Resources Policy 97 (2024) 105261

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Enhancing blasting efficiency: A smart predictive model for cost optimization and risk reduction

Hadi Fattahi [a], Hossein Ghaedi [a], Danial Jahed Armaghani [b,*]

[a] *Faculty of Earth Sciences Engineering, Arak University of Technology, Arak, Iran*
[b] *School of Civil and Environmental Engineering, University of Technology Sydney, Sydney, NSW, 2007, Australia*

ARTICLE INFO

Keywords:
Blasting costs
FF algorithm
GWO algorithm
Limestone mines
Sensitivity analysis

ABSTRACT

Mineral extraction involves distinct stages, including drilling, blasting, loading, transporting, and processing minerals at a designated facility. The initial phase is drilling and blasting, crucial for controlled dimensions of crushed stone suitable for the processing plant. Incorrect blasting can lead to unsuitable stone grading and destructive outcomes like ground vibrations, stone projection, air blasts, and recoil. Predicting and optimizing blasting costs (*BC*) is essential to achieve desired particle size reduction while mitigating adverse blasting consequences. *BC* varies with rock hardness, blasting techniques, and patterns. This study presents a *BC* prediction model using data from 6 Iranian limestone mines, employing firefly (FF) and gray wolf optimization (GWO) algorithms. With 146 data points and parameters like hole diameter (*D*), ANFO (*AN*), sub-drilling (*J*), uniaxial compressive strength (σ_c), burden (*B*), hole number (*N*), umolite (*EM*),spacing (*S*), specific gravity (γr), stemming (*T*), hole length (*H*), rock hardness (*HA*), and electric detonators (*Det*), the data was split into 80% for model construction and 20% for validation. Using statistical indicators, the model showed good performance, offering engineers, researchers, and mining professionals high accuracy. The @RISK software conducted sensitivity analysis, revealing T parameter as the most influential input factor, where minor T changes significantly affected *BC*. Lastly, the @RISK software was employed to conduct a sensitivity analysis on the model's outputs. The analyses demonstrated that, among the input factors, the *T* parameter had the most pronounced effect on the model's output. Even small changes in the value of *T* led to considerable fluctuations in the predicted BC.

1. Introduction

Drilling and blasting techniques are employed in both surface and underground mining to optimize profitability and reduce production expenditures. Obtaining the desired dimensions of crushed rock for processing facility input starts with effective drilling and blasting procedures. The economic performance of mining operations is significantly influenced by the rock fragmentation produced during blasting (Bhandari, 1997; Singh and Singh, 2005). Successful blasting leads to reduced rock crushing costs, improved drilling, loading, and hauling efficiency, eliminating the need for additional drilling, minimizing ground vibrations, reducing throw, and enhancing post-extraction drilling activities (Kalayci et al., 2010; Roy et al., 2017). Thus, meticulous planning and management of these operations not only reduce mining expenses but also enhance subsequent manufacturing phases, bolster safety measures, and improve overall efficiency (Ghasemi et al., 2012; Gokhale, 2010; Latham et al., 2006; Lowery et al., 2001; Qu et al., 2002; Rezaei et al., 2011). Identifying the variables impacting drilling and blasting operations is vital for achieving these objectives. Efficient blasting begins with recognizing the factors affecting drilling and blasting operations (input parameters). A well-designed blast pattern is then created based on these factors. Generally, two categories of characteristics influence blast pattern design: those beyond our control and those within our influence. Environmental factors beyond control, such as rock stiffness, joints, faults, humidity, temperature, and atmospheric conditions, must be considered during design (Kulatilake et al., 2010; Singh et al., 2016; Verma and Singh, 2011). On the other hand, adjustable parameters are flexible and contribute to optimal blasting. Controlled parameters include drilling pattern geometry, hole length, hole diameter, explosive physical properties, hole depth, delay duration, and explosive quantity (Dehghani and Ataee-Pour, 2011; Lowery et al., 2001; Monjezi et al., 2009). Based on the provided explanations and varying geological conditions, optimizing controlled parameters can significantly reduce uncontrollable factors such as uniform grain size distribution and

* Corresponding author.
E-mail address: danial.jahedarmaghani@uts.edu.au (D.J. Armaghani).

https://doi.org/10.1016/j.resourpol.2024.105261
Received 10 December 2023; Received in revised form 1 August 2024; Accepted 6 August 2024
Available online 13 August 2024

induced vibrations. In cases where rock resistance is lower, air and ground vibrations can be minimized with reduced blast power, resulting in a more suitable grain size distribution for effective blasting. Optimal blasting practices should also be applied to tunnels and underground mines. This is essential to mitigate unwanted damage during drilling and blasting (D&B) operations, which can affect the quality of the surrounding rock mass, blast efficiency, and the need for additional supports like shotcrete and concrete. Furthermore, it impacts the quality of tunnel slopes and contours, contributing to stability issues, damage reduction, and ultimately the cost and duration of the drilling project. Therefore, it is crucial to focus on optimal blasting in both open-pit and underground mining to minimize costs. Numerous studies have investigated blasting costs (BC) in mining. For instance, Nielsen examined the impact of optimal specific costs on open-pit iron ore mining expenses in Sidaragar, Norway, considering various mining subsystems. A computer model was developed to assess drilling and blasting, loading, shipping, and crushing costs (Nielsen, 1987). Jimeno et al. (1995) introduced a fundamental equation for calculating drilling cost per meter, encompassing direct (e.g., maintenance, personnel, energy) and indirect (e.g., depreciation, insurance, taxes) expenses. Jhanwar et al. (1999) review the theory of induced air deck explosions and provide a detailed description of air deck explosion experiments conducted in an opencast manganese mine in India. The results showed that using ANFO explosive with this technique reduced blasting costs by 31.6% and improved rock fragmentation. Kanchibotla (2003) explored the concept of "Optimum blasting—Minimum cost or maximum value of each ton of broken rock" by studying profitability, costs, and optimal blasting in gold and coal mines using computer simulation models and field research. Rajpot (2009) investigated the effect of post-explosion fragmentation properties on BC. Additionally, to estimate the impact of hole diameter on achieving fragmentation of d80 and to calculate the parameters of explosion design for particle sizes ranging from 350 to 75 mm, they presented a model. Usman and Muhammad (2013) applied principal component analysis (PCA) to data and parameters from 31 blasts in a cement mine in northern Pakistan to create a model for predicting blasting costs. Afum and Temeng (2015) investigated cost reduction in drilling-blasting operations in a Ghanaian open-pit gold mine through blast optimization using the Koz-Ram model, achieving an average reduction of 25–56 cm. Adebayo and Mutandwa (2015) examined the relationship between blast hole deviation, rock fragment size, and crushing costs, using various explosives in holes with diameters ranging from 191 to 311 mm, demonstrating that increased hole deviation leads to smaller rock fragments and higher drilling and BC. At a conference, Styles (2015) discussed the use of blast damage in modeling open slopes using numerical modeling with Slide software. Bilim et al. (2017) investigated and evaluated drilling-blasting design parameters, such as hole depth, hole diameter, hole distance, and load, to produce suitable aggregate and their effect on the total cost of extraction. They provided recommendations for production design to prevent increased explosion costs. Abbaspour et al. (2018) employed a system dynamic model (SDM) using Vensim simulation software to optimize drilling and blasting operations. The results indicated that this method, unlike deterministic methods, can perform better and significantly reduce drilling and blasting costs. Ghanizadeh Zarghami et al. (2018) collected data from three copper mines in Iran and developed a linear model for BC per cubic meter based on pit diameter, step height, uniaxial compressive strength, and seam direction using Comfar software and statistical methods. Miranda et al. (2019) conducted research employing numerical methods to ascertain the minimum blasting cost in comparison to traditional and experimental approaches. This model centers on developing a blasting pattern with automatic adjustments for parameters such as burden, row spacing, mud placement, over-drilling, and the number of holes. The aim is to ensure that the blasting volume meets production demands. Costamagna et al. (2021) investigated the damage and contour quality resulting from rock drilling and explored various stability solutions. Their findings included detailed excavation techniques based on real-world cases from tunnels and mines to reduce damage and improve stability. Nikkhah et al. (2022) conducted research using statistical and regression methods to analyze the distribution of rock fragmentation caused by blasting. They identified the Rock Fragmentation Distribution (RFD) factor as a crucial determinant in optimizing blasting conditions and influencing explosion costs at the Sarchesheme copper mine.

While numerous researchers have investigated BC, an essential consideration is that drilling and blasting techniques vary according to rock characteristics. Stronger rocks demand more energy for fragmentation, and an imbalance between rock strength and explosive power can lead to hazardous consequences such as ground vibrations, stone projection, and even loss of life. Therefore, aside from reducing damages, precise and controlled blasting also reduces costs and yields suitable rock fragmentation for processing plants. Given the significant uncertainties associated with parameters affecting BC, methods capable of accounting for these uncertainties are crucial. Intelligent methods, due to their inherent capabilities, serve as a promising alternative to traditional approaches. These intelligent methods can encompass all uncertainties in input parameters, providing a highly accurate and low-error estimate of BC (Ahangari et al., 2015; Álvarez-Vigil et al., 2012; Bakhshandeh Amnieh et al., 2019; Çanakcı et al., 2009; Dehghani, 2018; Hasanipanah et al., 2018; Jang and Topal, 2013; Monjezi et al., 2016; Nguyen et al., 2019; Trivedi et al., 2014; Wang et al., 2018; Yu et al., 2021).

Upon reviewing existing research, it becomes evident that there is a need for a precise model to evaluate and predict BC in limestone mines, one that accounts for all variables influencing these costs. In this study, firefly (FF) algorithm and gray wolf optimization (GWO) algorithm were employed to evaluate and predict BC using data from 6 limestone mines in Iran. Understanding the core principles of the FF and GWO algorithms used in this study is essential. Optimization algorithms, in general, are computational tools designed to improve the performance of complex systems by adjusting variables or parameters to achieve optimal outcomes. These algorithms mimic natural behaviors or evolutionary processes to seek optimal solutions in diverse scenarios. For instance, the FF algorithm simulates the collective behavior of fireflies based on their emitted light, which is used for mate attraction and hunting. Similarly, the GWO algorithm seeks optimal solutions by emulating the group hunting behavior of wolves. The strength of optimization algorithms lies in their capacity to navigate complex solution spaces characterized by numerous variables and intricate interactions, ultimately identifying optimal or near-optimal solutions. Traditional analytical methods often struggle with the non-linear and intricate interactions inherent in determining BC. However, optimization algorithms excel at detecting these complex patterns and fluctuations, offering a robust approach to quantifying uncertainty. In this paper, the researchers aim to provide a more precise and efficient alternative to conventional methods, which can be time-consuming, resource-intensive, and often limited in scope. By leveraging the capabilities of these algorithms, they seek to improve accuracy and efficiency in BC prediction. The iterative nature of optimization algorithms allows them to explore a wide range of potential solutions, honing in on the most favorable outcomes. By acknowledging the substantial variability and uncertainty in geological data, these algorithms enable the estimation of BC through a potent combination of computational efficiency and accuracy achieved by the FF and GWO algorithms. Their ability to navigate complex solution spaces and elucidate intricate connections provides a valuable means of addressing uncertainty in rock mechanics. The systematic and adaptable nature of optimization algorithms heralds a paradigm shift, enabling more accurate and efficient forecasts in domains like rock engineering, mining, and energy exploration, where informed decision-making is paramount. This advancement marks a significant step forward, offering enhanced tools for practitioners and researchers to achieve better outcomes in their respective fields.

2. Database utilized in this study

In this investigation, we harnessed data from 6 limestone mines situated in Iran to construct the model and validate the FF and GWO algorithms. Table 1 provides an overview of the characteristics of these mines, while Fig. 1 depicts their geographical distribution across Iran.

In alignment with the research's objectives and the pursuit of authentic data, the team collected blasting cost data from these 6 limestone mines spanning from the year 2011 to November 2018. Subsequently, they updated this dataset to reflect changes in explosive prices and expenses as of January 2017, which then served as the foundation for their research. The data revealed that, on average, the cost composition of each blasting event comprises 62.9% for explosive procurement, 16.8% for transportation, escort services, personnel, consumption monitoring, and containers, 8.5% for the blasting company's remuneration, and 11.8% for secondary fragmentation and adverse blasting effects. Fig. 2 offers a schematic representation of the distribution of these cost components as percentages (Bastami et al., 2020).

To assess factors such as fly rock and stone throw, the researchers employed a total station mapping camera and laser meter. The analysis of rock fragmentation in the six limestone mines was conducted using the Split Desktop program and image analysis techniques. Random imaging was performed with two scales positioned at the top and bottom of the explosive cut to account for dimensional variations. Subsequently, the images were subjected to scrutiny using Split Desktop 4 software to generate distinct dimensional distribution curves for each blast. Fig. 3 illustrates the sequential steps of image analysis by the Split Desktop program in one of the previously discussed mines (Bastami et al., 2020).

Moving forward, the dataset employed in this research encompasses information pertaining to design parameters, geomechanical data, and the outcomes of 146 blasting patterns across 6 limestone mines in Iran. The input parameters encompass burden (B), hole number (N), spacing (S), rock hardness (HA), uniaxial compressive strength (σc), sub-drilling (J), hole diameter (D), umolite (EM), hole length (H), specific gravity (γr), stemming (T), ANFO (AN), and the number of electric detonators (Det). BC serves as the output or estimation target in this study. Table 2 provides a snapshot of some of the input and output data used in constructing the model.

In order to comprehensively analyze the dataset utilized in this research, it is crucial to provide statistical descriptions of both the input and output data. Table 3 furnishes statistical summaries, encompassing minimum, maximum, average, mode, median, range, and standard deviation values for all input and output data.

To enhance the visual understanding of these data descriptions and characteristics, a data histogram can be generated. Fig. 4 presents a histogram chart portraying the data employed for BC modeling.

For a clearer progression through this study's primary objectives, we have schematically divided the main goal into three fundamental phases, as depicted in Fig. 5: data processing, division of data into training and testing groups, and model construction and evaluation.

Table 1
Characteristics of Limestone Mines in this Study (Bastami et al., 2020).

No.	Name of the mine in Iran	Nearest city to mine	Definite storage	Annual extraction capacity (tons)
1	Tajareh	Khorramabad, Iran	4300000	150000
2	Barkhordar1	Nurabad, Iran	1600000	160000
3	Tang Fani	Pol Dokhtar, Iran	900000	100000
4	Moslem Abad	Hamedan, Iran	7000000	300000
5	Abelou	Neka, Iran	89340000	4000000
6	Sepahan Mobarakeh	Esfahan, Iran	13500000	600000

3. Introduction of the algorithms used in this study

3.1. Firefly (FF) algorithm

The FF algorithm derives its inspiration from nature, specifically simulating the social behaviors of fireflies. This algorithm, which was introduced by Yang, was designed to tackle complex engineering problems (Yang, 2009). In essence, fireflies emit varying patterns of light, each with a unique intensity. They employ these light emissions to attract potential mates and also for hunting. The attractiveness of a firefly is directly linked to the intensity of its light emission. By considering the light intensity of each firefly as a representation of the objective function's value, one can model the behavior of fireflies as an optimization algorithm. To achieve this, it is imperative to delve into the life cycle of fireflies. As such, Fig. 6 illustrates the life cycle of fireflies.

To mathematically model the life of fireflies during the modeling process, three fundamental principles need to be taken into account (Fister et al., 2013; Yang, 2010a, 2010c, 2013; Yang and He, 2018):

All fireflies are treated as having the same gender, making them attracted to one another irrespective of their gender.

The level of attractiveness in fireflies is directly tied to their brightness. As a result, a firefly with reduced brightness will gravitate towards a brighter counterpart. In situations where no firefly surpasses another in brightness, they will navigate randomly.

The brightness of fireflies is determined by evaluating their individual objective functions. Within the FF algorithm, key elements include adjusting light intensity and defining attractiveness through a specific formula. For simplicity, the absorbability of a firefly is assumed to be dictated by its luminosity. In its most basic form, the brightness (I) of a firefly within a specific region (x) can be expressed as $I(x) \propto f(x)$, with I(x) representing the brightness of a firefly within a given region (Yang, 2010c):

$$I(r) = \frac{I_s}{r^2} \tag{1}$$

When considering a medium with a constant light absorption coefficient (γ), the light intensity ($I(r)$) undergoes changes with distance (r) as per the following equation:

$$I = I_0 e^{-\gamma r} \tag{2}$$

In this equation, I_0 represents the primary light intensity. The attractiveness of fireflies (β) is relative and depends on the distance between two fireflies in meters (r) and the light absorption coefficient (γ). This can be calculated using the equation:

$$\beta_{(r)} = \beta_0 e^{-\gamma r^2} \tag{3}$$

Here, β_0 signifies the higher brightness attractiveness at $r = 0$. The distance (m) between fireflies i and j, positioned at coordinates x_i and x_j, can be calculated utilizing the Cartesian equation:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{4}$$

For two dimensions, the equation simplifies to:

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{5}$$

The movement of firefly i towards a more attractive (brighter) firefly j can be defined as follows:

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha \varepsilon_i \tag{6}$$

The second part of this relationship is associated with brightness and attractiveness. Furthermore, α represents a random parameter, and ε is a random vector derived from a Gaussian or uniform distribution.

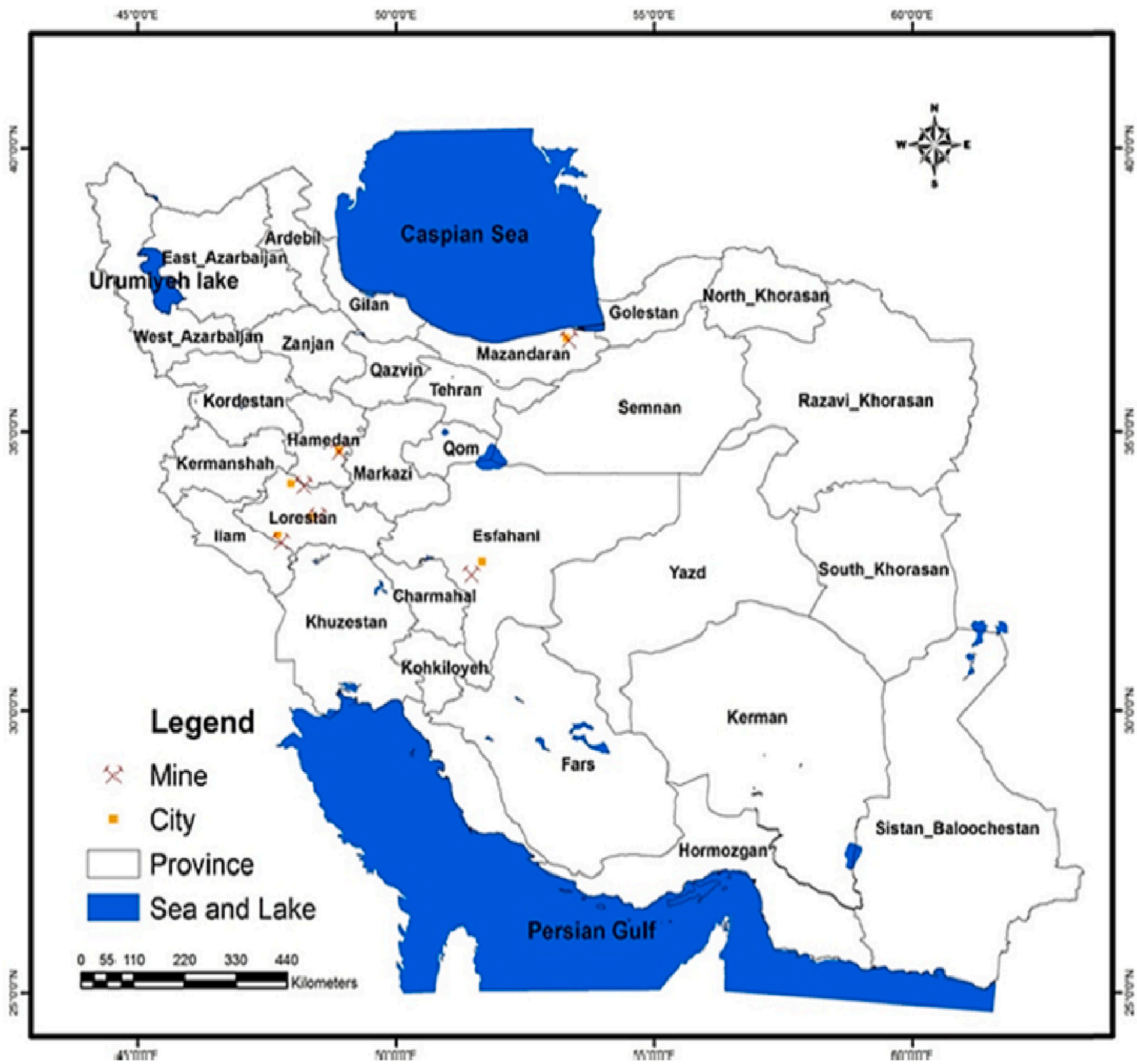

Fig. 1. Geographical Locations of Limestone Mines in this Study, Iran (Bastami et al., 2020).

It's important to note that ε_i can be substituted with a uniform distribution generating a random number within the interval [0,1]. In practice, α usually falls within the range of [0,1], and β_0 is set to one. The γ parameter dictates the convergence speed and the behavior of the FF algorithm. In theory, γ spans from [0,∞], but in practice, it typically ranges from 0.1 to 10 (Yang, 2010b). To provide a clearer understanding of the mathematical modeling, Fig. 7 offers a conceptual representation of the FF algorithm.

Subsequently, we present a concise flowchart of the FF algorithm in Fig. 8 to facilitate a better grasp of its functioning.

3.2. Gray wolf optimization (GWO) algorithm

The GWO Algorithm, introduced in 2014 by Mirjalali et al., was designed to tackle engineering problems. Gray wolves exhibit a semi-democratic social structure, living and hunting in organized packs (Mirjalili et al., 2014). Within these groups, which typically consist of 5–12 wolves, a strict and orderly social hierarchy is maintained. At the top of this hierarchy are the group leaders, known as alphas, consisting of one male and one female. Alphas hold the responsibility for making decisions related to hunting, territory defense, resting locations, wake-up times, and more. These decisions are communicated to the lower-ranking wolves within the pack. Interestingly, alphas are not necessarily the physically strongest members but excel in managing and shouldering responsibility, emphasizing the importance of leadership and discipline over sheer power. Betas, positioned beneath alphas, assist them in decision-making and can replace alpha wolves in cases of illness, aging, or death. Beta wolves take on the role of issuing commands to wolves with lower ranks, acting as advisors to the alpha wolves. The Omega wolves, occupying the lowest rank, primarily focus on providing protection and making sacrifices for the pack. Omega wolves follow the orders of all other wolves, emphasizing their submissive role in the hierarchy (see Fig. 9) (Mirjalili et al., 2014).

The hunting behavior of gray wolves is delineated into three primary

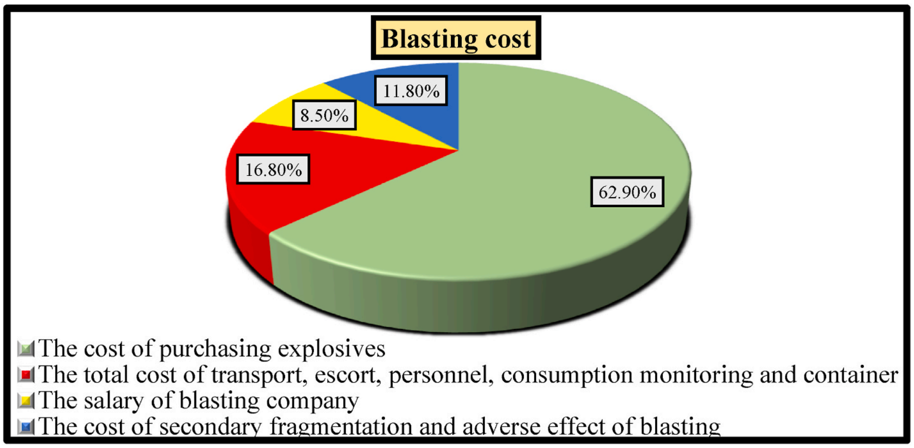

Fig. 2. Cost breakdown for limestone mine blasting (Bastami et al., 2020).

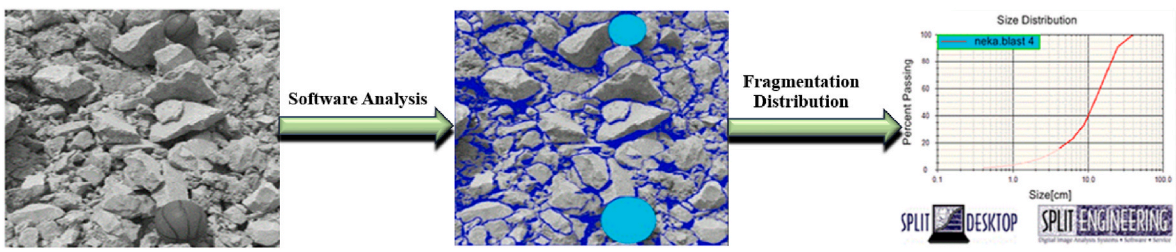

Fig. 3. Example of stone fragmentation analysis using split desktop software (Bastami et al., 2020).

Table 2
Partial inputs and output data for modeling (Bastami et al., 2020).

No.	Inputs													Output
	σ_c (Kg/cm^3)	T (m)	H (m)	γ_r (ton/m^3)	J (m)	B (m)	HA (Mhos)	S (m)	N	EM (Kg)	D (mm)	Det	AN (Kg)	BC (Rials/ton)
1	671	0.9	6.3	2.7	0.5	1.8	3.5	2.1	270	260	76	270	5500	18239
2	671	0.9	6.8	2.7	0.5	1.8	3.5	2.2	436	500	76	490	9300	15486
3	671	0.9	8	2.7	0.5	1.7	3.5	2	404	500	76	650	10000	18110
4	671	1	6	2.7	0.5	1.7	3.5	2	215	280	76	230	4300	23481
5	671	1.1	4	2.7	0.5	1.8	3.5	2	500	320	76	590	6200	20946

Table 3
Statistical characteristics of input and output data.

Type	Parameters	Maximum	Minimum	Std. Deviation	Mean
Input	σ_c (Kg/cm^3)	671	530	49.94	600.56
	γ_r (ton/m^3)	2.7	2.60	0.039	2.66
	B (m)	3.5	1.70	0.529	2.36
	N	553	29	136.608	271.48
	J (m)	1.5	0.2	0.415	0.82
	S (m)	4	1.90	0.613	2.79
	H (m)	20.40	4	3.217	9.52
	T (m)	3.6	0.9	0.552	1.83
	D (mm)	100	76	8.218	82.93
	Det	650	45	122.433	347.82
	HA (Mhos)	3.5	3	0.161	3.27
	EM (Kg)	600	40	115.374	295.40
	AN (Kg)	12400	1020	2598.485	8551.30
Output	BC (Rials/ton)	23481	7157	3994.762	13467.92

phases, as illustrated in Fig. 10 (Mirjalili and Lewis, 2016; Mirjalili et al., 2014):

a) Tracking, Chasing, and Approaching Prey
b) Chasing, Surrounding, and Harassing Prey Until It Stops Moving
c) Attacking the Prey

3.2.1. Modeling the prey encirclement process by gray wolves

Mathematical models for the encirclement behavior are described by the following equations, where t represents the repetition number, A and C denote multiplier vectors, X_{prey} signifies the prey's location vector, and X_G Wolf represents the location vector of each gray wolf (Mirjalili et al., 2014):

$$\vec{D} = \left| \vec{C}.\vec{X}_{\text{prey}}(t) - \vec{X}_{\text{G} \quad \text{Wolf}}(t) \right| \tag{7}$$

$$\vec{X}_{\text{G} \quad \text{Wolf}}(t+1) = \vec{X}_{\text{prey}}(t) - \vec{A}.\vec{D} \tag{8}$$

Vectors A and C are determined by the following formulas (Mirjalili et al., 2014):

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{9}$$

$$\vec{C} = 2.\vec{r}_2 \tag{10}$$

$$a = 2 - iter \times \left(\frac{2}{Max - iter} \right) \tag{11}$$

In these equations, the components of vector A progressively decrease from 2 to zero across successive repetitions. Additionally, r_1 and r_2 are

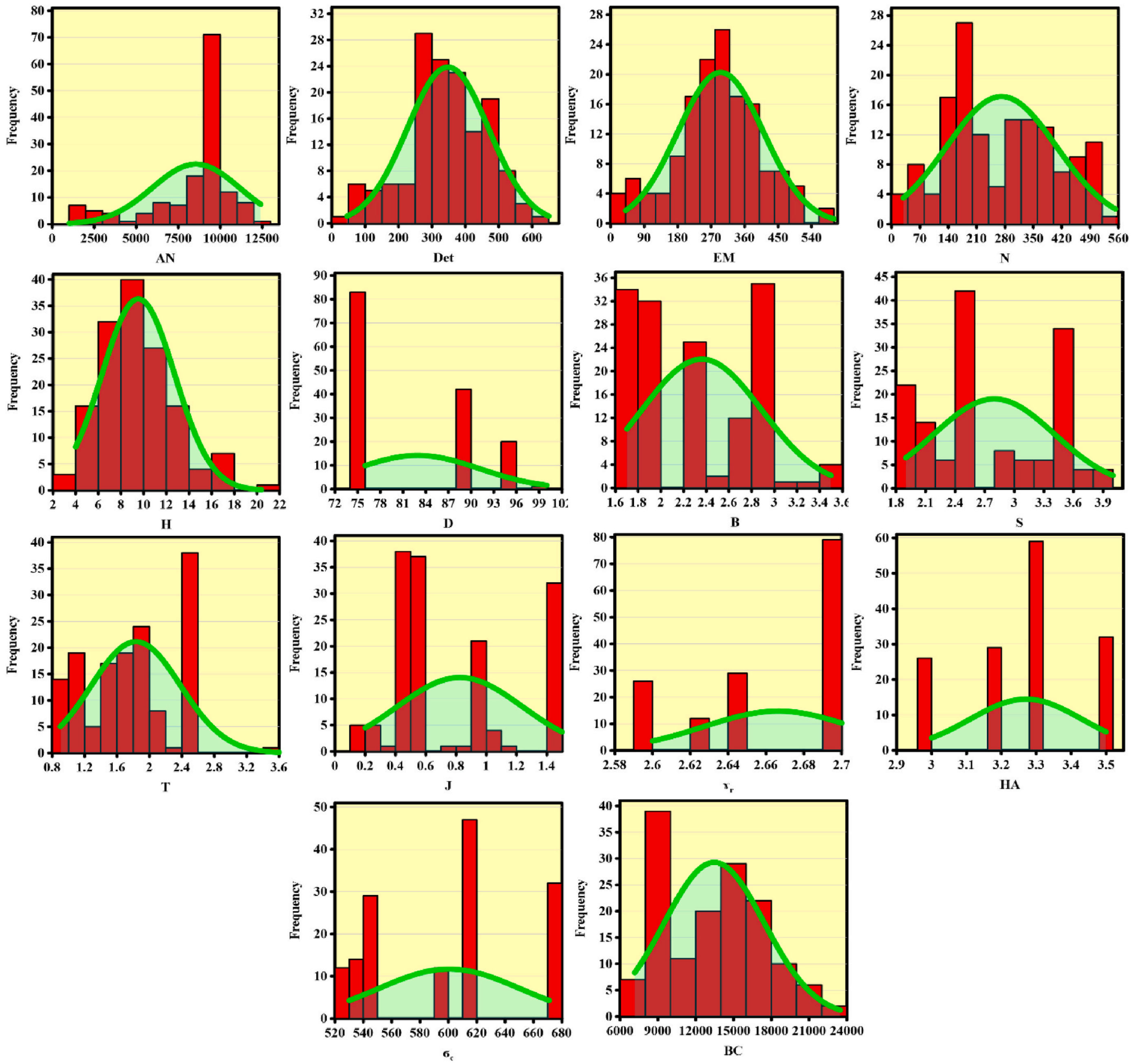

Fig. 4. Histogram chart of input and output data.

random vectors ranging from zero to one. Fig. 11 illustrates the position of each gray wolf in two-dimensional and three-dimensional forms (Mirjalili et al., 2014).

3.2.2. *Modeling the hunting process*

During this phase, given that delta, alpha, and beta wolves hold superior knowledge regarding potential prey locations, other search agents, including omega (as outlined in relationships 30 to 32), are required to adjust their positions based on the information from the most effective search agents (Mirjalili et al., 2014):

$$\vec{D}_a = \left|\vec{C}_1.\vec{X}_a - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{12}$$

$$\vec{X}_1 = \vec{X}_a - \vec{A}_1.\left(\vec{D}_a\right), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \tag{13}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{14}$$

Once the prey is encircled by the wolves and stops moving, the attack is initiated under the guidance of the alpha wolf. Modeling this process involves reducing the vector a. Notably, the range of vector $A\rightarrow$ is constrained by $a\rightarrow$. Essentially, $A\rightarrow$ is a random value within the interval [*-2a, 2a*], while a decreases from 2 to 0 during iterations. When the random values of $A\rightarrow$ fall within the interval [−1, 1], a search agent's next position can be anywhere between its current location and the prey's position. Fig. 12 presents the mathematical model for the hunting operations of gray wolves (Mirjalili et al., 2014).

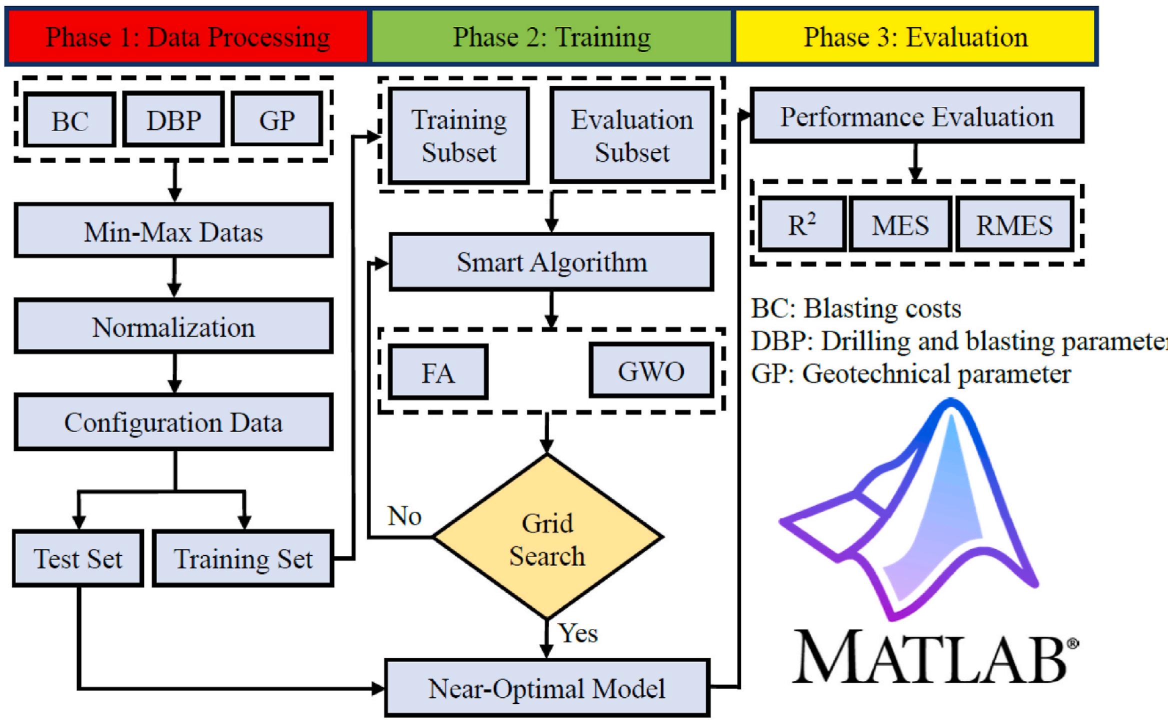

Fig. 5. Flowchart illustrating model development process.

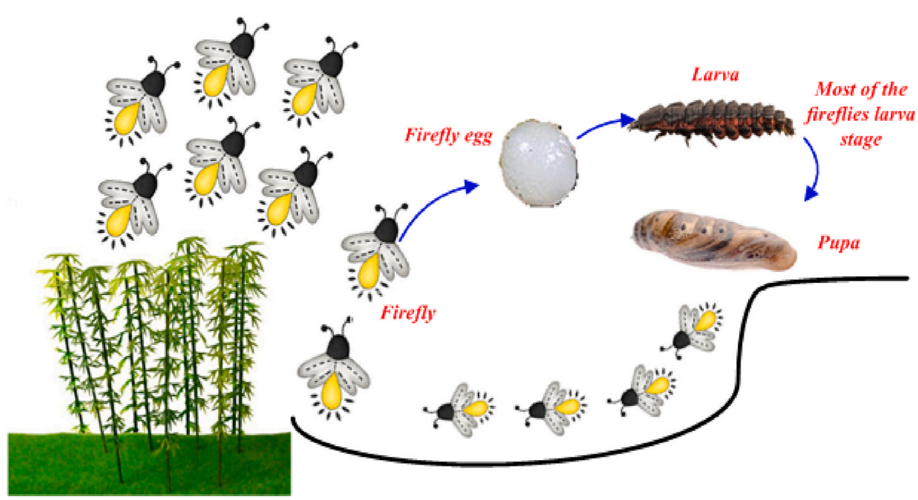

Fig. 6. Life cycle of the FF algorithm (Nand et al., 2021).

3.2.3. Hunting search stage

Gray wolves predominantly rely on the positions of delta, alpha, and beta wolves in their search strategy. They disperse from each other during the search for prey and converge to collaborate in the attack. To express this separation mathematically, vector A→, with a randomly assigned value greater than 1 or less than −1, is employed to guide search agents away from the prey. If $|A\rightarrow|$ is less than 1, the alpha wolf approaches the prey, while if $|A\rightarrow|$ exceeds 1, the wolf moves away from the prey. The GWO algorithm requires that all wolves update their positions based on those of the delta, alpha, and beta wolves. Fig. 13 illustrates the convergence and divergence of gray wolves in relation to prey in the form of a mathematical model (Mirjalili et al., 2014).

In summary, for a comprehensive understanding of the mathematical model of the GWO algorithm, Fig. 14 provides a flowchart illustrating the GWO Algorithm (Mirjalili et al., 2014).

4. Predicting blasting costs (BC) with the FF and GWO algorithms

Today, the mining industry relies heavily on blasting operations to break down and crush rocks into smaller sizes, which serve as vital feedstock for processing plants. Effective blasting can lead to substantial cost savings. Recognizing the significant impact of BC on the quality of crushed stones, it is crucial to monitor and manage these costs meticulously. In various aspects of this research, it has become evident that predicting BC is strongly influenced by various rock parameters. For instance, factors like hole length, hole number, hole diameter, the quantity of emolite and anfo explosives, among others, are all contingent on the geological strength and characteristics of the rock formations in the vicinity. As a rule of thumb, harder rocks necessitate more energy for blasting, resulting in the alteration of these aforementioned parameters in response to fluctuations in rock conditions. Given these complex and

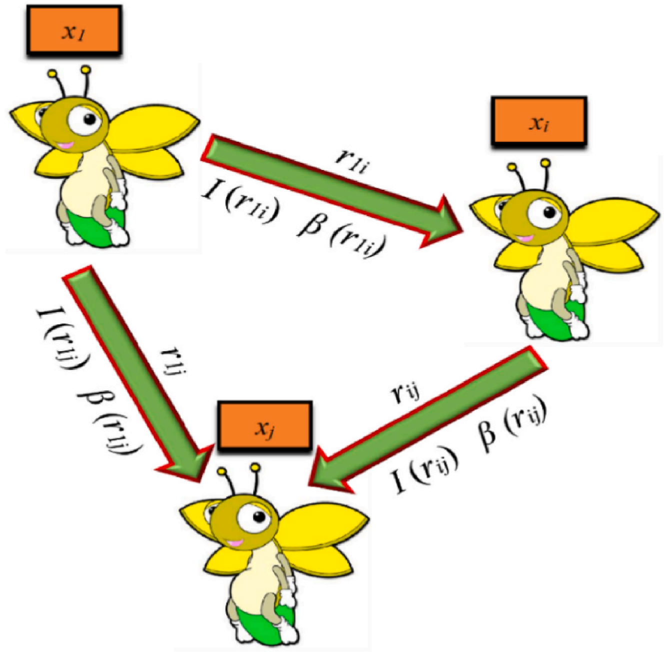

Fig. 7. Conceptual overview of the FF algorithm (Louzazni et al., 2018; Nand et al., 2021).

dynamic considerations, it is clear that the values of these parameters, as extensively detailed in the database section, are in a constant state of flux and are subject to considerable uncertainty. Consequently, conventional methods, including analytical, experimental, and numerical techniques, which do not adequately account for parameter uncertainties, may produce less accurate BC evaluations.

In light of these challenges, intelligent methods offer a promising alternative to traditional approaches. They are adept at handling uncertainties, reducing time and costs, and enabling the construction of non-linear, intricate models. Therefore, this research leverages two highly potent algorithms: the FF and the GWO to formulate an optimal BC prediction model.

Building a reliable BC model using the FF and GWO algorithms requires a substantial volume of data to enhance modeling precision. As discussed in the database section, 146 data points were employed in this study for BC assessment. To ensure accurate outcomes, the data is initially divided into two distinct groups: training and testing sets. In this study, 117 data points, equivalent to 80% of the dataset, were designated for training and model development, while the remaining 29 data points, constituting 20% of the dataset, were set aside for testing and validating the created model. It is essential to emphasize that for effective modeling, a thorough analysis of input data is paramount. To this end, data normalization is applied to bring the data within a specified range, thus eliminating outliers and ensuring that it aligns with the desired parameters. Equation (15) outlines the process of normalizing input data to a range between 0 and 1:

$$X_n = [(X_{mea} - X_{\min}) / (X_{\max} - X_{\min})] \tag{15}$$

In Equation (15), X_n represents the output of normalized data, X_{mea} corresponds to the actual raw, unnormalized data, and $X_{\min}$ and $X_{\max}$ denote the minimum and maximum values of the data prior to normalization.

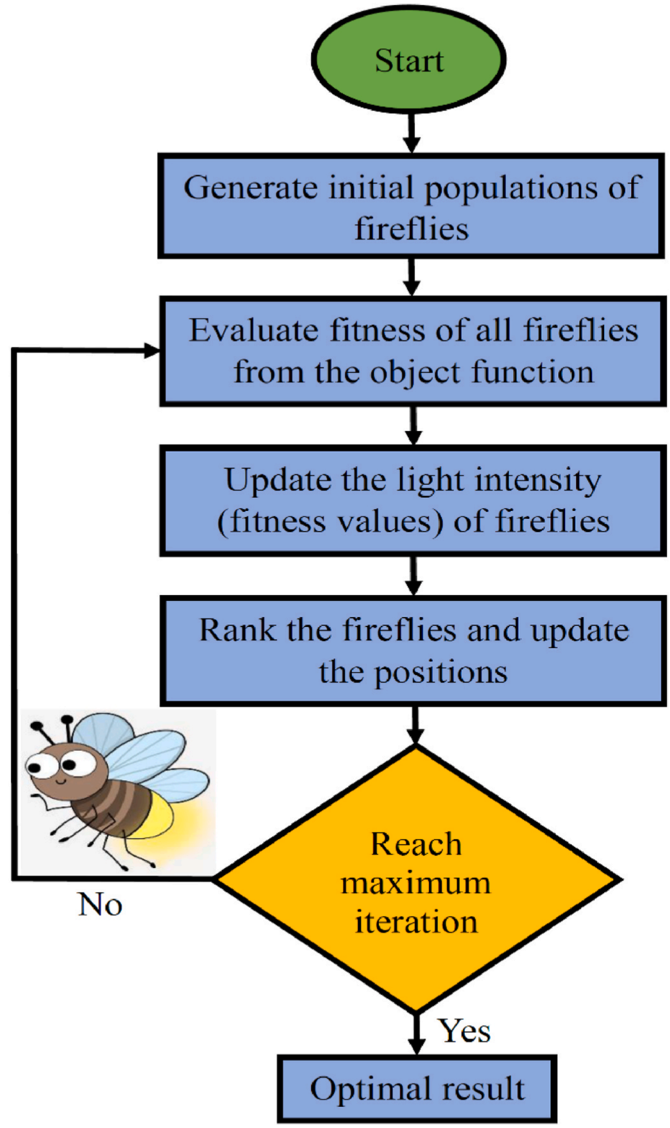

Fig. 8. Flowchart illustrating the FF algorithm (Yang, 2009).

Once the input data has been normalized and integrated, the process of model construction commences. In this phase, both the FF and GWO algorithms are harnessed to build the model within the MATLAB software platform. The resultant non-linear relationship used for BC prediction and evaluation takes the form of Equation (16):

$$RFR(Rials / ton) = w_1AN - w_2\,Det - w_3EM - N^{w_4} - w_5H - w_6 \exp(D)^{w_7} - w_8B^{w_9} - w_{10} \exp(S)^{w_{11}} - w_{12}T^{w_{13}} - w_{14}J^{w_{15}} - w_{16}\gamma_r - w_{17}HA - w_{18}\sigma_c - w_{19} \tag{16}$$

In Equation (16), 'w_i' represents the weight variables associated with input parameters, and their values are determined through iterations facilitated by the FF and GWO algorithms. This relationship evolves after numerous trials, and Equation (16) stands as the most accurate model for estimating BC, characterized by high accuracy and minimal error. To quantify the performance of the established equation, a performance function is defined as depicted in Equation (17):

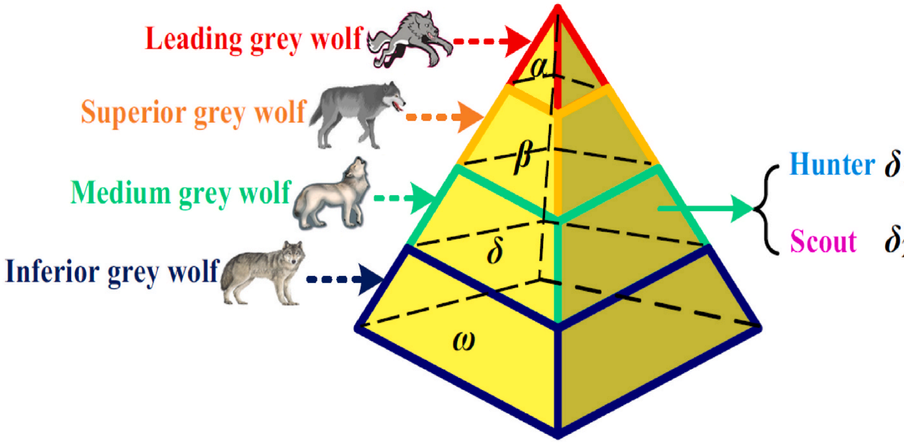

Fig. 9. Hierarchical structure of group hunting in wolves (Mirjalili et al., 2014).

Fig. 10. Gray wolf hunting behavior (Mirjalili et al., 2014).

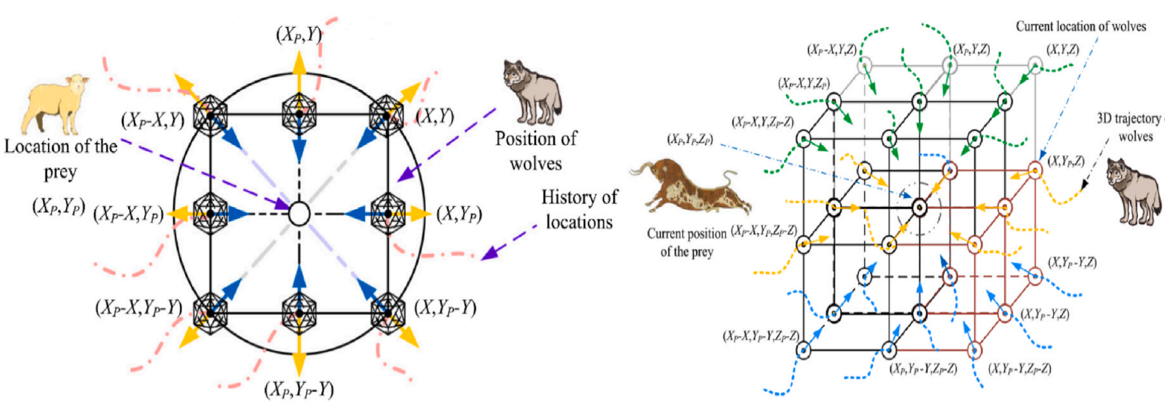

Fig. 11. Spatial vectors and possible next positions of wolves (Mirjalili et al., 2014).

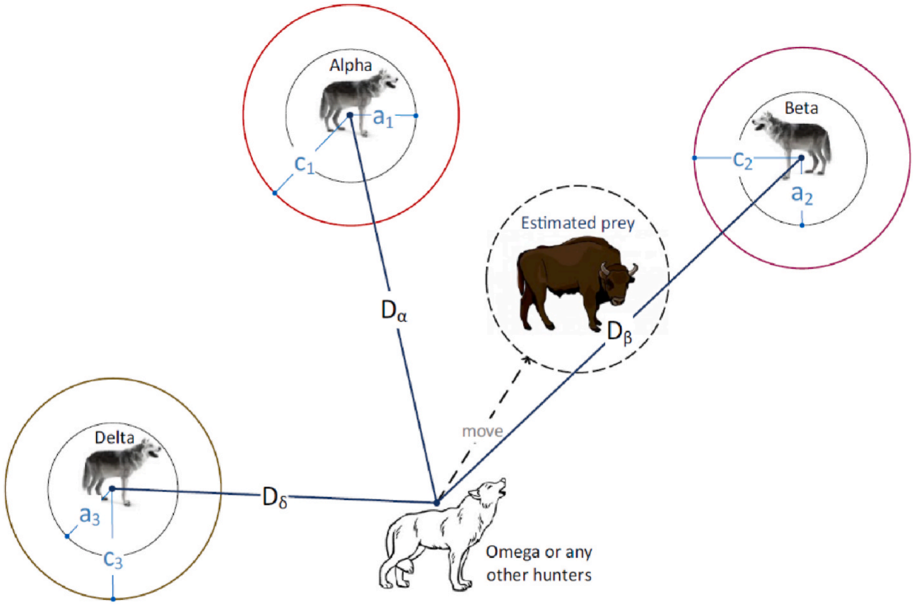

Fig. 12. Update position in GWO (Mirjalili et al., 2014).

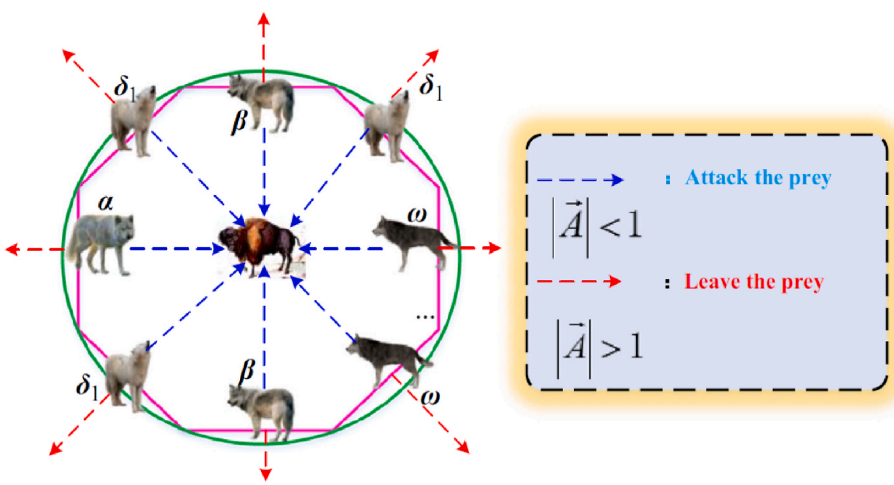

Fig. 13. Attacking and searching for prey (Mirjalili et al., 2014).

$$F(v) = \sum_{i=1}^{m} \left(Y_{mea} - Y_{pre}\right)^2 \tag{17}$$

Within the aforementioned equation, 'Y_{mea}' and 'Y_{pre}' respectively denote the actual and predicted BC values, while the parameter 'm' signifies the number of data points used in this research.

It's worth noting that, in addition to the general relationship form, the parameters intrinsic to the FF and GWO algorithms, which are encoded within the MATLAB environment, significantly influence the refinement and accuracy of the model. These parameters are adjusted by the user through trial and error to enhance the quality of the model. The values of these tuning parameters for the FF and GWO algorithms are determined by the user, as outlined in Table 4:

Following the construction of the relationship and fine-tuning of its parameters, the generalized form of the equation created for BC estimation and evaluation using both the FF and GWO algorithms within the MATLAB environment can be expressed as follows:

$$\begin{aligned} RFR(Rials/ton) = {} & 0.0481AN - (-0.2661\,Det) - (-0.029EM) - N^{0.4527} - 0.4313H - \left(-0.111\exp(D)^{-0.7903}\right) - 0.4072B^{6.8635} \\ & - \left(-0.7207\exp(S)^{-3.4604}\right) - 7.5923T^{8.3173} - 0.152J^{3.3636} - (-0.08239\gamma_r) - (-0.2092HA) - 0.0873\sigma_c + 0.797 \end{aligned} \tag{18}$$

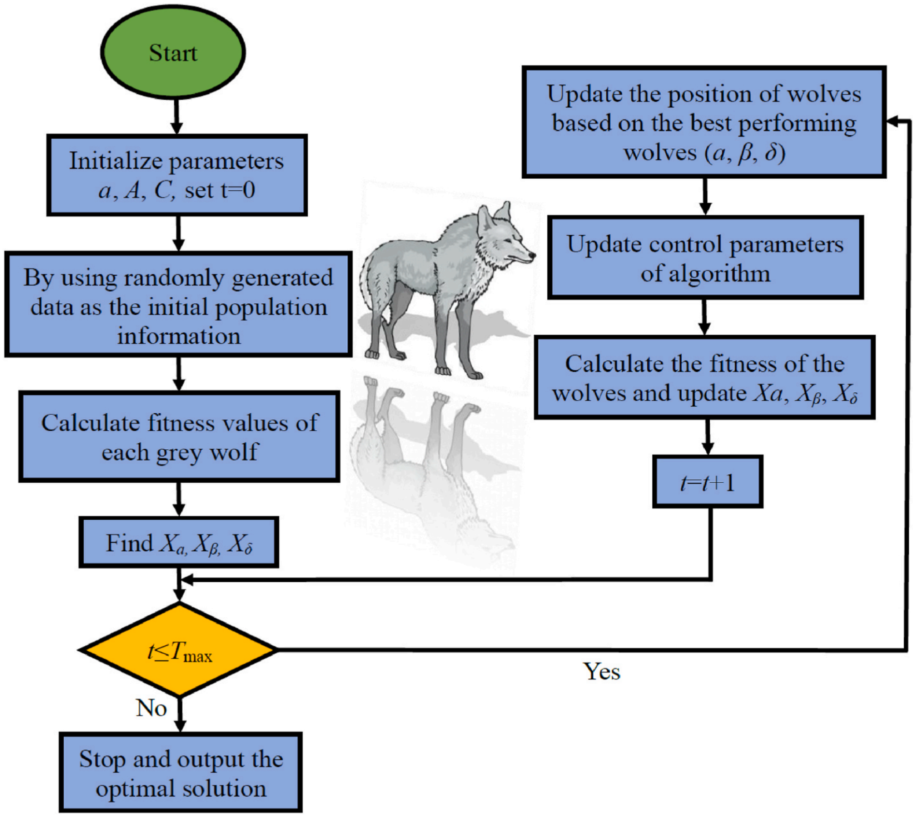

Fig. 14. Step-by-step flowchart of GWO (Mirjalili et al., 2014).

Table 4
Tuning parameters for FF and GWO algorithms.

Algorithms	Parameters	Value
FA	Maximum iterations	3000
	Attraction Coefficient Base Value	2
	Mutation Coefficient Damping Ratio	0.99
	Number of Fireflies (Swarm Size)	20
	Mutation Coefficient	2
	Light Absorption Coefficient	2
GWO	Maximum iterations	3500
	Number of search agents	50

Table 5
Statistical indicator values for the model during the training and testing phases.

Algorithm	Description	R^2	MSE	RMSE
FA	Train	0.9617	0.00241	0.04915
	Test	0.9843	0.00076	0.02774
GWO	Train	0.9604	0.00249	0.04996
	Test	0.9807	0.00094	0.03046

$$\begin{aligned} RFR(Rials/ton) = & -0.0917AN - (-0.2193\ Det) - (-0.0382EM) \\ & - N^{0.4653} - 0.4536H - \left(-0.1069\exp(D)^{-0.8719}\right) - 0.2022B^{7.5796} \\ & - \left(-0.7128\exp(S)^{-3.476}\right) - 8.2921T^{8.7375} - 0.1349J^{3.8826} \\ & - (-0.0964\gamma_r) - (-0.2382HA) - 0.0853\sigma_c + 0.5829 \end{aligned} \tag{19}$$

5. Validation and assessment of the established model

To ascertain the accuracy and reliability of the BC prediction model developed through the FF and GWO algorithms, well-recognized statistical metrics, namely R^2 (coefficient of determination), MSE (mean squared error), and RMSE (root mean squared error), can be employed (Fattahi et al., 2021, 2024; Fattahi and Hasanipanah, 2021; Fattahi and Zandy Ilghani, 2021). These statistical relationships are defined as follows:

$$R^2 = 1 - \frac{\sum_{k=1}^{n}\left(Y_{mea} - Y_{pre}\right)^2}{\sum_{k=1}^{n} Y_{mea}^2 - \frac{\sum_{i=1}^{n} Y_{pre}^2}{n}} \tag{20}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{mea} - Y_{pre}\right)^2 \tag{21}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{mea} - Y_{pre}\right)^2} \tag{22}$$

In each of the above equations, 'Y_{mea}' represents the actual values, and 'Y_{pre}' denotes the values predicted by the model for estimating BC, measured in *Rials/ton*. Additionally, 'n' indicates the number of data points used to construct the model. It is important to note that while the predicted values may differ slightly from the actual values, they will never be negative due to the squared terms in the equations (Fattahi, 2016, 2020a, 2020b; Fattahi et al., 2016, 2018). In accordance with the definitions of these statistical indicators, when the R^2 value of the predictive model approaches 1, and MSE and RMSE values are close to 0, it signifies that the actual values closely align with the predicted values. In such a scenario, it can be confidently stated that the model exhibits high reliability, and the accuracy of the equation is notably high. In the subsequent stages of this research, the statistical indices R^2, MSE, and RMSE are calculated for the BC prediction model generated by the FF and GWO algorithms, across both the training and testing phases, as outlined in Table 5:

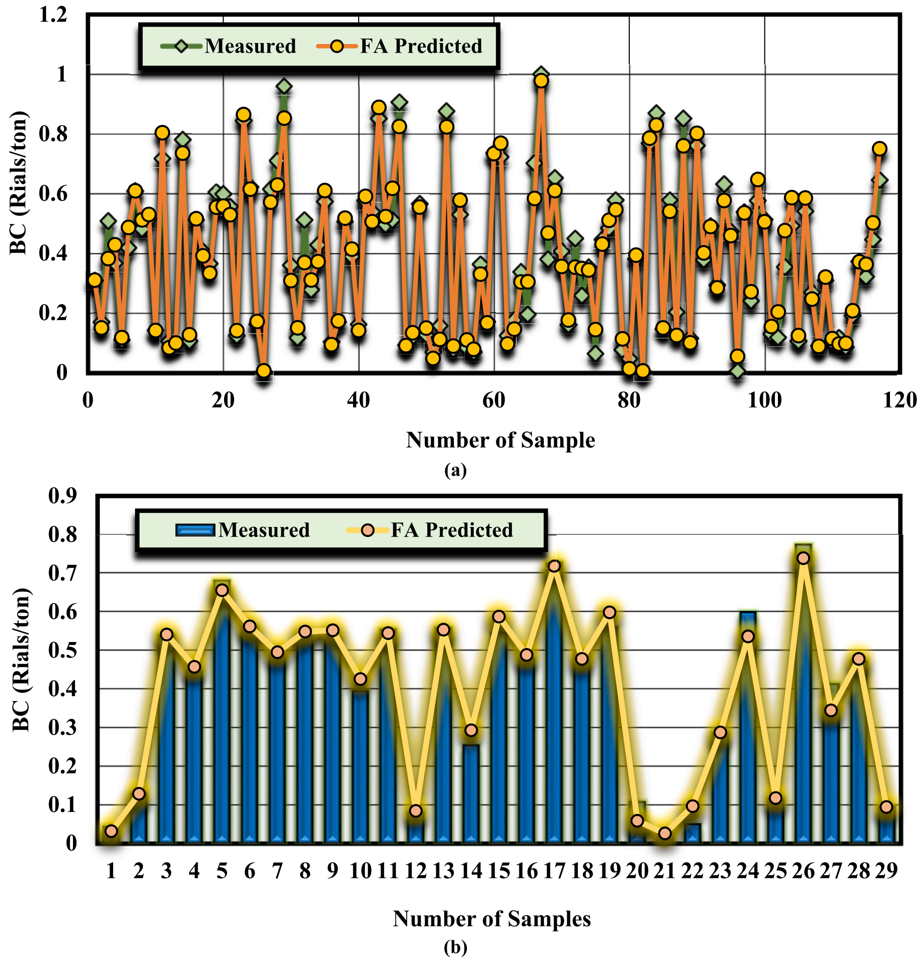

Fig. 15. Comparative analysis of actual and FA-estimated BC data: (a) Training, (b) testing.

Figs. 15 and 16 provide a visual representation of the comparison between the actual and predicted values for both the FF and GWO algorithms during the testing and training phases. These figures illustrate how well the predicted values align with the real data, offering insights into the accuracy and effectiveness of the algorithms used.

Figs. 15 and 16 reveal that throughout the training and testing stages, the actual and predicted data values closely coincide, indicating minimal disparities between them. These findings underscore the alignment of point-to-point values calculated by the algorithms with the real-world values gathered from the field. This validates the efficacy of models constructed using these sophisticated techniques for estimating and assessing BC indirectly. Consequently, based on the outcomes depicted in these charts, it becomes apparent that if the geological and geotechnical conditions of other regions bear similarity to those discussed in this study, the established relationship can be applied to those areas as well. However, in cases where geological conditions significantly differ, the findings from this research can serve as a basis for modifying the model and developing a new one tailored to the specific area.

6. Sensitivity analysis

Sensitivity analysis represents an invaluable and practical approach applied in many engineering projects characterized by substantial complexity. This method provides engineers with insights into the impact of input parameters on the model, elucidating the overall behavior of the model and the relative significance of individual input variables. By systematically varying one input parameter while keeping others constant, sensitivity analysis enables the identification of which variables exert substantial influence on the model's output. This technique allows engineers to understand the key drivers of the model's performance and make informed decisions to optimize and improve the system's efficiency. In the context of BC evaluation, sensitivity analysis plays a pivotal role in dealing with model complexities and understanding the central role of each parameter within the model.

The analysis helps researchers measure model output changes in response to variations in individual parameters, providing a clearer perspective on the values derived from the model. Furthermore, sensitivity analysis effectively distinguishes between parameters that exert a substantial impact on the output and those with less influence. Due to its profound importance, this study extensively conducts sensitivity analysis on the BC prediction model constructed using the FF and GWO algorithms. The primary objective is to enable researchers, engineers, and industry professionals to discern which input parameters, including *EN, AN, T, J, M, D, B, Det*, σ_c, *H, S*, γr, and *HA*, hold greater sway over the BC model.

To achieve this objective, statistical software tool @RISK was employed. The results of sensitivity analysis for the models generated by the FF and GWO algorithms are showcased in Figs. 17 and 18, respectively. As evident from the @RISK software outputs, the *'T'* parameter exerts a significant influence on the BC model. This implies that even the slightest variations in the *'T'* parameter yield the most pronounced changes in BC output values. In essence, the 'T' parameter stands out as a critical factor, demanding heightened attention from engineers and researchers. Notably, the 'T' parameter emerges as a pivotal factor for both the FF and GWO algorithms. This underscores the importance of a

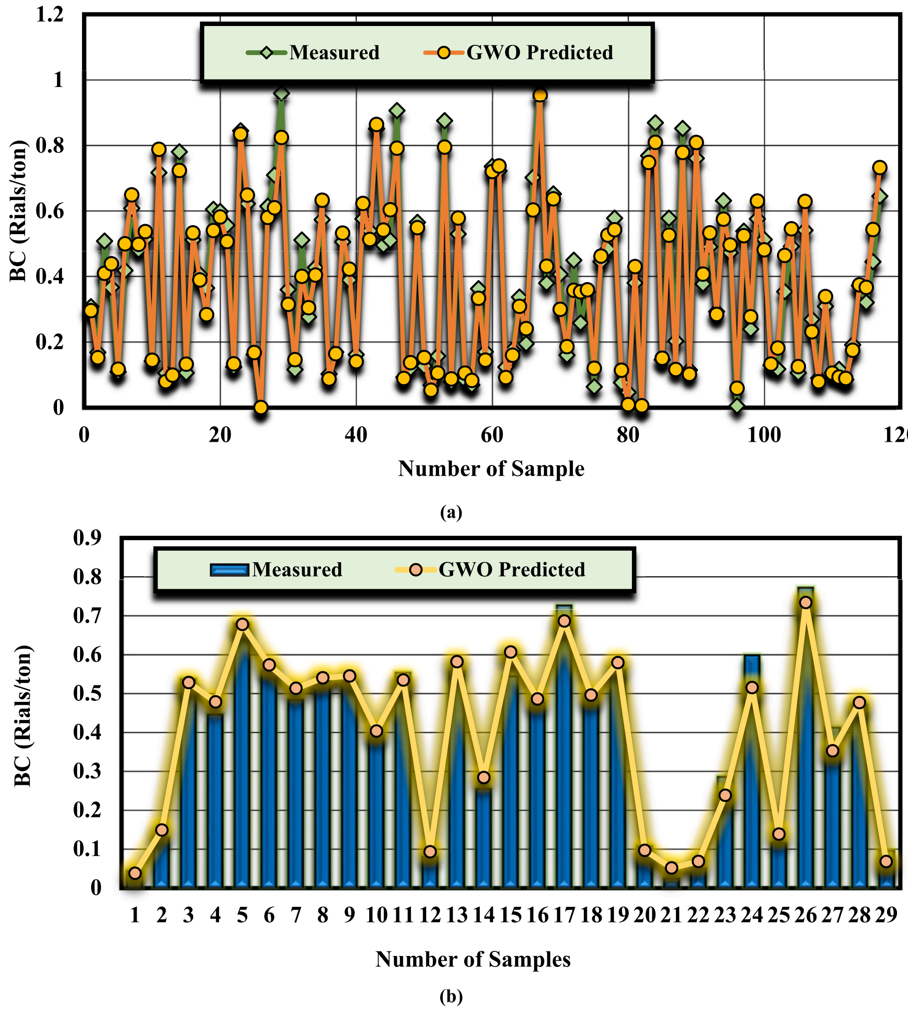

Fig. 16. Comparative Analysis of Actual and GWO- estimated BC Data: (a) Training, (b) Testing.

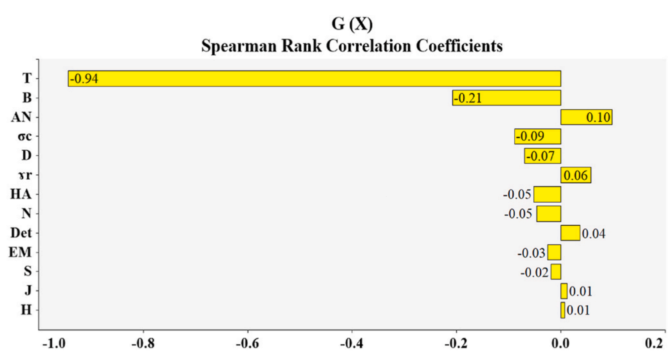

Fig. 17. Results of sensitivity analysis based on the FF Algorithm.

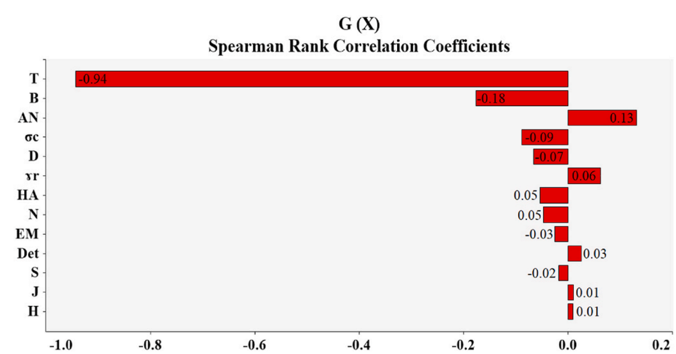

Fig. 18. Results of sensitivity analysis based on the GWO Algorithm.

precise understanding of input parameters, as it ultimately enhances the accuracy and efficacy of industrial projects. By identifying the most influential element affecting BC with heightened speed and precision, project processes can be expedited.

7. Discussion and conclusions

Blasting remains the most widely used large-scale production technique in open-pit mines and limestone quarries. Therefore, meticulous execution of blasting operations is crucial for maximizing profitability and minimizing production costs. The primary goal of drilling-blasting operations in surface mining, such as limestone extraction, is to ensure optimal and efficient rock fragmentation. Drilling and blasting are the initial steps in breaking down rock formations to produce crushed rock of the required size for processing. Effective rock fragmentation achieved through blasting not only reduces overall rock crushing costs but also improves the efficiency of drilling, loading, transportation, and processing activities. However, it is essential to consider the adverse effects associated with blasting, such as ground vibrations, ejected rocks, air shockwaves, and recoil. Failing to account for these consequences can undermine the assessment of BC and make it meaningless. Thus, optimizing and predicting BC are vital for achieving both effective rock fragmentation and a reduction in the negative impacts of blasting. Rock explosion and fragmentation are influenced by two main groups of variables. The first group includes uncontrollable mass properties, while the second consists of controllable drilling and blasting design parameters that can be optimized. These design parameters include load, spacing, hole length, hole diameter, sub-drilling, load weight, charge length, stem length, and load density. By optimizing these controllable parameters, both the cost of blasting and the quality of rock fragmentation can be improved. Given these considerations, evaluating and predicting BC, especially in limestone mining, is a task of significant sensitivity and necessity. Traditional methods for precise BC assessment often struggle with the uncertainties related to input parameters like drilling and blasting conditions and geological characteristics, leading to potential inaccuracies.

In this study, the researchers utilized powerful algorithms, specifically the FF and GWO algorithms, to develop a highly accurate, nonlinear model that addresses the inherent uncertainties of input parameters. By leveraging intelligent methodologies like FF and GWO, which establish robust connections between input parameters (geological attributes and drilling and blasting conditions) and BC, engineers, practitioners, and researchers in rock engineering gain access to valuable tools for precise modeling. The model was developed using data from six limestone mines in Iran, incorporating a range of input parameters including *EN, AN, T, J, M, D, B, Det,* σ_c*, H, S,* γr*,* and *HA*. The data was divided into two subsets: 80% for model training and 20% for testing and validation. Statistical metrics such as R^2, MSE, and RMSE were used to assess the model's accuracy, revealing a minimal margin of error and demonstrating the model's effectiveness in forecasting BC through FF and GWO algorithms. These results highlight the potential of these advanced techniques to overcome the limitations of traditional methods and improve BC prediction accuracy. Furthermore, this study includes a sensitivity analysis using @RISK software, identifying the parameter T as having the most significant influence on the model's output. This finding emphasizes the model's sensitivity to variations in T and its crucial role in shaping predictions. The implications of this research extend beyond blasting cost estimation. The insights gained can lead to cost and time savings across various mining projects by improving design, extraction, and production processes. Additionally, it can enhance overall production efficiency while reducing environmental impacts associated with suboptimal blasting practices. With the adoption of intelligent algorithms, engineers can now effectively assess BC across different mining scenarios, making informed decisions to improve economic viability. Given the context, the discussed algorithms are highly effective for modeling BC in the presence of substantial uncertainties and large datasets. However, for scenarios with limited data and no uncertainties, traditional methods may be more appropriate. Intelligent methods, which require extensive data for training, tend to perform better with larger datasets. It is important to note that the developed model is specific to the mines studied, and its results may not be applicable to other mines with different conditions. If geological and blasting conditions match those in the study, the model can be utilized. Its flexibility allows for the creation of accurate models for different case studies using local data, making it particularly useful for the mines discussed. Mining professionals can leverage these intelligent algorithms, particularly FF and GWO, to optimize blasting cost management and enhance the economic efficiency of mining operations.

Ethical approval

This study does not involve studies with human participants or animals conducted by any of the authors.

Informed consent

All individual participants included in the study provided informed consent.

Data availability statement

To reproduce the simulations in the present study, the corresponding files can be found in (Bastami et al., 2020).

CRediT authorship contribution statement

Hadi Fattahi: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Formal analysis, Conceptualization. **Hossein Ghaedi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Danial Jahed Armaghani:** Writing – review & editing, Writing – original draft, Validation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Abbaspour, H., Drebenstedt, C., Badroddin, M., Maghaminik, A., 2018. Optimized design of drilling and blasting operations in open pit mines under technical and economic uncertainties by system dynamic modelling. Int. J. Min. Sci. Technol. 28, 839–848.

Adebayo, B., Mutandwa, B., 2015. Correlation of blast-hole deviation and area of block with fragment size and fragmentation cost. Intern. Res. J. Eng. Techn. 2, 402–406.

Afum, B.O., Temeng, V.A., 2015. Reducing drill and blast cost through blast optimisation–a case study. Ghana mining J 15, 50–57.

Ahangari, K., Moeinossadat, S.R., Behnia, D., 2015. Estimation of tunnelling-induced settlement by modern intelligent methods. Soils Found. 55, 737–748.

Álvarez-Vigil, A.E., González-Nicieza, C., Gayarre, F.L., Álvarez-Fernández, M.I., 2012. Predicting blasting propagation velocity and vibration frequency using artificial neural networks. Int. J. Rock Mech. Min. Sci. 55, 108–116.

Bakhshandeh Amnieh, H., Hakimiyan Bidgoli, M., Mokhtari, H., Aghajani Bazzazi, A., 2019. Application of simulated annealing for optimization of blasting costs due to air overpressure constraints in open-pit mines. J. Mining. Environ 10, 903–916.

Bastami, R., Aghajani Bazzazi, A., Hamidian Shoormasti, H., Ahangari, K., 2020. Prediction of blasting cost in limestone mines using gene expression programming model and artificial neural networks. J. mining environ. 11, 281–300.

Bhandari, S., 1997. Engineering Rock Blasting Operations.

Bilim, N., Çelik, A., Kekeç, B., 2017. A study in cost analysis of aggregate production as depending on drilling and blasting design. J. Afr. Earth Sci. 134, 564–572.

Çanakcı, H., Baykasoğlu, A., Güllü, H., 2009. Prediction of compressive and tensile strength of Gaziantep basalts via neural networks and gene expression programming. Neural Comput. Appl. 18, 1031–1041.

Costamagna, E., Oggeri, C., Vinai, R., 2021. Damage and contour quality in rock excavations for quarrying and tunnelling: assessment for properties and solutions for stability. In: IOP Conference Series: Earth and Environmental Science. IOP Publishing, 012137.

Dehghani, H., 2018. Forecasting copper price using gene expression programming. J. Mining. Environ 9, 349–360.

Dehghani, H., Ataee-Pour, M., 2011. Development of a model to predict peak particle velocity in a blasting operation. Int. J. Rock Mech. Min. Sci. 48, 51–58.

Fattahi, H., 2016. A hybrid support vector regression with ant colony optimization algorithm in estimation of safety factor for circular failure slope. Intern.J. optimiz. civil eng. 6, 63–75.

Fattahi, H., 2020a. Analysis of rock mass boreability in mechanical tunneling using relevance vector regression optimized by dolphin echolocation algorithm. Intern.J. optimiz. civil eng. 10, 481–492.

Fattahi, H., 2020b. A new approach for evaluation of seismic slope performance. Intern. J. Optimiz. Civil Eng. 10, 261–275.

Fattahi, H., Babanouri, N., Varmaziyari, Z., 2018. A Monte Carlo simulation technique for assessment of earthquake-induced displacement of slopes. J Min Environ 9, 959–966.

Fattahi, H., Ghaedi, H., Malekmahmoodi, F., 2024. Prediction of rock drillability using gray wolf optimization and teaching–learning-based optimization techniques. Soft Comput. 28, 461–476.

Fattahi, H., Hasanipanah, M., 2021. An indirect measurement of rock tensile strength through optimized relevance vector regression models, a case study. Environ. Earth Sci. 80, 748.

Fattahi, H., Hasanipanah, M., Zandy Ilghani, N., 2021. Investigating correlation of physico-mechanical parameters and P-wave velocity of rocks: a comparative intelligent study. J Min Environ 12, 863–875.

Fattahi, H., Nazari, H., Molaghab, A., 2016. Hybrid ANFIS with ant colony optimization algorithm for prediction of shear wave velocity from a carbonate reservoir in Iran. Int. J. Min. Geol. Eng. 50, 231–238.

Fattahi, H., Zandy Ilghani, N., 2021. Hybrid wavelet transform with artificial neural network for forecasting of shear wave velocity from wireline log data: a case study. Environ. Earth Sci. 80, 5.

Fister, I., Fister Jr, I., Yang, X.-S., Brest, J., 2013. A comprehensive review of firefly algorithms. Swarm Evol. Comput. 13, 34–46.

Ghanizadeh Zarghami, A., Shahriar, K., Goshtasbi, K., Akbari, A., 2018. A model to calculate blasting costs using hole diameter, uniaxial compressive strength, and joint set orientation. J. S. Afr. Inst. Min. Metall 118, 869–877.

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. Int. J. Rock Mech. Min. Sci. 52, 163–170.

Gokhale, B.V., 2010. Rotary Drilling and Blasting in Large Surface Mines. CRC Press.

Hasanipanah, M., Amnieh, H.B., Arab, H., Zamzam, M.S., 2018. Feasibility of PSO–ANFIS model to estimate rock fragmentation produced by mine blasting. Neural Comput. Appl. 30, 1015–1024.

Jang, H., Topal, E., 2013. Optimizing overbreak prediction based on geological parameters comparing multiple regression analysis and artificial neural network. Tunn. Undergr. Space Technol. 38, 161–169.

Jhanwar, J., Cakraborty, A., Anireddy, H., Jethwa, J., 1999. Application of air decks in production blasting to improve fragmentation and economics of an open pit mine. Geotech. Geol. Eng. 17, 37–57.

Jimeno, C.L., Jimeno, E.L., Carcedo, F.J.A., de Ramiro, Y.V., 1995. Drilling Änd Blasting of Rocks, vol. 41. CRS Press, USA, 35947.

Kalayci, U., Ozer, U., Karadogan, A., Celiksirt, M.C., Erkan, V., 2010. Delpat applications and ground vibration analysis caused by blasting at excavation of boyabat dam and HPP construction. International Multidisciplinary Scientific GeoConference: SGEM 1, 395.

Kanchibotla, S.S., 2003. Optimum blasting? Is it minimum cost per broken rock or maximum value per broken rock? Fragblast 7, 35–48.

Kulatilake, P., Qiong, W., Hudaverdi, T., Kuzu, C., 2010. Mean particle size prediction in rock blast fragmentation using neural networks. Eng. Geol. 114, 298–311.

Latham, J.-P., Van Meulen, J., Dupray, S., 2006. Prediction of fragmentation and yield curves with reference to armourstone production. Eng. Geol. 87, 60–74.

Louzazni, M., Khouya, A., Amechnoue, K., Gandelli, A., Mussetta, M., Crăciunescu, A., 2018. Metaheuristic algorithm for photovoltaic parameters: comparative study and prediction with a firefly algorithm. Appl. Sci. 8, 339.

Lowery, M., Kemeny, J., Girdner, K., 2001. TECHNICAL PAPERS.(peer reviewed and approved)-Advances in blasting practices through the accurate quantification of blast fragmentation. Min. Eng. 53, 55–61.

Miranda, V., Leite, F., Frank, G., 2019. A Numerical Approach Blast Pattern Expansion. O-Pitblast Lda, Porto, Portugal.

Mirjalili, S., Lewis, A., 2016. The whale optimization algorithm. Adv. Eng. Software 95, 51–67.

Mirjalili, S., Mirjalili, S.M., Lewis, A., 2014. Grey wolf optimizer. Adv. Eng. Software 69, 46–61.

Monjezi, M., Baghestani, M., Shirani Faradonbeh, R., Pourghasemi Saghand, M., Jahed Armaghani, D., 2016. Modification and prediction of blast-induced ground vibrations based on both empirical and computational techniques. Eng. Comput. 32, 717–728.

Monjezi, M., Rezaei, M., Varjani, A.Y., 2009. Prediction of rock fragmentation due to blasting in Gol-E-Gohar iron mine using fuzzy logic. Int. J. Rock Mech. Min. Sci. 46, 1273–1280.

Nand, R., Sharma, B.N., Chaudhary, K., 2021. Stepping ahead firefly algorithm and hybridization with evolution strategy for global optimization problems. Appl. Soft Comput. 109, 107517.

Nguyen, H., Bui, X.-N., Tran, Q.-H., Le, T.-Q., Do, N.-H., Hoa, L.T.T., 2019. Evaluating and predicting blast-induced ground vibration in open-cast mine using ANN: a case study in Vietnam. SN Appl. Sci. 1, 1–11.

Nielsen, K., 1987. Model studies of loading capacity as a function of fragmentation from blasting. Proceedings of 3rd Mini-Symposium on Explosives and Blasting Research, pp. 71–80.

Nikkhah, A., Vakylabad, A.B., Hassanzadeh, A., Niedoba, T., Surowiak, A., 2022. An evaluation on the impact of ore fragmented by blasting on mining performance. Minerals 12, 258.

Qu, S., Hao, S., Chen, G., Li, B., Bian, G., 2002. The BLAST-CODE model–A computer-aided bench blast design and simulation system. Fragblast 6, 85–103.

Rajpot, M.A., 2009. The Effect of Fragmentation Specification on Blasting Cost, Masters Abstracts International.

Rezaei, M., Monjezi, M., Varjani, A.Y., 2011. Development of a fuzzy model to predict flyrock in surface mining. Saf. Sci. 49, 298–305.

Roy, M., Paswan, R.K., Sarim, M., Kumar, S., 2017. Geological discontinuities, blast vibration and frag-mentation control—a case study. In: Proceedings of the 7th Asian Mining Congress and International Mining Exhibition, Kolkata, India, pp. 8–11.

Singh, J., Verma, A., Banka, H., Singh, T., Maheshwar, S., 2016. A study of soft computing models for prediction of longitudinal wave velocity. Arabian J. Geosci. 9, 1–11.

Singh, T., Singh, V., 2005. An intelligent approach to prediction and control ground vibration in mines. Geotech. Geol. Eng. 23, 249–262.

Styles, T., 2015. Application of blast damage when modelling open pit slopes. In: Proceedings of the Mineral and Metals Production from Mine to Market, Cambridge, UK.

Trivedi, R., Singh, T., Raina, A., 2014. Prediction of blast-induced flyrock in Indian limestone mines using neural networks. J. Rock Mech. Geotech. Eng. 6, 447–454.

Usman, T., Muhammad, K., 2013. Modeling of blasting cost at deewan cement quarry, hattar using multivariate regression. J. Eng. Appl. Sci. 32.

Verma, A.K., Singh, T.N., 2011. Intelligent systems for ground vibration measurement: a comparative study. Eng. Comput. 27, 225–233.

Wang, M., Shi, X., Zhou, J., Qiu, X., 2018. Multi-planar detection optimization algorithm for the interval charging structure of large-diameter longhole blasting design based on rock fragmentation aspects. Eng. Optim. 50, 2177–2191.

Yang, X.-S., 2009. Firefly algorithms for multimodal optimization. International Symposium on Stochastic Algorithms. Springer, pp. 169–178.

Yang, X.-S., 2010a. Engineering Optimization: an Introduction with Metaheuristic Applications. John Wiley & Sons.

Yang, X.-S., 2010b. Firefly algorithm, stochastic test functions and design optimisation. Int. J. Bio-Inspired Comput. 2, 78–84.

Yang, X.-S., 2010c. Nature-inspired Metaheuristic Algorithms. Luniver press.

Yang, X.-S., 2013. Multiobjective firefly algorithm for continuous optimization. Eng. Comput. 29, 175–184.

Yang, X.-S., He, X.-S., 2018. Why the firefly algorithm works? Nature-Inspired Algorithms and Applied Optimization 245–259.

Yu, Z., Shi, X., Miao, X., Zhou, J., Khandelwal, M., Chen, X., Qiu, Y., 2021. Intelligent modeling of blast-induced rock movement prediction using dimensional analysis and optimized artificial neural network technique. Int. J. Rock Mech. Min. Sci. 143, 104794.