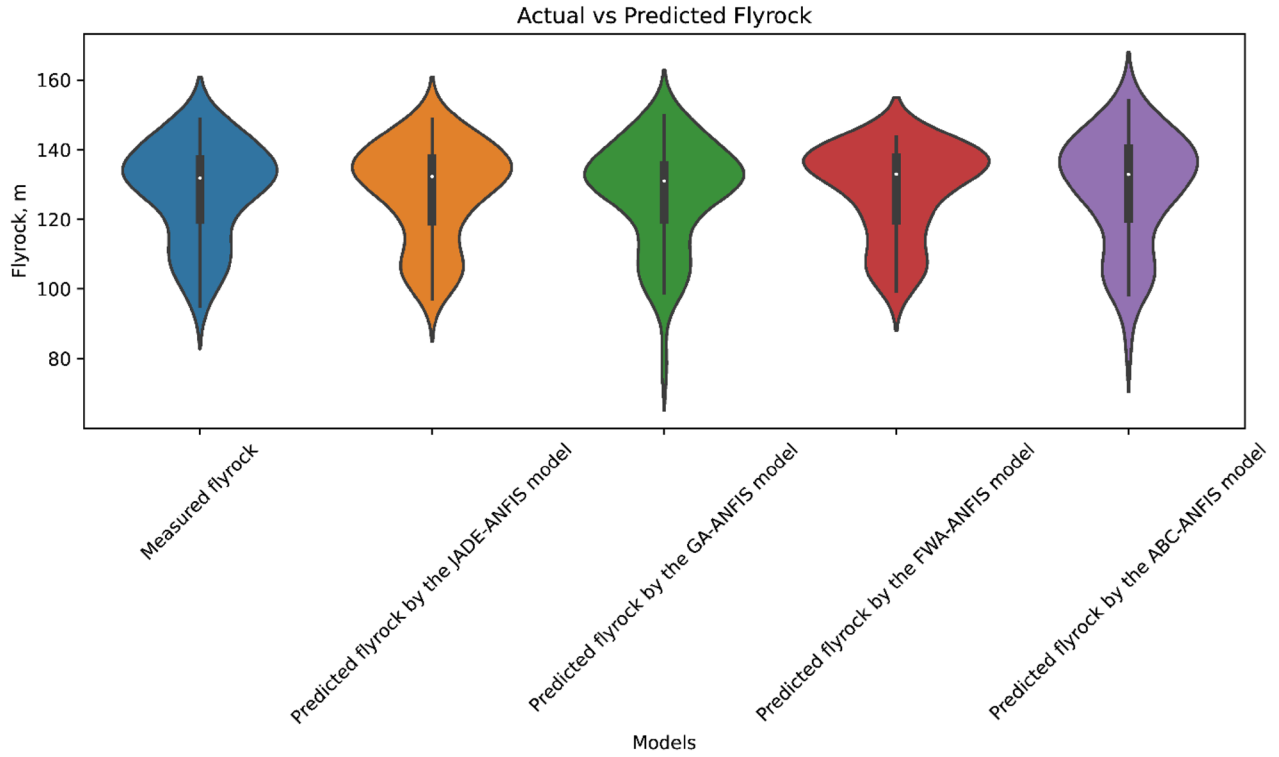


Figure 22. Violin plot of the predicted BIFRD by various developed hybrid models.

of the whole dataset was randomly selected and used as training dataset, and the remaining 30% of the dataset was used as testing dataset.

Tuning the parameters of the optimization algorithms (GA, JADE, ABC, FWA) is very important to get the best performance of the ANFIS model, and these parameters should be defined first. However, selecting and tuning these parameters can be challenging and time-consuming if too many parameter values are considered. Conversely, if these parameters are not tuned, the optimization process itself may not be good. Thus, we defined a range of values for each parameter and used k -fold cross-validation ($k = 5$) and three repeats to find the best parameters for these algorithms. The ranges for the GA, JADE, ABC, FWA algorithms were as follows:

For JADE: “miu_f”: [0.5, 0.6, 0.7]; “miu_cr”: [0.5, 0.55, 0.6]; “pt”: [0.1, 0.15, 0.2, 0.3]; “ap”: [0.1, 0.2, 0.3]; epochs: 1000; population size: 50.

For GA: (crossover probability) “pc”: [0.80, 0.85, 0.90]; “pm”: [0.05, 0.06, 0.08]; epochs: 1000; population size: 50.

For ABC: “n_elites”: [14, 16, 20]; “n_others”: [4, 6, 8]; “patch_size”: [5.0, 5.5, 6.0]; “patch_reduction”: [0.980, 0.985, 0.990]; “n_sites”: [3]; “n_elite_sites”: [1, 2, 3]; epochs: 1000; population size: 50.

For FWA: “max_sparks”: [50, 80, 100]; (const parameter) “p_a”: [0.04, 0.06, 0.08]; “p_b”: [0.8, 1.0]; “max_ea”: [40, 50, 60]; “m_sparks”: [5, 7, 10]; epochs: 1000; population size: 50.

After the k -fold ($k = 5$) cross-validation with three repeats during training of the hybrid models, the best set of parameters for each optimization algorithm was found, and they were used to retrain the models on the whole training dataset and to evaluate the performance of the trained models on the testing dataset. Due to the random mechanism of the metaheuristics algorithms, the models were retrained with five trials to evaluate the mean of accuracy they achieved. The RMSE was used as the fitness function during training of the ANFIS-based hybrid models. In addition, RMSE_test (with coefficient of 0.5) and MAPE_test (with coefficient of 0.5) were used for evaluating the models’ performance when selecting the best parameters under the consideration of k -fold cross-validation, and it can

Table 2. Performance indices for training and testing of the developed hybrid ANFIS-based models

Model's name	Training time	Training performance				Testing performance			
		RMSE	R^2	MAPE	VAF	RMSE	R^2	MAPE	VAF
JADE-ANFIS	54.333	2.524	0.975	0.013	97.495	2.035	0.978	0.011	97.807
GA-ANFIS	52.951	2.616	0.973	0.013	97.491	2.684	0.962	0.014	96.520
FWA-ANFIS	160.821	5.304	0.888	0.031	88.919	4.401	0.897	0.027	89.700
ABC-ANFIS	89.027	5.260	0.890	0.031	89.013	4.623	0.886	0.030	88.726

be considered as the objective function for selecting the best parameters, as described in Eq. 7. During retraining the models with the best parameters selected, “RMSE_train,” “MAPE_train,” “RMSE_test,” “MAPE_test” (with coefficients of 0.1, 0.1, 0.6, 0.2, respectively) were used to select the best model, as the objective function (8). The source code for all metaheuristic algorithms used in this study can be found in the Mealpy library (Van Thieu & Mirjalili 2023). The performance metrics used in the paper are available in the PerMetrics framework (Van Thieu 2024).

$$\text{Objectivefunction1} = 0.5 * \text{RMSE_test} + 0.5 * \text{MAPE_test} \quad (7)$$

$$\text{Objective function2} = 0.1 * \text{RMSE_train} + 0.1 * \text{MAPE_train} + 0.6 * \text{RMSE_test} + 0.2 * \text{MAPE_test} \quad (8)$$

where RMSE and MAPE are performance metrics, which can be calculated, respectively, as:

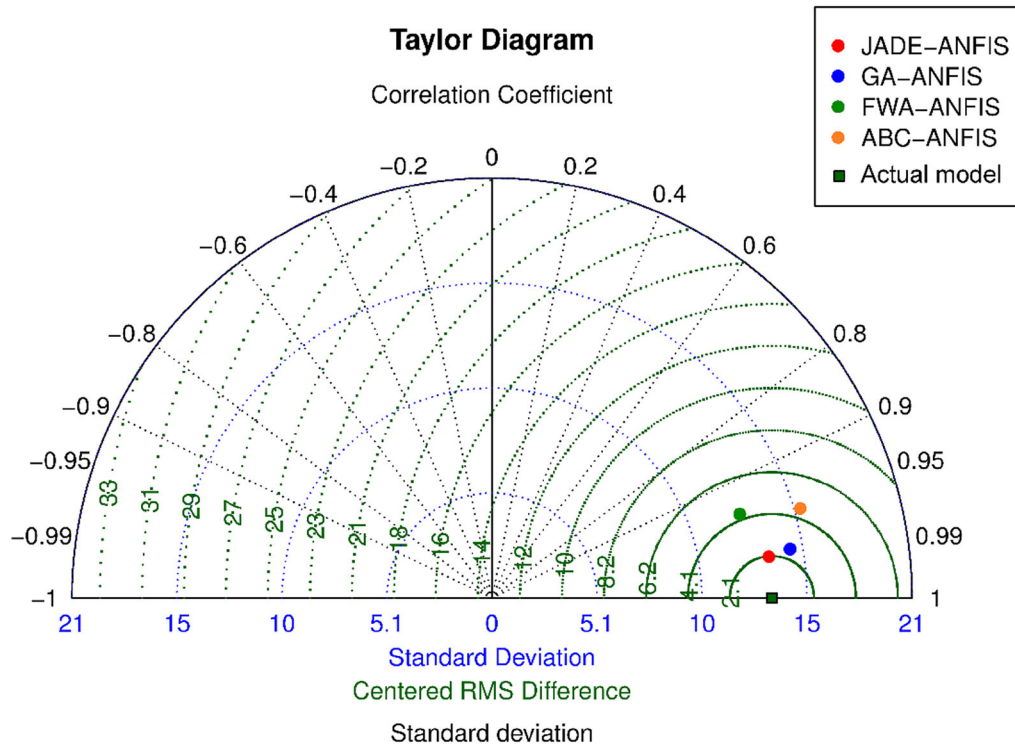


Figure 23. Taylor diagram of various developed hybrid models.

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$$\text{RMSE} = \sqrt{\frac{1}{n_{\text{blast}}} \sum_{i=1}^{n_{\text{blast}}} (\text{Flyrock}_i - \widehat{\text{Flyrock}}_i)^2} \quad (9)$$

$$\text{MAPE} = \frac{1}{n_{\text{blast}}} \sum_{i=1}^{n_{\text{blast}}} \frac{|\text{Flyrock}_i - \widehat{\text{Flyrock}}_i|}{\text{Flyrock}_i} \times 100 \quad (10)$$

It is important to note that the above objective functions were used to select the best model by considering multiple performance indicators, not just one performance index as done previously (Nguyen et al., 2023). This approach ensures a more comprehensive selection of the predictive model. The coefficients in Eqs. 7 and 8 can be chosen based on experience, or the importance level of the training, or testing and performance indicators.

The number of rules directly impacts the expressiveness and complexity of the ANFIS model. In this study, 16 rules were selected, with each rule representing a specific fuzzy if-then rule capturing distinct patterns or relationships within the data. A higher number of rules enable the model to capture more intricate and detailed patterns in the input-output mapping, potentially enhancing its ability to generalize to unseen data. For optimization, 50 populations were chosen, iterated over 1000 generations to ensure model convergence during training for predicting BIFRD. Figure 18 illustrates the optimized membership functions of the ANFIS model under the GA, JADE, ABC, and FWA algorithms. Moreover, Figure 19 displays the training and testing performance of the GA-ANFIS, JADE-ANFIS, ABC-ANFIS, and FWA-ANFIS models, with their comparative analysis presented in Figure 20.

Figure 18 illustrates that, after applying optimization algorithms, all fuzzy rules in the ANFIS-based hybrid models normalized, highlighting the significant role of these algorithms in enhancing fuzzy rule performance. Additionally, Figure 19 reveals that all hybrid models exhibit well-performing curves without overfitting, despite the testing loss line's lack of smoothness due to the utilization of the complex objective functions outlined in Eqs. 7 and 8. While the lowest RMSE of the GA-ANFIS and JADE-ANFIS models may appear similar, a closer examination of Figure 19 indicates that the performance curves of the JADE-ANFIS model surpassed those of the GA-ANFIS model in stability and overall performance. The other hybrid models

exhibited higher RMSE values in both training and testing phases.

The comparison in Figure 20 illustrates that the JADE-ANFIS model demonstrated superior performance in the training phase and maintained stable performance in the testing phase, although slightly less effective than the GA-ANFIS model in the latter. This underscores the JADE-ANFIS model's capability to provide stable predictions for practical engineering applications, particularly in predicting BIFRD for unseen datasets. Figure 21 elucidates the outcomes and errors of the developed ANFIS-based hybrid models.

As illustrated in Figure 21, it is evident that the JADE-ANFIS model outperformed the GA-ANFIS model, given that the error range of the JADE-ANFIS model fell between -5 and 7.5 m without any outliers. In contrast, the GA-ANFIS model exhibited an error range of -5 to 15 m, with noticeable outliers apparent in its regression plot. Furthermore, the FWA-ANFIS and ABC-ANFIS models demonstrated even higher error ranges and weaker convergence in their regression plots. This assessment can be further elucidated through the violin plot depicted in Figure 22.

As shown in Figure 22, the shape of the JADE-ANFIS model's violin plot closely resembles that of the measured BIFRD (actual model). While the FWA-ANFIS model's violin plot also exhibits some similarity to the actual model, it falls short of the accuracy demonstrated by the JADE-ANFIS model. Conversely, the shapes produced by the GA-ANFIS and ABC-ANFIS models diverge significantly from the actual model, indicating lower accuracy in predicting BIFRD in this study.

To evaluate the performance of the developed models, four metrics—RMSE, R^2 , MAPE, and VAF (variance accounted for)—were calculated for the separate datasets (i.e., training and testing). These metrics were chosen because they cover different aspects of the model's performance, while RMSE measures the average magnitude of the errors, as in Eq. 9. It gives more weight to larger errors, which is useful in applications like blast-induced flyrock distance prediction where large deviations are critical for safety. Lower RMSE means better model performance as it shows smaller differences between predicted and observed values. R^2 or coefficient of determination represents the proportion of variance in the dependent variable that is explained by the independent variables, as in Eq. 11. It is a widely used metric to assess the goodness of fit of a model.

R^2 values range from 0 to 1, where values closer to 1 mean better fit. Higher R^2 means the model can explain most of the variability in the data which is important for predicting complex phenomena like flyrock. Besides, MAPE measures the accuracy of the predictions as a percentage, as in Eq. 10. It is scale independent, so it is easier to compare different models or datasets. Lower MAPE values mean higher prediction accuracy. Since MAPE is in percentage, it gives you an idea how far off the model's predictions are from the actual values relative to the magnitude of the data. Finally, VAF is used to evaluate the percentage of variance explained by the model, as in Eq. 12. Like R^2 , it gives you an idea how well the model explains the variation in the data. VAF values close to 100% mean the model explains almost all the variability in the data which is a good predictive model.

$$R^2 = 1 - \frac{\sum_{i=1}^n (\text{Flyrock}_i - \widehat{\text{Flyrock}}_i)^2}{\sum_{i=1}^n (\text{Flyrock}_i - \text{Mean}_{\text{Flyrock}_i})^2} \quad (11)$$

$$\text{VAF} = \left(1 - \frac{\text{Var}(\text{Actual}_{\text{Flyrock}_i} - \text{Predicted}_{\text{Flyrock}_i})}{\text{Var}(\text{Actual}_{\text{Flyrock}_i})} \right) \times 100 \quad (12)$$

By combining these four we have a complete picture of the model. RMSE helps us to minimize the large errors, R^2 and VAF to see how well the model explains the variability in the data and MAPE to have a clear scale independent measure of accuracy. All these metrics give us a balanced view of the model's ability to predict blast-induced flyrock distance. Results are shown in Table 2.

As shown in Table 2, all the developed ANFIS-based metaheuristic models demonstrated high performance, with accuracy ranging from 89% to approximately 97.5% on the training dataset and from 88.7 to 97.8% on the testing dataset. Notably, the MAPE of these models ranged from 1.3 to 3.1% on the training dataset and from 1.1 to 3.0% on the testing dataset.

It is clear that the JADE-ANFIS model was the standout performer among the four hybrid developed models. With training RMSE of 2.524 and testing RMSE of 2.035, it showed the lowest error rates, indicating highly accurate predictions. The R^2 values of 0.975 for training and 0.978 for testing

demonstrated excellent fit and generalizability. Additionally, the MAPE values of 0.013 (training) and 0.011 (testing) highlighted its precision. With VAF close to 97.8% for both phases, the model explained almost all the variance in the data. The training time of 54.333 s was relatively efficient, making JADE-ANFIS a well-balanced model in terms of performance and computational efficiency. The main disadvantage could be the complexity involved in implementing the JADE algorithm, which might require more expertise and resources.

For the GA-ANFIS model, it also performed well, though slightly less effectively than JADE-ANFIS. It had a training RMSE of 2.616 and a testing RMSE of 2.684, showing slightly higher error rates. The R^2 values of 0.973 (training) and 0.962 (testing) indicated strong predictive capability, though not as robust as JADE-ANFIS. The MAPE values were comparable to those of JADE-ANFIS, with 0.013 for training and 0.014 for testing, suggesting good accuracy. The VAF values of approximately 97.5% (training) and 96.5% (testing) were high, though slightly lower than those of JADE-ANFIS. The training time of 52.951 s was the shortest among the models, which is a significant advantage in terms of efficiency. However, the slight drop in testing performance suggests it might not generalize as well as JADE-ANFIS.

The FWA-ANFIS model showed a significant drop in performance compared to JADE-ANFIS and GA-ANFIS. With a training RMSE of 5.304 and a testing RMSE of 4.401, it had higher error rates, indicating less accurate predictions. The R^2 values of 0.888 (training) and 0.897 (testing) were considerably lower, suggesting that the model did not fit the data as well. The MAPE values of 0.031 for training and 0.027 for testing were also higher, reflecting less precision. The VAF values of around 89% for both phases indicated that a substantial portion of variance was unexplained. Furthermore, the training time of 160.821 s was significantly longer, which is a major drawback in terms of computational efficiency. The primary advantage of FWA-ANFIS might be its robustness in dealing with certain types of data, but overall, it is less competitive.

The ABC-ANFIS model's performance was similar to that of FWA-ANFIS, with training RMSE of 5.260 and testing RMSE of 4.623. The R^2 values of 0.890 (training) and 0.886 (testing) indicate that it did not capture the relationship between variables as effectively as the top models. The MAPE values of

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0.031 (training) and 0.030 (testing) showed higher prediction errors. The VAF values of around 89% for both phases were slightly better than FWA-ANFIS but still significantly lower than the top performers. The training time of 89.027 s was shorter than FWA-ANFIS but still relatively high. The ABC-ANFIS model might offer some advantages in specific scenarios where the ABC algorithm's characteristics are beneficial, but generally, it is less efficient and accurate.

Without a doubt, the JADE-ANFIS was the most effective model, combining high accuracy, excellent generalizability, and reasonable training time for predicting BIFRD in this study. The GA-ANFIS followed closely, with slightly lower performance but the advantage of the shortest training time. Both the FWA-ANFIS and ABC-ANFIS lagged behind in terms of accuracy and efficiency in predicting BIFRD at the Ta Phoi open-pit copper mine, with higher error rates and longer training times. While they might have niche applications, they are generally less competitive than the JADE-ANFIS and GA-ANFIS for predicting blast-induced flyrock in this study.

Figure 23 of a Taylor diagram further demonstrates the accuracy of the developed hybrid ANFIS-based models for predicting BIFRD in this study. As indicated in Figure 23, the JADE-ANFIS model was evidently closest to the actual model when considering standard deviation and centered RMS difference. Following this was the GA-ANFIS model, with the FWA-ANFIS and ABC-ANFIS models showing similar performance. These results align with the previous discussions and confirm that the JADE-ANFIS model was the most accurate for predicting BIFRD in the current application.

Although the JADE-ANFIS model was the most accurate for predicting BIFRD at the Ta Phoi open-pit copper mine, evaluating the sensitivity of

the input variables that affect its accuracy is necessary. This evaluation helps to identify which variables significantly contribute to the JADE-ANFIS model's predictive power and how to optimize them to control the flyrock phenomenon in open-pit mines. Here, the multivariate adaptive regression splines method (Friedman, 1991) was applied to analyze the sensitivity of the input variables based on the developed JADE-ANFIS model. The results, shown in Figure 24, clearly indicate that among the four input variables used to develop the JADE-ANFIS model, the length of stemming (ST) had the highest importance level in predicting BIFRD in this open-pit copper mine. In contrast, the other three variables had very low impacts. This suggests that the ST variable should be carefully calculated and used to control BIFRD in this mine. However, using this variable to control BIFRD must be carefully balanced with ensuring proper rock fragmentation, as effective blasting is the primary goal in open-pit mining.

CONCLUSIONS

Flyrock in open-pit mines is a big risk especially in high terrain areas where it can put human lives and infrastructure at risk. This study proposed a safety system to accurately and quickly predict BIFRD using UAV and metaheuristics-optimized ANFIS neural networks with focus on the JADE-ANFIS model. By using advanced objective functions, the JADE-ANFIS model achieved 97.8% prediction accuracy, which is practical applicable. The model, which combines UAV data and JADE-ANFIS neural networks, qualifies as a safety system by allowing rapid and accurate predictions of BIFRD. By predicting the flyrock distances before the blast the model helps in the following:

1. *Pre-emptive risk assessment:* By predicting the maximum flyrock distance, the model allows mine operators to identify high-risk areas and create safety exclusion zones so that personnel or equipment should not be in the blast area.
2. *Blast optimization:* The model allows for optimization of blasting parameters so that fragmentation is effective and flyrock is minimized. This reduces the risk of bad outcomes.
3. *Decision support:* The model gives mine engineers and safety officers information to make

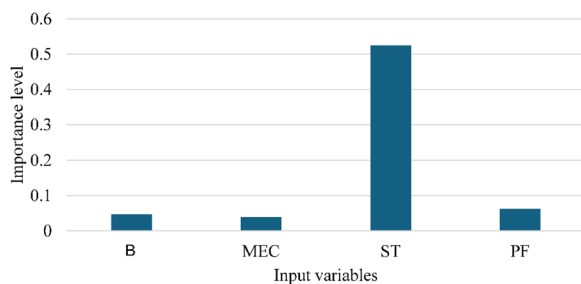


Figure 24. Sensitivity analysis of the JADE-ANFIS model for predicting BIFRD.

informed decisions on blasting designs to avoid risks.

The analysis showed that stemming is the most important factor in determining BIFRD in the studied mine, and so it must be taken into account in designing blast pattern to minimize the risk of fly-rock. This finding highlights the importance of optimized blasting design and the role of machine learning-based prediction model in open pit

Although the JADE–ANFIS model showed high accuracy, future research can improve its accuracy by adding more parameters such as blast delay timing or geological variability. The model's scalability to larger dataset and adaptability to different mining environment should be tested to make it more applicable. Testing the model in real-time condition across various open-pit mines will validate the practicality and refine it for site specific prediction. Further integration of advanced UAV technologies and AI techniques could also enhance automation in mine safety monitoring, making the system more efficient and cost-effective.

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DECLARATIONS

Conflict of Interest We, the authors, claim that we have no conflicts of interest.

REFERENCES

- Abdel-Basset, M., Abdel-Fatah, L., & Sangaiah, A. K. (2018). Metaheuristic algorithms: A comprehensive review. *Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications*. <https://doi.org/10.1016/B978-0-12-813314-9.00010-4>.
- Ahmad, M. F., Isa, N. A. M., Lim, W. H., & Ang, K. M. (2022). Differential evolution: A recent review based on state-of-the-art works. *Alexandria Engineering Journal*, 61(5), 3831–3872.
- Alhijawi, B., & Awajan, A. (2024). Genetic algorithms: Theory, genetic operators, solutions, and applications. *Evolutionary Intelligence*, 17(3), 1245–1256.
- Armaghani, D. J., Hajihassani, M., Mohamad, E. T., Marto, A., & Noorani, S. (2014). Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. *Arabian Journal of Geosciences*, 7, 5383–5396.
- Armaghani, D. J., Koopialipoor, M., Bahri, M., Hasanipanah, M., & Tahir, M. M. (2020). A SVR-GWO technique to minimize flyrock distance resulting from blasting. *Bulletin of Engineering Geology and the Environment*, 79(8), 4369–4385.
- Bajpayee, T., Rehak, T., Mowrey, G., & Ingram, D. (2004). Blasting injuries in surface mining with emphasis on flyrock and blast area security. *Journal of Safety Research*, 35(1), 47–57.
- Barkhordari, M. S., Armaghani, D. J., & Fakharian, P. (2022). Ensemble machine learning models for prediction of flyrock due to quarry blasting. *International Journal of Environmental Science and Technology*, 19(9), 8661–8676.
- Chen, Y., Wang, M., Yin, H., & Zhang, T. (2024). Prediction of flyrock distance induced by blasting using particle swarm optimization and multiple regression analysis: An engineering perspective. *Acta Geophysica*, 72(1), 287–301.
- Choi, T. J., Togelius, J., & Cheong, Y.-G. (2020). Advanced cauchy mutation for differential evolution in numerical optimization. *IEEE Access*, 8, 8720–8734.
- Cuevas, E., Enríquez, L., Zaldívar, D., & Pérez-Cisneros, M. (2018). A selection method for evolutionary algorithms based on the golden section. *Expert Systems with Applications*, 106, 183–196.
- Cui, L., Li, G., Lin, Q., Chen, J., & Lu, N. (2016). Adaptive differential evolution algorithm with novel mutation strategies in multiple sub-populations. *Computers & Operations Research*, 67, 155–173.
- Dehghani, H., Pourzafar, M., & Asadi zadeh, M. (2021). Prediction and minimization of blast-induced flyrock using gene expression programming and cuckoo optimization algorithm. *Environmental Earth Sciences*, 80(1), 12.
- DJI. (2024). Consumer drones comparison. Retrieved Sept 17, 2024 from <https://www.dji.com/global/products/comparison-consumer-drones>.
- Fattahi, H., & Hasanipanah, M. (2021). An integrated approach of ANFIS-grasshopper optimization algorithm to approximate flyrock distance in mine blasting. *Engineering with Computers*, 38(3), 2619–2631.
- Fletcher, L. R., & D'Andrea, D. V. (1987). Reducing accidents through improved blasting safety. *Surface Mine Blasting: Proceedings*, 9135, 6.
- Friedman, J. H. (1991). Multivariate adaptive regression splines. *The Annals of Statistics*, 19(1), 1–67.
- Gallagher, K., & Sambridge, M. (1994). Genetic algorithms: A powerful tool for large-scale nonlinear optimization problems. *Computers & Geosciences*, 20(7–8), 1229–1236.
- Ghasemi, E., Sari, M., & Ataei, M. (2012). Development of an empirical model for predicting the effects of controllable blasting parameters on flyrock distance in surface mines. *International Journal of Rock Mechanics and Mining Sciences*, 52, 163–170.
- Goswami, D., & Chakraborty, S. (2015). Parametric optimization of ultrasonic machining process using gravitational search and fireworks algorithms. *Ain Shams Engineering Journal*, 6(1), 315–331.
- Guo, H., Zhou, J., Koopialipoor, M., Jahed Armaghani, D., & Tahir, M. M. (2019). Deep neural network and whale optimization algorithm to assess flyrock induced by blasting. *Engineering with Computers*, 37(1), 173–186.
- Han, H., Jahed Armaghani, D., Tarinejad, R., Zhou, J., & Tahir, M. M. (2019). Random forest and bayesian network tech-

Measurement and Prediction of Blast-Induced Flyrock Distance

- niques for probabilistic prediction of flyrock induced by blasting in quarry sites. *Natural Resources Research*, 29(2), 655–667.
- Hasanipanah, M., & Bakhshandeh Amnieh, H. (2020). A fuzzy rule-based approach to address uncertainty in risk assessment and prediction of blast-induced flyrock in a quarry. *Natural Resources Research*, 29(2), 669–689.
- Hasanipanah, M., Jahed Armaghani, D., Bakhshandeh Amnieh, H., Majid, M. Z. A., & Tahir, M. M. D. (2016). Application of PSO to develop a powerful equation for prediction of flyrock due to blasting. *Neural Computing and Applications*, 28(1), 1043–1050.
- Hudaverdi, T. (2022). Prediction of flyrock throw distance in quarries by variable selection procedures and ANFIS modelling technique. *Environmental Earth Sciences*, 81(10), 281.
- Islam, S. M., Das, S., Ghosh, S., Roy, S., & Suganthan, P. N. (2011). An adaptive differential evolution algorithm with novel mutation and crossover strategies for global numerical optimization. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 42(2), 482–500.
- Jahed Armaghani, D., Tonnizam Mohamad, E., Hajihassani, M., Alavi Nezhad Khalil Abad, S. V., Marto, A., & Moghaddam, M. R. (2015). Evaluation and prediction of flyrock resulting from blasting operations using empirical and computational methods. *Engineering with Computers*, 32(1), 109–121.
- Jamei, M., Hasanipanah, M., Karbasi, M., Ahmadianfar, I., & Taherifar, S. (2021). Prediction of flyrock induced by mine blasting using a novel kernel-based extreme learning machine. *Journal of Rock Mechanics and Geotechnical Engineering*, 13(6), 1438–1451.
- Jang, J.-S. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665–685.
- Jin, H., Jin, Z., Kim, Y.-G., & Fan, C. (2023). Intelligence-based simulation of solubility of hydrogen in bitumen at elevated pressure and temperature: Models optimization using fireworks algorithm. *Journal of Molecular Liquids*, 390, 122948.
- Lawal, A. I., Ojo, O. J., Kim, M., & Kwon, S. (2022). Determination of blast-induced flyrock using a drone technology: A bibliometric overview with practical soft computing implementation. *Arabian Journal of Geosciences*, 15(19), 1581.
- Li, C., Zhou, J., Du, K., Armaghani, D. J., & Huang, S. (2023). Prediction of flyrock distance in surface mining using a novel hybrid model of harris hawks optimization with multi-strategies-based support vector regression. *Natural Resources Research*, 32(6), 2995–3023.
- López-Ibáñez, M., Dubois-Lacoste, J., Cáceres, L. P., Birattari, M., & Stützle, T. (2016). The irace package: Iterated racing for automatic algorithm configuration. *Operations Research Perspectives*, 3, 43–58.
- Lu, X., Hasanipanah, M., Brindhadevi, K., Bakhshandeh Amnieh, H., & Khalafi, S. (2019). ORELM: A novel machine learning approach for prediction of flyrock in mine blasting. *Natural Resources Research*, 29(2), 641–654.
- Mishra, R., Mishra, A. K., & Choudhary, B. S. (2023). High-speed motion analysis-based machine learning models for prediction and simulation of flyrock in surface mines. *Applied Sciences*, 13(17), 9906.
- Mohamed, A. W., & Suganthan, P. N. (2018). Real-parameter unconstrained optimization based on enhanced fitness-adaptive differential evolution algorithm with novel mutation. *Soft Computing*, 22, 3215–3235.
- Monjezi, M., Dehghani, H., Shakeri, J., & Mehrdanesh, A. (2021). Optimization of prediction of flyrock using linear multivariate regression (LMR) and gene expression programming (GEP): Topal Novin mine, Iran. *Arabian Journal of Geosciences*, 14(15), 1483.
- Monjezi, M., Mohamadi, H. A., Barati, B., & Khandelwal, M. (2014). Application of soft computing in predicting rock fragmentation to reduce environmental blasting side effects. *Arabian Journal of Geosciences*, 7, 505–511.
- Murlidhar, B. R., Kumar, D., Jahed Armaghani, D., Mohamad, E. T., Roy, B., & Pham, B. T. (2020). A Novel intelligent ELM-BBO technique for predicting distance of mine blasting-induced flyrock. *Natural Resources Research*, 29(6), 4103–4120.
- Murlidhar, B. R., Nguyen, H., Rostami, J., Bui, X., Armaghani, D. J., Ragam, P., et al. (2021). Prediction of flyrock distance induced by mine blasting using a novel Harris Hawks optimization-based multi-layer perceptron neural network. *Journal of Rock Mechanics and Geotechnical Engineering*, 13(6), 1413–1427.
- Nguyen, H., & Bui, X.-N. (2022). Optimized adaptive neuro-fuzzy inference system for predicting blast-induced ground vibration in quarries based on hunger games search optimization. *International Journal of Mining, Reclamation and Environment*, 36(10), 724–748.
- Nguyen, H., Bui, X.-N., & Topal, E. (2023). Enhancing predictions of blast-induced ground vibration in open-pit mines: Comparing swarm-based optimization algorithms to optimize self-organizing neural networks. *International Journal of Coal Geology*, 275, 104294.
- Pant, M., Zaheer, H., Garcia-Hernandez, L., & Abraham, A. (2020). Differential evolution: A review of more than 2 decades of research. *Engineering Applications of Artificial Intelligence*, 90, 103479.
- Persson, P.-A. (2020). The relationship between strain energy, rock damage, fragmentation, and throw in rock blasting. In *rock fragmentation by blasting* (pp. 113–120). CRC Press.
- Protodiakonov, M., Koifman, M., Chirkov, S., Kuntish, M., & Tedder, R. (1964). *Rock strength passports and methods for their determination*. Nauka.
- Raina, A. K., & Bhatawdekar, R. M. (2022). Blast-induced flyrock: Risk evaluation and management. In *Risk, reliability and sustainable remediation in the field of civil and environmental engineering* (pp. 209–247). Elsevier.
- Reeves, C. R. (2010). Genetic algorithms. In *Handbook of metaheuristics*, pp. 109–139.
- Roy, P. P., Sawmliana, C., & Singh, R. K. (2022). Strategic planning to reduce ground vibration, air overpressure and flyrock in a mine at a sensitive area. *Current Science*, 123(8), 995.
- Sevelka, T. (2022). Preventing the potentially deadly consequences of flyrock: Mandatory minimum setbacks and separation distances required. *Journal of Natural Resources*, 5(4), 66–98.
- Sevelka, T. (2023). Flyrock throw calculations unscientific and unreliable—the “hits” just keep on coming. *J. Envtl. L. & Pol’y*, 3, 1.
- Ss, V. C., & Hs, A. (2022). Nature inspired meta heuristic algorithms for optimization problems. *Computing*, 104(2), 251–269.
- Stojadinović, S., Lilić, N., Obradović, I., Pantović, R., & Denić, M. (2015). Prediction of flyrock launch velocity using artificial neural networks. *Neural Computing and Applications*, 27(2), 515–524.
- Tan, Y. (2015). *Fireworks algorithm* (Vol. 10, pp. 978–973). Springer.
- Valdez, F., Melin, P., & Castillo, O. (2014). A survey on nature-inspired optimization algorithms with fuzzy logic for dynamic parameter adaptation. *Expert Systems with Applications*, 41(14), 6459–6466.
- Venkatraman, S., & Yen, G. G. (2005). A generic framework for constrained optimization using genetic algorithms. *IEEE Transactions on Evolutionary Computation*, 9(4), 424–435.
- Van Thieu, N., & Mirjalili, S. (2023). MEALPY: An open-source library for latest meta-heuristic algorithms in Python. *Journal of Systems Architecture*, 139, 102871. <https://doi.org/10.1016/j.sysarc.2023.102871>.

- Va Thieu, N. (2024). PerMetrics: A framework of performance metrics for machine learning models. *Journal of Open Source Software*, 9(95), 6143. <https://doi.org/10.21105/joss.06143>.
- Yardimci, A. G., & Erkayaoglu, M. (2023). Simulation of blast-induced ground vibrations using a machine learning-assisted mechanical framework. *Environmental Earth Sciences*, 82(21), 508.
- Zhang, J., & Sanderson, A. C. (2009). JADE: adaptive differential evolution with optional external archive. *IEEE Transactions on Evolutionary Computation*, 13(5), 945–958.
- Zhang, R., Li, Y., Gui, Y., Armaghani, D. J., & Yari, M. (2024). A stacked deep multi-kernel learning framework for blast induced flyrock prediction. *International Journal of Rock Mechanics and Mining Sciences*, 177, 105741.
- Zhu, C., Xu, Y., Wu, Y., He, M., Zhu, C., Meng, Q., et al. (2022). A hybrid artificial bee colony algorithm and support vector machine for predicting blast-induced ground vibration. *Earthquake Engineering and Engineering Vibration*, 21(4), 861–876.

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