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Prediction of Rock Fragmentation using Ant Lion Optimizer and Crow Search Algorithm

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Abstract

Rock-fragmentation is generally regarded as a crucial indicator within the mining industry for evaluating the effects of blasting operations. In this work, a database was primarily constructed using field data to predict rock fragmentation in the mines of Anguran and Sarcheshmeh. The datasets comprised the input parameters such as Burden (m), spacing (m), powder factor (kg/m³), and stemming (m), with fragmentation (cm) as the output parameter. The analysis of these datasets was conducted using the Ant Lion Optimizer (ALO) and Crow Search Algorithm (CSA) methodologies. To assess the predictive models' accuracy, metrics including the coefficient of determination (R^2), Variance Accounted For (VAF), and Root Mean Square Error (RMSE) were employed. The application of ALO and CSA to the database yielded results indicating that for ALO, $R^2 = 0.99$, RMSE = 0.005, and VAF (%) = 99.38, while for CSA, $R^2 = 0.98$, RMSE = 0.02, and VAF (%) = 98.11. Ultimately, the findings suggest that the predictive models yield satisfactory results, with ALO demonstrating a greater level of precision.

1. Introduction

The initiation of the mining process through blasting significantly influences the size distribution, which, in turn, likely impacts the ultimate quality and quantity of the extracted products. Therefore, by effectively managing the blasting procedure to achieve an optimal size distribution, it becomes feasible to enhance the overall economic performance of the mine and processing plant [1]. Rock fragmentation plays a crucial role in blasting operations. This significance arises from the substantial impact that the degree and size distribution of the fragments have on subsequent loading and crushing processes. Ideally, the rock should be fragmented to a point, where no additional processing is required, post-blast. Consequently, the dimensions of the fragments must not only be compatible with the loading machinery but also suitable for the crushing equipment [2]. The economic efficiency of a mine and its associated processing plant can be significantly improved by implementing strategic management practices in the blasting process. This involves carefully planning and executing blasting operations to achieve an optimal size distribution of the fragmented rock material [3]. When blasting is conducted effectively, it can lead to several key benefits that enhance the overall economic performance. Firstly, achieving the right size distribution of rock fragments minimizes the need for additional crushing and grinding, which are energy-intensive processes. By reducing the amount of energy and resources required for further processing, operational costs can be lowered, leading to an increased profitability [4]. Moreover, well-managed blasting can improve the overall recovery of valuable minerals from the ore. When the rock is fragmented to the ideal size, it allows for a more efficient separation and extraction of the desired materials during the processing phase. This not only maximizes the yield of valuable resources but also minimizes waste, contributing to a more sustainable operation

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[5]. Additionally, strategic blasting management can enhance safety and reduce environmental impacts. By optimizing blast designs, the risk of fly rock and ground vibrations can be minimized, leading to safer working conditions for the personnel and surrounding communities. Furthermore, effective blasting can reduce the environmental footprint of mining operations by limiting the disturbance to the surrounding ecosystem [6]. Blasting serves as a prevalent method for rock fragmentation in mining activities, as well as in various civil engineering projects including tunneling and road construction. During blasting operations, it is observed that merely 20–30% of the energy generated is effectively employed to fragment and displace the rock mass [7,8]. Numerous empirical models have been established to estimate rock fragmentation resulting from blasting [9]. Hjelmberg [10] introduced a fragmentation prediction model, which utilizes the type of rock mass and drilling pattern to forecast the average size of fragments. In a separate investigation, Stagg et al. [11] created a model aimed at evaluating the distribution of fragment sizes based on two key parameters: fracture strength and rock density. Additionally, Roy and Dhar [12] integrated the influence of joint orientation into their fragmentation model. In the process of developing empirical models, it has been observed that only a limited number of effective parameters, specifically one or two, were considered in relation to rock fragmentation. These parameters include explosive characteristics, blast-hole diameter, and compressive strength [13]. This limitation contributes to the inaccuracy and unreliability of these models.

The limitations of empirical models have prompted the researchers to emphasize the use of soft computing techniques such as Artificial Neural Networks (ANN) and fuzzy systems (FSs) for predicting rock fragmentation. In a study by Monjezi et al. [14], a fuzzy system model was introduced to estimate the rock fragmentation caused by blasting operations at the Gol-E-Gohar iron mine. Furthermore, the studies conducted by Bahrami et al. [13], Sayadi et al. [15], Ebrahimi et al. [16], and Rabbani et al. [17] employed Artificial Neural Network (ANN) techniques to predict fragmentation. Raj et al. [18] and Zhang et al. [19] introduced a methodology for predicting rock fragmentation, utilizing machine learning techniques.

Liu et al. [20], conducted a comprehensive study aimed at predicting blasting fragmentation in open-pit coal mining operations, a critical aspect that significantly influences the efficiency and effectiveness of mining processes. Sanchidrián and Ouchterlony [21] conducted an extensive research focused on the prediction of blast fragmentation, a critical aspect in fields such as mining, construction, and demolition. Their work is grounded in the principles of the fragment size-energy fan concept, which provides a theoretical framework for understanding how explosive energy is distributed, and how it influences the size and distribution of fragments produced during a blast event. Chandrahas et al. [22] undertook an extensive investigation into an innovative methodology for the simultaneous prediction of average fragmentation size and maximum particle velocity, employing advanced datasets through the enhanced genetic XG boost algorithm techniques. This study aims to establish a new framework for forecasting two essential parameters within the domain of fragmentation analysis: average fragmentation size and maximum particle velocity. Zheng et al. [23] conducted a comprehensive study aimed at enhancing the performance of the Least Squares Support Vector Machine (LSSVM) model, specifically in the context of predicting rock fragmentation size. Rock fragmentation is a critical aspect in various fields such as mining, construction, and geology, as it directly influences the efficiency of operations and the quality of the end-product. The researchers recognized that the traditional methods of predicting rock fragmentation often fell short in accuracy and reliability, prompting the need for more advanced modeling techniques. Ling et al. [24] conducted an experimental investigation into the characteristics of rock fragmentation using pressurized pulsed water jets, aiming to understand the underlying mechanisms and efficiency of this innovative method for breaking down rock materials. Their research work focused on several key aspects including the impact of various parameters such as water pressure, pulse frequency, and jet nozzle design on the fragmentation process.

Yari et al. [25] conducted a research on an innovative ensemble machine learning model, specifically designed to forecast rock fragmentation resulting from mine blasting activities. This study aimed to address the challenges associated with predicting the size and distribution of rock fragments generated during blasting operations, which is crucial for optimizing subsequent mining processes and improving overall efficiency. Sharma et al. [26] conducted a comprehensive study focused on the prediction of rock fragmentation within a fiery seam of an open-pit coal mine situated in India. This research work aimed to address the challenges associated with managing rock fragmentation in environments, where coal seams are prone to spontaneous combustion, which can complicate mining operations and pose safety risks. Liu et al. [27] conducted a comprehensive study focused on developing an intelligent framework that effectively integrates theoretical principles with empirical data to predict the size of rock fragments generated by blasting operations. This research addresses a critical aspect of mining and construction industries, where understanding the fragmentation process is essential for optimizing blasting techniques, improving safety, and enhancing operational efficiency.

The primary objective of this work is to develop a predictive model for rock fragmentation by leveraging two advanced optimization algorithms: the Ant Lion Optimizer (ALO) and the Crow Search Algorithm (CSA). Rock fragmentation is a critical aspect in various fields such as mining, civil engineering, and geology, as it directly influences the efficiency of extraction processes, the stability of structures, and the overall economic viability of projects. To achieve this aim, the work will first involve a comprehensive review of existing literature on rock fragmentation and the methodologies currently employed to predict it. This will include an analysis of the factors that influence fragmentation such as the rock properties, blast design, and environmental conditions. Subsequently, the work will focus on the implementation of the Ant Lion Optimizer and the Crow Search Algorithm. The ALO is inspired by the hunting behavior of ant lions, which use a unique strategy to trap their prey, while the CSA mimics the foraging behavior of crows. Both algorithms are known for their efficiency in solving complex optimization problems, and will be utilized to fine-tune the parameters that affect rock fragmentation. Data collection will be a crucial component of this research work involving the gathering of empirical data from field studies, laboratory experiments, and simulations. This data will serve as the foundation for training and validating the predictive models developed using ALO and CSA. The study will also include a comparative analysis of the performance of the two algorithms in predicting rock fragmentation outcomes. By evaluating their accuracy, computational efficiency, and robustness, the research work aims to identify the most effective approach for this specific application. Ultimately, the findings of this work are expected to contribute significantly to the field of rock mechanics and optimization techniques. The successful prediction of rock fragmentation could lead to improved operational efficiencies, reduced costs, and enhanced safety in various geological and engineering applications.

2. Materials and Methods

2.1. Anguran mine

In this research work, a site assessment was performed at the Anguran lead and zinc mine, located 135 kilometers southwest of the Zanjan province in Iran, at an elevation of 2,950 meters above sea level. The Anguran mine is recognized as the largest and oldest lead and zinc mining operation in the country [16].

The Anguran mine is recognized as one of the premier mineral deposits globally, particularly noted for its exceptional quality [28, 29]. The minerals extracted from this site, ranked by their significance, include smithsonite, quartz, hemimorphite, cerussite, sphalerite, galena, pyrite, arsenopyrite, mimetite, beudantite, scorodite, various clay minerals, zincite, and hydrozincite. This deposit is composed of three distinct components: oxide, sulfur, and mixed materials. The oxide component is situated at the uppermost section of the deposit, while the sulfur component is found at the lowest section. The mixed component is positioned in the intermediate area between the two. In terms of morphology, the deposit exhibits a lenticular form in the north-south profiles, an oven-like shape in the east-west section, and can be generally described as pear-shaped, with a southern slope of approximately 25 degrees [30, 31]. The mineral deposit is situated at the core of the mine, encircled by three primary faults. The configuration of the mine is triangular, positioned between these three faults. Specifically, there is a fault to the north, a secondary fault to the northwest, and a third fault located in the southern section of the vein. The mineral exhibits an average thickness of 70 meters, with a slope length of 550 meters. The width of the ore varies, measuring approximately 60 meters in the lower section and around 250 meters at the surface. The Anguran mine exhibits significant geological diversity, characterized by a variety of rock types that display differing resistance properties over relatively short distances. This variability necessitates the application of a geomechanical classification system to streamline operations, tailored to the specific rock types and geological conditions present in the mining area. Based on data derived from surface exploration borehole logs, as well as information collected by the workshop team and its integration with geological cross-sections of the mine, it has been determined that the predominant mineral and associated rock masses are categorized primarily into classes II and III. Specifically, within the underground section of the Angouran lead and zinc mine, the mineral and its host rock are classified as follows: a portion falls into class II, indicating medium to high-quality rock masses (RMR values ranging from 50 to 60), while another segment is classified as class III, representing medium to low-quality rock masses (RMR values between 35 and 50). Additionally, some rock masses are classified as class IV, denoting poor quality (RMR values below 35) [30, 31]. Figure 1 provides a detailed overview of the geographical location of the Anguran mine, highlighting its position in relation to nearby landmarks, infrastructure, and natural features. This map serves as a crucial reference for understanding the mine's accessibility and its environmental context. Figure 2 offers a comprehensive geological map of the Anguran mine, showcasing the various rock formations, mineral deposits, and structural features present in the area. This geological representation is essential for assessing the mine's potential resources, and understanding the geological processes that have shaped the region. Figure 3 illustrates the boulders that have been generated as a direct result of the blasting operations carried out at the Anguran mine. This visual representation highlights the scale and impact of these operations, providing insight into the mining process and the management of rock debris. The depiction of these boulders is important for evaluating the environmental implications of blasting and for planning subsequent site rehabilitation efforts.

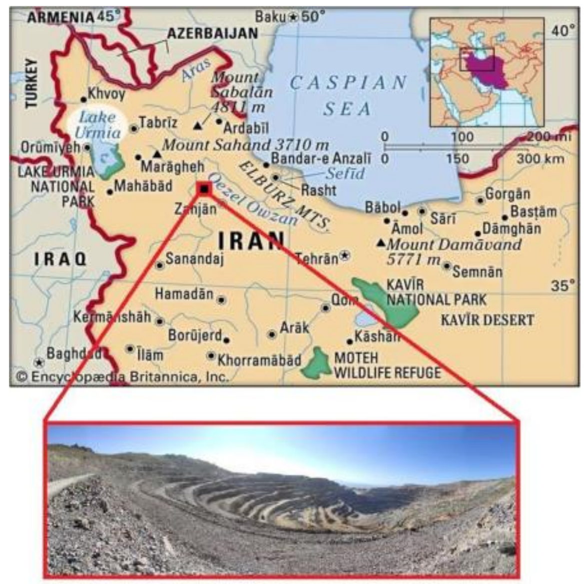

Figure 1. Location of Anguran mine [28, 29].

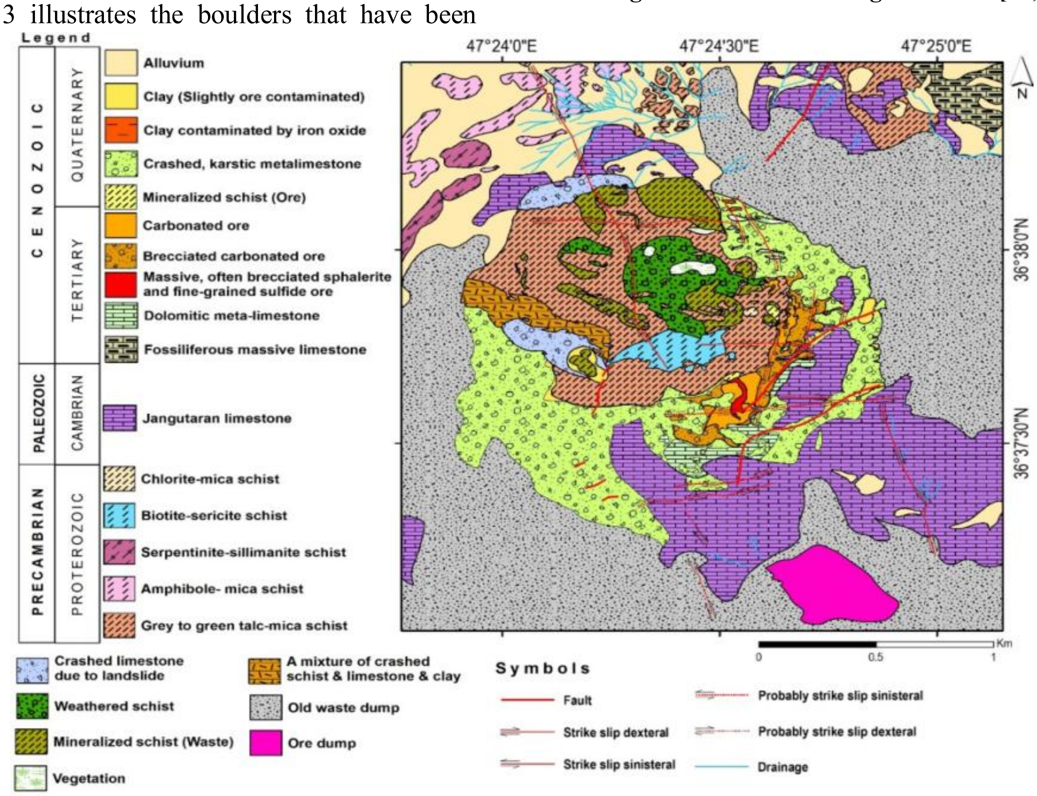

Figure 2. Geological map of Anguran mine [30, 31].

Figure 3. Boulders produced as a consequence of blasting activities at the Anguran mine [16]

2.2. Sarcheshmeh copper mine

In order to fulfill the objectives of this research work, the Sarcheshmeh copper mine in Iran was chosen as the focal point. Situated in the Kerman province in southern Iran, this mine boasts a proven reserve of approximately 826 million tons, making it the largest copper mine in the country and one of the most significant globally. The geological composition of the Sarcheshmeh deposit primarily consists of folded and faulted Tertiary volcanic-sedimentary rocks [32, 33].

The geological characteristics of the Sarcheshmeh copper mine indicate that its formation and development commenced approximately 60 million years ago, marked by the deposition of a sequence of sub-marine andesitic lavas during the Eocene epoch. The present-day plateau and its elevations have resulted from the ongoing erosion of the leached zone, which contains some copper oxides, alongside the creation of a secondary enriched zone. The lithological composition of the mine comprises the following rock types:

1. Porphyry granodiorite, which includes quartz, potassium feldspar, and plagioclase.

2. Altera andesite, characterized by either massive or fine-grained textures.

3. Porphyry dike, which contains pyrite, chalcopyrite, and quartz with molybdenite.

Sulfur mineralization is characterized by two distinct zones: the supergene zone and the hypogene zone. The supergene zone serves as a repository for secondary copper minerals, resulting from the leaching of minerals from the oxide zone and their subsequent accumulation as secondary sulfur, consequently, the copper concentration in this zone surpasses the average grade found in the mine. This zone is primarily composed of chalcopyrite and molybdenite. In contrast, the oxide zone is characterized by the presence of copper oxide minerals including cuprite, tenorite, and malachite, as well as carbonates such as azurite, copper sulfates, and various iron oxides including hematite, simonite, and gunite. Figure 4 provides a detailed representation of the geographical positioning of the Sarcheshmeh copper mine, highlighting its location within the surrounding landscape and its accessibility in relation to nearby infrastructure such as roads, rivers, and urban centers. This map serves to contextualize the mine's significance within the region, illustrating not only its physical coordinates but also its proximity to other geological features and resources that may influence mining operations. In contrast, Figure 5 offers a comprehensive geological map of the Sarcheshmeh porphyry copper deposit. This map delineates the various geological formations and structures present in the area, showcasing the distribution of different rock types, mineralization zones, and fault lines. By providing insights into the geological characteristics of the deposit, Figure 5 aids in understanding the processes that led to the formation of the copper mineralization and informs potential exploration and extraction strategies. Together, these figures contribute to a holistic understanding of the Sarcheshmeh copper mine's location and geological context, which are crucial for both academic research and practical mining operations.

2.3. Metaheuristic algorithms

Metaheuristic algorithms constitute an advanced category of search methodologies that are widely acknowledged as effective optimization techniques. These algorithms are specifically designed to address intricate and formidable optimization challenges that frequently surpass the capabilities of conventional algorithms. While the traditional optimization approaches may perform adequately for less complex problems, they often encounter difficulties when confronted with the complexities and diverse characteristics of real-world situations, where the solution landscape is extensive, and filled with local optima. In the real-world applications, both individuals and organizations routinely encounter obstacles that are limited by various resources such as computational capacity, time constraints, and occasionally financial restrictions. For example, in sectors like logistics, finance, engineering, and artificial intelligence, the problems presented can be highly non-linear, multi-dimensional, and subject to a multitude of constraints [37]. In these scenarios, the exhaustive search techniques employed by traditional algorithms may become impractical, due to the vast number of potential solutions that must be assessed. Conversely, metaheuristic algorithms are engineered to traverse these complex environments more effectively. They utilize strategies that facilitate intelligent exploration of the solution space, often drawing inspiration from natural phenomena or human cognitive processes. Notable examples of widely used metaheuristic algorithms include genetic algorithms, simulated annealing, particle swarm optimization, and ant colony optimization, each of which incorporates distinct principles that direct the search process, allowing them to evade local optima and move towards more globally optimal solutions. A significant benefit of metaheuristic algorithms is their capacity to yield satisfactory solutions within a reasonable timeframe, even when operating under constrained computational resources. They typically necessitate fewer evaluations of the objective function compared to traditional methods, which can be particularly advantageous in resource-limited scenarios [38].

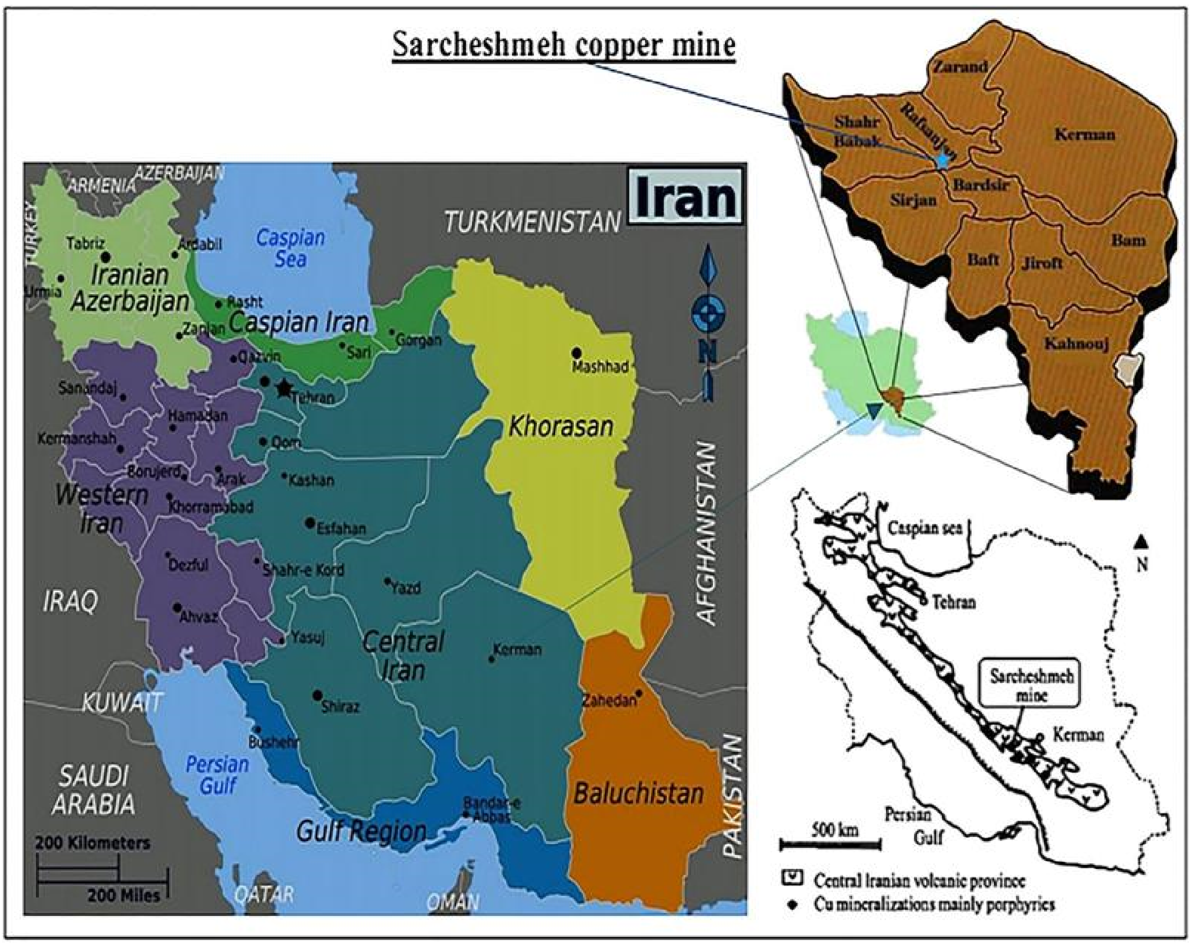

Figure 4. The geographical location of the Sarcheshmeh copper mine [34]

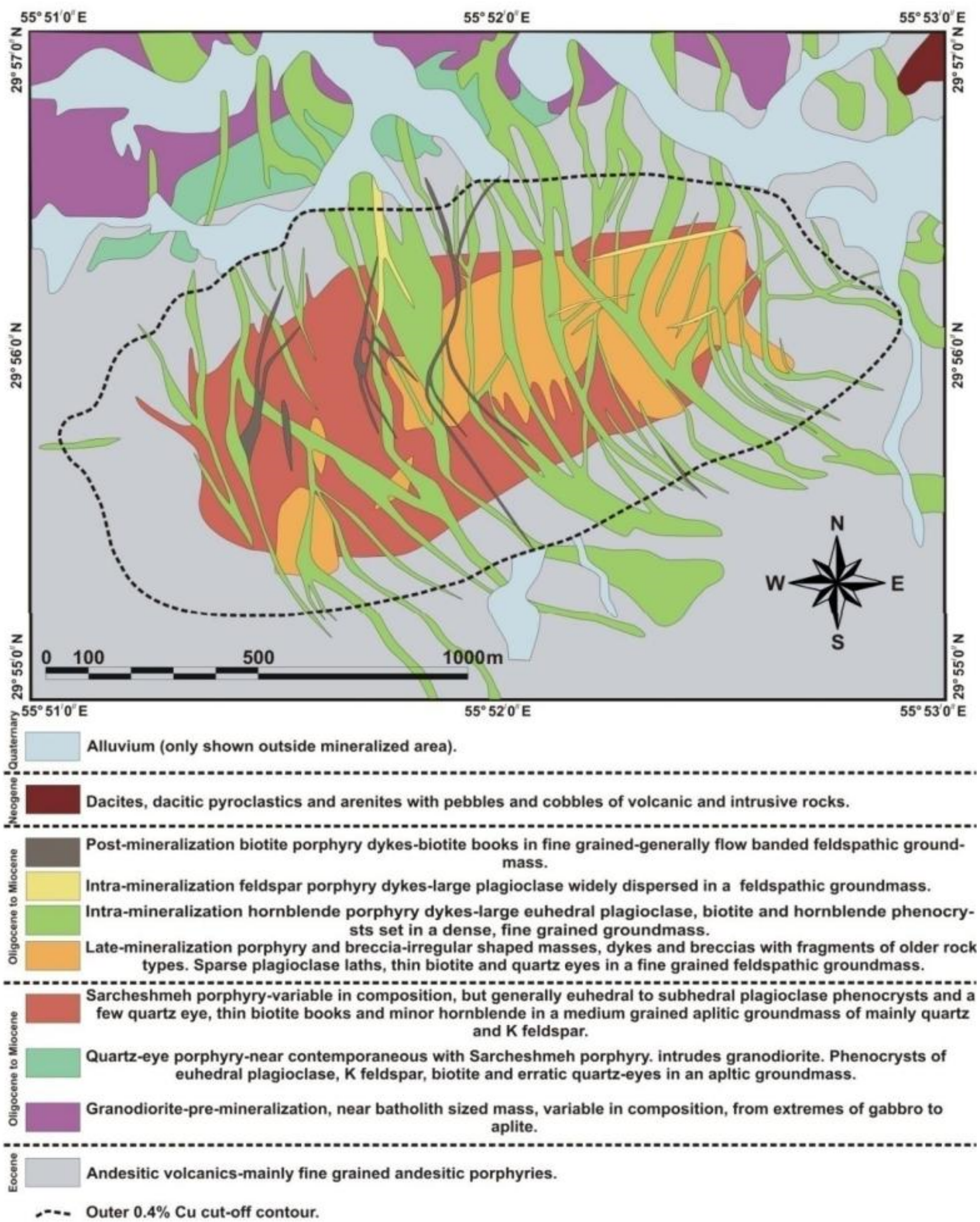

Figure 5. Geological map of Sarcheshmeh porphyry copper deposit [35, 36]

2.4. Ant lion optimizer

The Ant Lion Optimization (ALO) algorithm emulates the dynamics of ant behavior within a trapping environment. To effectively represent this interaction, it is essential for the ants to navigate through the search space. The ants are permitted to pursue their targets, thereby, enhancing their proficiency in utilizing the traps. Given that ants exhibit a completely random movement pattern while foraging in their natural habitat, a random walk equation is employed to characterize the movement of the ants in this context [39].

$$X(t) = [0, cumsum(2r(t_1) - 1), \ldots \ldots \ldots .., cumsum(2r(t_n) - 1)] \tag{1}$$

In the equation presented above, the cumulative sum is computed by Cumsum, with n denoting the maximum number of iterations. In this context, t signifies the step of the random walk, while r(t) is defined as a random function. Here, t again refers to the random walk step, and rand represents a random number generated uniformly within the interval [0,1].

$$r(t) = \begin{cases} 1 \; if \; rand > 0.5 \\ 0 \; if \; rand \leq 0.5 \end{cases} \tag{2}$$

Subsequently, the associations pertaining to the ALO metaheuristic algorithm, as well as the positions of the ants throughout the optimization process, are recorded and utilized in the subsequent matrix.

$$M_{Ant} = \begin{bmatrix} A_{1,1} & A_{1,2} & \dots & \dots & A_{1,d} \\ A_{2,1} & A_{2,2} & \dots & \dots & A_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{n,1} & A_{n,2} & \dots & \dots & A_{n,d} \end{bmatrix} \tag{3}$$

When M_{Ant} is considered as the matrix that holds the positional data of each ant, n denotes the total count of ants, while d signifies the number of variables involved.

The MAnt matrix serves as a repository for the locations of all ants or the parameters of all potential solutions throughout the optimization process. Additionally, a fitness function, also referred to as an objective function, is employed to assess the performance of each ant during the optimization phase [39].

$$M_{\text{OAL}} = \begin{bmatrix} f([AL_{1,1}, AL_{1,2,}, \dots, AL_{1,d}]) \\ f([AL_{2,1}, AL_{2,2,}, \dots, AL_{2,d}]) \\ \vdots \\ \vdots \\ f([AL_{n,1}, AL_{n,2,}, \dots, AL_{n,d}]) \end{bmatrix} \tag{4}$$

The matrix M_{OAL} serves as the fitness preservation matrix for each individual ant. Here, n represents the total number of ants, while f denotes the objective function [39].

2.5. Crow search algorithm

In the theoretical framework of the algorithm, it is posited that a d-dimensional environment encompasses a certain quantity of crows. The total number of crows, denoted as N, represents the group size, while the position of the i-th crow at a given time (iteration iter) within the search space is represented by the vector $x^{i,iter}$. Here, i ranges from 1 to N, and iter spans from 1 to Maxiter. The calculation of $x^{i,iter}$ within the d-dimensional space is conducted as follows[40]:

$$x^{i,iter} = [x_1^{i,iter}, \dots, x_d^{i,iter}] \tag{5}$$

Each crow possesses a memory that retains the location of its concealed food source. In the iteration denoted as iter, the location of the hiding place for crow i is indicated by $m^{i,iter}$, which represents the optimal position that crow i has attained thus far. Consequently, every crow has its most favorable experience regarding its hiding place recorded in its memory. Crows navigate their surroundings in search of superior food sources (hiding places). For instance, in the iteration iter, if crow j intends to revisit its hiding place, it is represented as $m^{j,iter}$. In this iteration, crow i opts to pursue crow j in order to approach crow j's concealed location. In this scenario, two potential outcomes may arise [40]:

1. Scenario 1: Unaware of being observed

Crow j remains unaware of the presence of crow i in its vicinity. Consequently, crow i advances towards the location, where crow j is concealed. The updated position of crow i is determined as follows:

$$x^{i,iter+1} = [x^{i,iter} + r_i \times fl^{i,iter} \times (m^{j,iter} - x^{i,iter})] \tag{6}$$

In this context, r_i represents a random variable uniformly distributed within the interval [0, 1], while $fl^{i,iter}$ denotes the flight duration of crow i during iteration iter. Lower values of fl result in localized search patterns, whereas higher values facilitate a more global search approach [40].

2. Scenario 2: Awareness of surveillance

Crow j is aware that crow i is tracking its movements. Consequently, crow j employs a strategy of deception by relocating to a different area within the search space to safeguard its cache from potential appropriation. Overall, cases 1 and 2 can be articulated as follows [40]:

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times (m^{j,iter} - x^{i,iter}) & r_j \geq AP^{j,iter} \\ a\ random\ position & otherwise \end{cases} \quad (7)$$

In this context, r_j denotes a random variable uniformly distributed between 0 and 1, while $AP^{j,iter}$ indicates the probability of awareness for crow j at iteration iter. Metaheuristic algorithms must effectively balance the aspects of diversification and intensification. Within the Crow Search Algorithm (CSA), the parameters governing intensity and diversity are primarily influenced by the Awareness Probability (AP). A reduction in the awareness probability leads the algorithm to focus its search within a localized area, where a satisfactory solution has already been identified. Consequently, employing lower values of AP enhances the intensity of the search. Conversely, an increase in the awareness probability diminishes the likelihood of exploring around existing high-quality solutions, prompting CSA to engage in a more global exploration of the search space (randomization). Thus higher values of AP contribute to an increase in diversity [40].

2.6. Database

The rationale for employing burden, spacing, powder factor, and stemming in the prediction of rock fragmentation is multi-faceted and deeply rooted in the principles of blasting engineering. Each of these parameters plays a critical role in optimizing blasting operations, as they directly influence the efficiency and effectiveness of fragmentation outcomes, which are essential for successful mining and construction activities.

Burden is defined as the distance from the blast hole to the closest free face of the rock. This measurement is essential, as it influences the amount of explosive energy that can be harnessed to fracture the rock. An appropriately measured burden distance guarantees that the explosive energy is efficiently focused on the rock mass, promoting effective fragmentation. A burden that is insufficient may result in the underutilization of explosive energy, causing excessive fly rock and sub-optimal fragmentation. On the other hand, an excessively large burden can lead to the dissipation of energy prior to its ability to fracture the rock, which may produce larger, unbroken fragments.

Spacing, on the other hand, pertains to the distance between adjacent blast holes. This parameter significantly impacts the overall fragmentation pattern, and the uniformity of the rock breakage. Proper spacing ensures that the explosive energy from one hole can effectively interact with the energy from adjacent holes, leading to a more controlled and predictable fragmentation outcome. If the spacing is too close, it can result in overlapping energy zones, causing excessive fragmentation and potentially hazardous conditions. If too far apart, the energy may not effectively combine, leading to larger, unbroken rock pieces.

The powder factor refers to the quantity of explosive utilized for each unit volume of rock, commonly measured in kilograms per cubic meter. This metric is crucial for assessing the energy imparted to the rock mass. A precisely calibrated powder factor guarantees the appropriate amount of explosive is employed to attain the intended fragmentation, thereby avoiding resource wastage and miti-gating adverse environmental effects. An ideal powder factor strikes a balance between providing adequate energy for rock fragmentation, and reducing the likelihood of over-blasting, which can result in heightened vibration, noise, and the displacement of rock fragments.

Stemming refers to the substance employed to seal the explosive charge within the blast hole. It plays a vital role in optimizing the transfer of energy to the surrounding rock. By adequately containing the gases produced by the explosion, stemming directs the energy towards fracturing the rock instead of allowing it to dissipate into the environment. The selection of stemming material and its dimensions can greatly affect the overall effectiveness of the blast. Effective stemming can improve the fragmentation process, resulting in smaller, more manageable rock fragments that facilitate subsequent handling and processing.

The variables involved in the predictive modeling of rock fragmentation, both input and output, are presented in Table 1. At this stage, the data from the two aforementioned mines, which serve as case studies, are consolidated, with the descriptive statistics of this combined data displayed in Table 2.

Table 1. Input and output variables.

Input	Burden (m) Spacing(m) Poweder factor (kg/m3) Stemming (m)
Output	Fragmenation(cm)

Table 2. Descriptive statistics of the data.

Parameter	Symbol	Min	Max
Burden (m)	B	2.6	7.5
Spacing(m)	S	3.5	10
Poweder factor (kg/m^3)	PF	0.13	0.95
Stemming (m)	ST	3	8
Fragmenation (cm)	Fr	13.8	40
N=219			

2.7. Reason for selecting the Ant Lion Optimizer and Crow Search Algorithm for the prediction rock fragmentation and the limitation

The rationale for choosing the Ant Lion Optimizer (ALO) and the Crow Search Algorithm (CSA) for predicting rock fragmentation, along with their respective limitations, is outlined as follows. Both algorithms are recognized for their efficacy in solving complex optimization problems, making them suitable for the intricate nature of rock fragmentation prediction. However, it is essential to acknowledge the constraints associated with each method, which may impact their performance in specific scenarios. The selection of the Ant Lion Optimizer (ALO) and the Crow Search Algorithm (CSA) for the purpose of predicting rock fragmentation is based on their proven capabilities in addressing complex optimization challenges. These algorithms are particularly adept at navigating the multi-faceted variables involved in rock fragmentation. The ALO, inspired by the hunting behavior of ant lions, utilizes a unique mechanism of exploration and exploitation that allows it to effectively search through large solution spaces. This characteristic is particularly beneficial in rock fragmentation prediction, where numerous factors such as rock type, size distribution, and environmental conditions must be considered. Similarly, the CSA, which mimics the intelligent behavior of crows in searching for food, employs a strategy that balances exploration and exploitation. This balance is crucial in optimization tasks, as it enables the algorithm to avoid local optima, and converge towards a more accurate solution. The CSA's ability to adaptively adjust its search strategy based on the quality of solutions found further enhances its applicability to the dynamic and complex nature of rock fragmentation.Nonetheless, it is crucial to consider the limitations inherent to each algorithm, as these may influence their effectiveness in certain contexts. For instance, the ALO may struggle with convergence speed in highly complex landscapes, potentially leading to longer computation times or suboptimal solutions if not properly tuned. Additionally, its performance can be sensitive to the initial parameters set by the user, which may require extensive experimentation to optimize.On the other hand, while the CSA is robust in exploring diverse solution spaces, it may face challenges in scenarios with high-dimensional data or when the objective function is highly nonlinear. The algorithm's reliance on the quality of previous solutions can also lead to premature convergence, where the search becomes trapped in local optima rather than exploring potentially better solutions. In conclusion, the ant lion optimizer and the crow search algorithm present promising approaches for predicting rock fragmentation, due to their strengths in handling complex optimization problems. However, understanding their limitations is essential for effectively applying these algorithms in practice, ensuring that their deployment is tailored to the specific challenges posed by rock fragmentation prediction.

2.8. Performance of model

In this study, the accuracy of predictive models was assessed using the coefficient of determination (R^2), Variance Accounted For (VAF), and Root Mean Square Error (RMSE).When the Root Mean Square Error (RMSE) is 0, it signifies that the coefficient of determination (R^2) is 1 and the variance accounted for VAF is 100, indicating an exemplary model. The values for the coefficient of determination (R^2), variance accounted for (VAF), and Root Mean Square Error (RMSE) are computed as follows:

$$R^2 = \frac{\sum_{i=1}^{N}(B_i - B)(C_i - \bar{C})}{\sqrt{\sum_{i=1}^{N}(B_i - \bar{B})^2 \sum_{i=1}^{N}(C - \bar{C})^2}} \tag{8}$$

$$VAF = [1 - \frac{var(B_i - C_i)}{var(B_i)}] \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(B_i - C_i)^2} \tag{10}$$

In this context, Bi represents the actual measured values, while Ci denotes the predicted values, with N indicating the total number of testing samples.$\overline{B}$ and $\overline{C}$ represent the means of the observed (actual) values and the predicted values, respectively.

3. Research Results

3.1. Prediction of rock fragmentation using ant lion optimizer

The Ant Lion Optimizer (ALO) is a novel optimization algorithm inspired by the predatory behavior of antlions, which are fascinating insects known for their unique hunting techniques in their natural environment. In the wild, antlions create conical pits in sandy soil to trap unsuspecting ants and other small insects. When an ant falls into the pit, the antlion quickly captures it, demonstrating a highly effective predatory strategy. In the context of optimization, the ALO algorithm mimics this behavior to solve complex problems by simulating the interactions between antlions and ants. The algorithm operates through a series of iterations that represent the hunting process. Initially, potential solutions to an optimization problem are treated as ants, while the antlions represent the optimal solutions that are being sought. The process begins with the generation of a population of candidate solutions (the ants) that explore the solution space. As the algorithm progresses, the antlions (the best solutions) attract the ants towards them, guiding them to more promising areas of the search space. This attraction is akin to the way antlions use their pits to lure and capture prey. The algorithm incorporates mechanisms for both exploration and exploitation, allowing it to effectively search for optimal solutions, while avoiding local minima. As the iterations continue, the ants that are closer to the antlions are more likely to be selected for further exploration, while those that stray too far may be discarded. This dynamic interaction between the ants and antlions helps the algorithm converge towards the best possible solution over time. The ALO has been applied to various optimization problems across different fields including engineering, computer science, and operations research. Its ability to balance exploration and exploitation, along with its simple yet effective mechanism, makes it a valuable tool for tackling complex optimization challenges. By drawing inspiration from the natural world, the ant lion optimizer exemplifies how biological processes can inform and enhance computational techniques in optimization.

1. Ants traverse the entire search space in a random manner.
2. The movement of the ants is applied indiscriminately across all dimensions.
3. The movement is influenced randomly by the presence of anteater traps.
4. Anteaters have the capability to excavate larger pits based on the objective function.
5. The excavation of larger pits by the anteater results in a higher number of trapped ants.
6. Each anteater possesses the ability to capture a single ant at a time.
7. The captured ant is subsequently concealed beneath the sand by the anteater.
8. Following each capture, the anteater relocates to pursue another ant and modifies the pit accordingly.
9. When an ant descends into the pit, the anteater dislodges stones at the pit's edges to induce a collapse, thereby preventing the ant's escape.
10. In the concluding phase of the hunting process, the captured ant descends to the pit's lowest point and into the anteater's mouth. The anteater then drags the ant into the sand, ultimately consuming it. It is assumed that the hunting occurs once the ant is buried. To enhance the likelihood of subsequent captures, the anteater shifts its position back to where it initially caught the ant.The coefficient of determination (R^2), root mean square error (RMSE), Variance Accounted For (VAF), and the distribution diagram of ALO model for predicting rock fragmentation are illustrated in Figure 6. Additionally, Figure 7 presents the comparison between the measured or target values and the predicted values generated by the ALO predictive model.

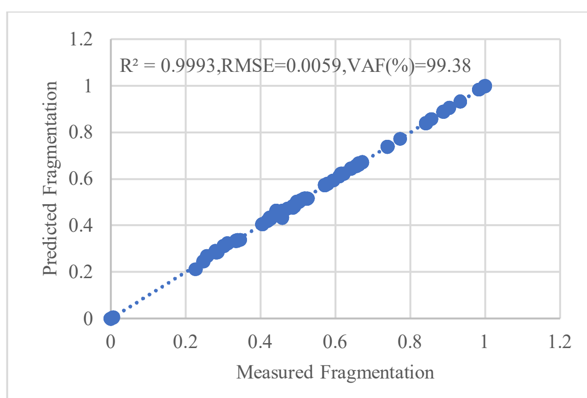

Figure 6. Distribution diagram of ALO model for predicting rock fragmentation.

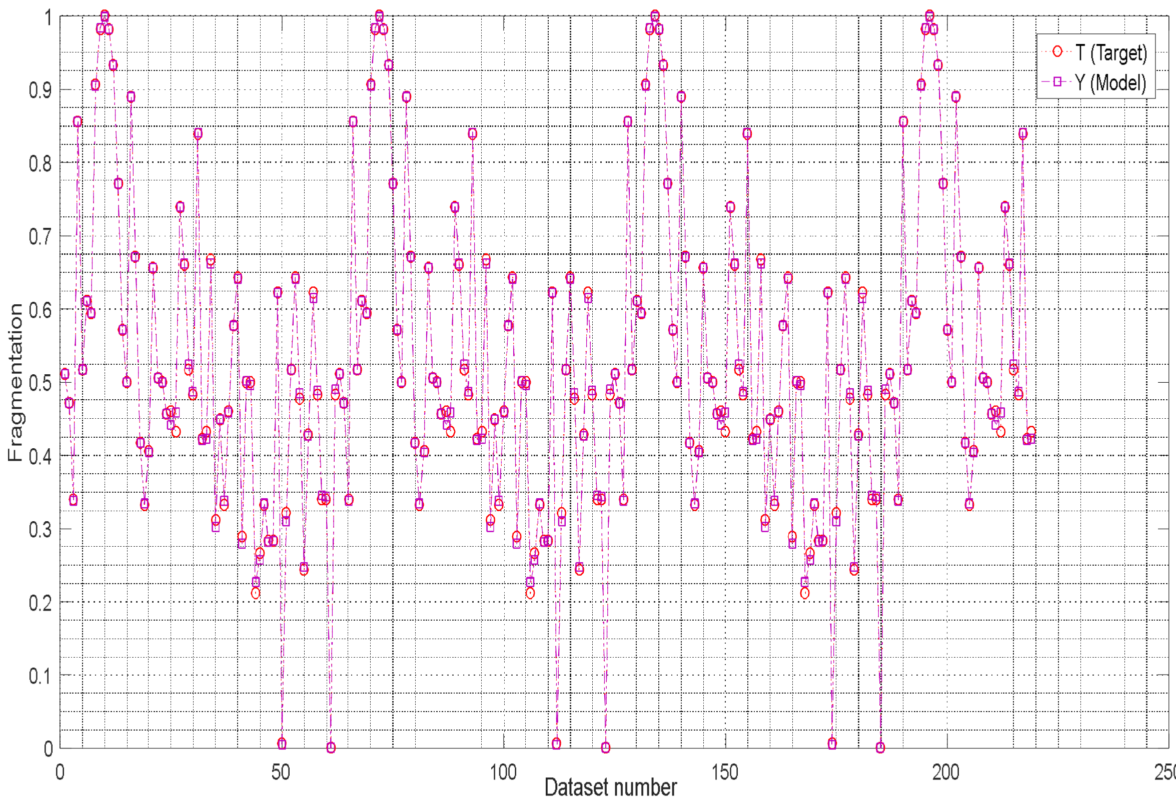

Figure 7. Comparison between the measured or target values and the predicted values by ALO

3.2. Prediction of rock fragmentation using crow search algorithm

The Crow Search Algorithm (CSA) represents a novel metaheuristic approach that draws inspiration from the cognitive and memory-driven behaviors exhibited by crows in their food storage and retrieval practices. This algorithm is fundamentally structured around two primary behaviors observed in crows: the act of food storage and the strategies employed to thwart theft by other crows. Crows are known for their remarkable intelligence and problem-solving abilities, which are particularly evident in their food caching behaviors. When crows find food, they often store it in various locations to ensure a supply for future consumption. This process involves not only the selection of optimal storage sites, but also the ability to remember these locations over time. The CSA mimics this behavior by utilizing a population of candidate solutions that represent potential solutions to optimization problems. Each solution, akin to a crow's food cache, is evaluated based on its quality, and the algorithm iteratively refines these solutions to converge on the optimal or near-optimal result. In addition to food storage, crows exhibit sophisticated strategies to protect their caches from potential thieves including other crows. They may engage in deceptive behaviors cache food in less conspicuous places to avoid detection. This aspect of crow behavior is mirrored in the CSA through mechanisms that introduce diversity and exploration in the search process. By incorporating strategies that prevent premature convergence on suboptimal solutions, the algorithm enhances its ability to explore the solution space more thoroughly.The CSA operates through a series of iterations, where each crow (solution) evaluates its position based on both its own experience and the experiences of its peers. This collaborative aspect allows for the sharing of information, akin to how crows might observe and learn from one another's caching behaviors. The algorithm employs a balance between exploration and exploitation, ensuring that while some solutions are refined based on their performance, others are allowed to explore new areas of the solution space, thereby avoiding local optima. Furthermore, the CSA can be applied to a wide range of optimization problems including but not limited to engineering design, scheduling, and resource allocation. Its flexibility and adaptability make it a valuable tool in various fields, from operations research to artificial intelligence. As researchers continue to explore and refine the CSA, its potential applications and effectiveness in solving complex optimization challenges are likely to expand, further demonstrating the power of nature-inspired algorithms in computational problem-solving. The foundational principles of the crow search algorithm are outlined as follows:

1. Crows exhibit social behavior by living in groups.
2. Crows are adept at remembering the locations of their concealed resources.
3. Crows engage in observational learning to pilfer from one another.
4. Crows take measures to safeguard their caches against potential theft.

The coefficient of determination (R^2), Root Mean Square Error (RMSE), Variance Accounted For (VAF), and the distribution diagram of the CSA utilized for predicting rock fragmentation are illustrated in Figure 8. Additionally, Figure 9 presents the comparison between the measured or target values and the predicted values generated by the CSA predictive model.

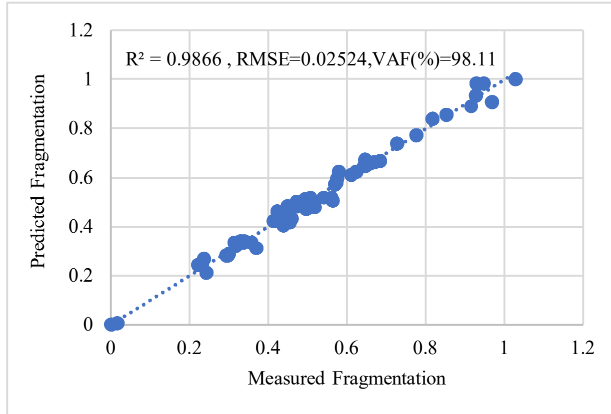

Figure 8. Distribution diagram of CSA model for predicting rock fragmentation.

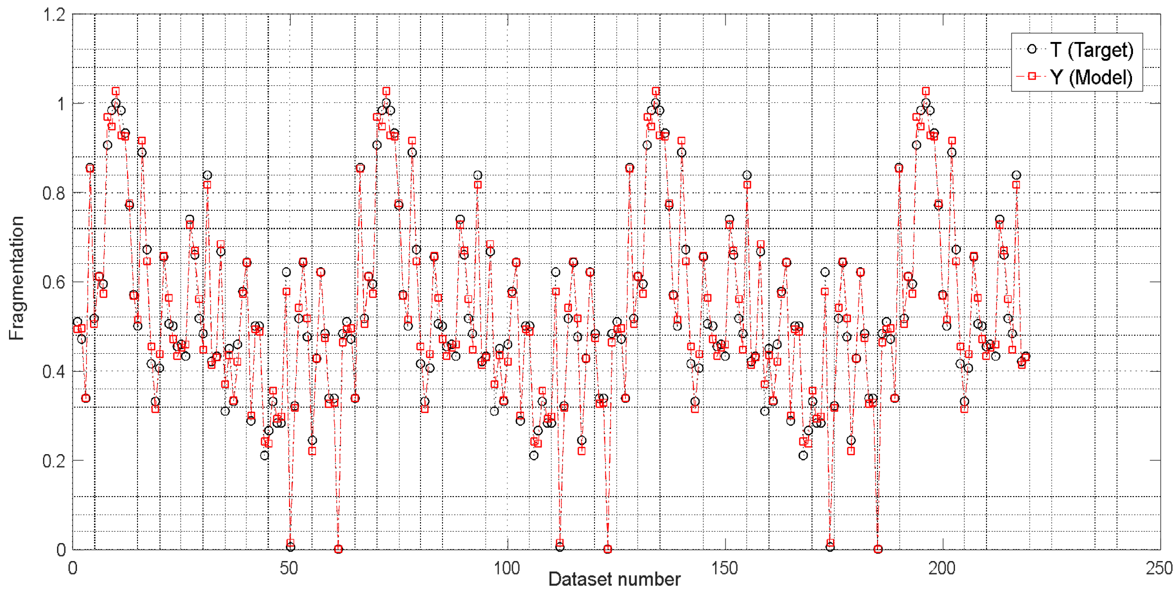

Figure 9. Comparison between the measured or target values and the predicted values by CSA

3.3. Sensitivity analysis

Sensitivity analysis serves as a methodological approach to assess which input parameters exert the greatest influence on the resulting outputs. The cosine amplitude method, as described by Yang and Zang [41], can be employed to facilitate this evaluation. This approach is represented by the Equation 11.

$$R_{ij}=\frac{\sum_{l=1}^{n}(y_{il}\times y_{jl})}{\sum_{l=1}^{n}{y_{il}}^2\sum_{l=1}^{n}{y_{jl}}^2}$$

In this context, yi and yj denote the input and output parameters, respectively, while n signifies the total number of datasets. The relationships between the input and output parameters are illustrated in Table 3. As you can see in Figure 10, the most influential parameter in the model's prediction is burden.

Table 3. Sensitivity analysis of input and output parameters.

Input parameter	Symbol	r_{ij}
Burden (m)	B	0.991
Spacing (m)	S	0.971
Poweder factor (kg/m^3)	PF	0.915
Stemming (m)	ST	0.901

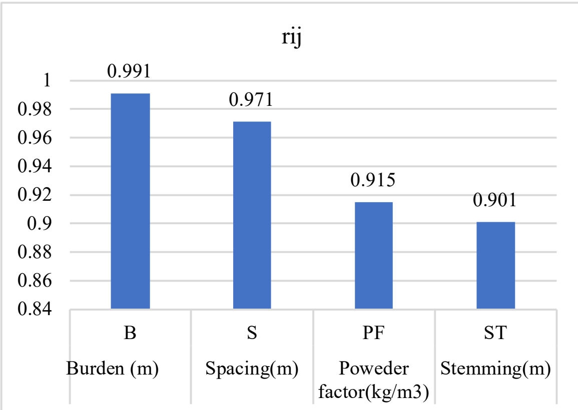

Figure 10. Parameter sensitivity analysis.

3.4. Comparison of the results

The findings of this work regarding prediction fragmentation are analyzed in relation to results obtained from a similar research work conducted in the field. By drawing comparisons between the two sets of findings, we aim to identify common patterns, discrepancies, and potential implications for the future studies. This comparative analysis not only enhances our understanding of prediction fragmentation, but also situates our results within the broader context of existing literature. Through this examination, we can better assess the validity and reliability of our findings, as well as explore how they contribute to the ongoing discourse in this area of research. Additionally, we will consider the methodologies employed in the analogous studies to evaluate their impact on the outcomes and interpretations of prediction fragmentation. Ultimately, this comprehensive comparison seeks to enrich the academic conversation surrounding this topic, and provide a foundation for further investigation. Table 4 reveals that the models implemented in this research work outperform other models in terms of efficiency. This outcome is significant as it not only validates the effectiveness of our chosen methodologies but also suggests that our models could serve as a benchmark for future research endeavors. The enhanced efficiency demonstrated by our models may lead to broader applications across various domains, potentially influencing best practices in model selection and implementation. Furthermore, the implications of this efficiency extend beyond mere performance metrics, as they may also contribute to cost savings and increased scalability in real-world applications.

Table 4. Comparing the results of models.

Model	R^2	Technique	Output	Rank
This study (ALO)	0.99	ALO	Rock fragmentation	1
This study (CSA)	0.98	CSA	Rock fragmentation	2
Bahrami et al. [13]	0.97	ANN	Rock fragmentation	3
Monjezi et al. [14]	0.96	FS	Rock fragmentation	4
Shams et al. [32]	0.92	FS	Rock fragmentation	5
Sayadi et al. [15]	0.85	ANN	Rock fragmentation	6
Ebrahimi et al. [16]	0.78	ANN	Rock fragmentation	7

4. Discussion

Rock fragmentation plays a crucial role in blasting operations, as it directly impacts the efficiency and effectiveness of subsequent processes such as loading and crushing. The primary goal of blasting is to break down large volumes of rock into smaller, manageable pieces that can be easily handled and processed. The degree of fragmentation achieved during blasting is a key factor that determines how well the rock can be loaded onto transport vehicles, and how effectively it can be crushed for further processing. The effectiveness of blasting operations is largely influenced by two main factors: the degree of fragmentation and the distribution of fragment sizes. Ideally, the fragmentation should be uniform, with a range of sizes that are suitable for the equipment used in the loading and crushing stages. If the fragments are too large, they may not fit into the loading machinery, leading to inefficiencies and increased operational costs. Conversely, if the fragments are too small, they may result in excessive dust generation and loss of material, which can also hinder the loading and crushing processes. Achieving the optimal outcome in rock fragmentation means striving for a level of fragmentation that minimizes or even eliminates the need for additional processing after the blast. This is particularly important in large-scale mining and construction operations, where time and cost efficiency are paramount. When the size of the fragments aligns perfectly with the requirements of both the loading machinery and the crushing equipment, it streamlines the entire operation, reducing downtime and enhancing productivity. To achieve this ideal fragmentation, careful planning and execution of blasting techniques are essential. Factors such as the type of explosives used, the timing of the blasts, and the geological characteristics of the rock must all be taken into consideration. By optimizing these variables, operators can enhance the fragmentation process, ensuring that the resulting rock is not only easier to handle, but also more conducive to efficient crushing. In summary, rock fragmentation is a critical component of blasting operations, with a direct impact on the efficiency of loading and crushing processes. The goal is to achieve a fragmentation level that meets the operational requirements of machinery while minimizing the need for further processing. By focusing on the degree of fragmentation and the distribution of fragment sizes, operators can significantly improve the overall effectiveness of their blasting operations, leading to enhanced productivity and reduced costs. The locations of the Crow Search Algorithm (CSA), the Ant Lion Optimizer (ALO), and the target are illustrated in Figure 11. In this figure, the positions of the CSA and ALO are represented as distinct points within the search space, showcasing their respective strategies for exploring and optimizing solutions. The target, which signifies the optimal solution or goal of the optimization process, is also marked, providing a reference point for evaluating the effectiveness of both algorithms. The CSA, inspired by the social behavior of crows, utilizes a unique mechanism of exploration and exploitation to navigate the search space, while the ALO, based on the hunting strategies of ant lions, employs a different approach to find optimal solutions. By comparing their locations relative to the target, we can gain insights into the performance and efficiency of each algorithm in reaching the desired outcome. Figure 11 serves as a visual representation of these dynamics, highlighting the interaction between the algorithms and the target, and illustrating how each method approaches the optimization problem. This comparison can help in understanding the strengths and weaknesses of the CSA and ALO in various scenarios, ultimately contributing to the development of more effective optimization techniques. Figure 12 provides a comprehensive visual representation of three key performance metrics: R-squared (R^2), Root Mean Square Error (RMSE), and Variance Accounted For (VAF). R^2 is a statistical measure that indicates the proportion of the variance in the dependent variable that can be explained by the independent variables in the model. A higher R^2 value suggests a better fit of the model to the data, indicating that a significant amount of the variability is accounted for by the predictors. RMSE, on the other hand, quantifies the average magnitude of the errors between the predicted and observed values. It is calculated as the square root of the average of the squared differences between the predicted and actual values. A lower RMSE value signifies a more accurate model, as it indicates that the predictions are closer to the actual observations. VAF is another important metric that reflects the proportion of the total variance in the observed data that is explained by the model. It is similar to R^2 but is often used in contexts, where the focus is on the explanatory power of the model rather than its predictive accuracy. It can ultimately be inferred that both the Ant Lion Optimizer (ALO) and the Crow Search Algorithm (CSA) yield satisfactory results in their respective applications. Both algorithms demonstrate a commendable ability to solve complex optimization problems, showcasing their effectiveness in various scenarios. However, a closer examination reveals that the ant lion optimizer stands out for its superior performance, particularly in terms of producing outcomes that are not only more accurate but also more realistic. The ALO's unique approach, which mimics the hunting behavior of ant lions, allows it to explore the solution space more efficiently and effectively. This results in a higher likelihood of converging on optimal or near-optimal solutions, thereby enhancing the precision of the results obtained. In contrast, while the CSA also provides valuable solutions, it may not consistently achieve the same level of accuracy as ALO, particularly in more complex or nuanced optimization tasks. Furthermore, the realistic nature of the outcomes generated by ALO can be attributed to its robust mechanism for balancing exploration and exploitation within the search space. This balance enables ALO to avoid local optima and better approximate the true global optimum, leading to solutions that are not only theoretically sound but also applicable in real-world scenarios. In summary, while both the ant lion optimizer and the crow search algorithm are effective tools for optimization, the ALO demonstrates a distinct advantage in delivering results that are both accurate and realistic, making it a preferred choice for practitioners seeking reliable solutions in complex optimization challenges.

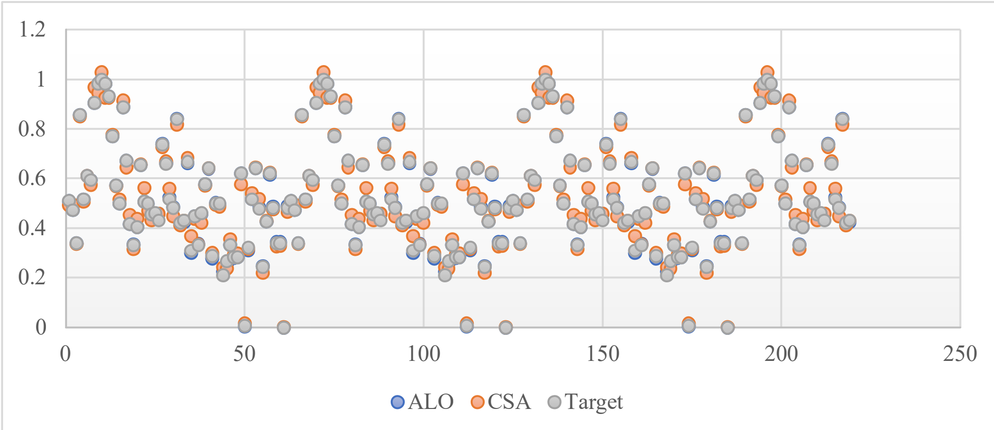

Figure 11. Position of CSA and ALO and target.

Table 5. Analysis of models.

Model	R^2	RMSE	VAF (%)
CSA	0.98	0.02	98.11
ALO	0.99	0.005	99.38

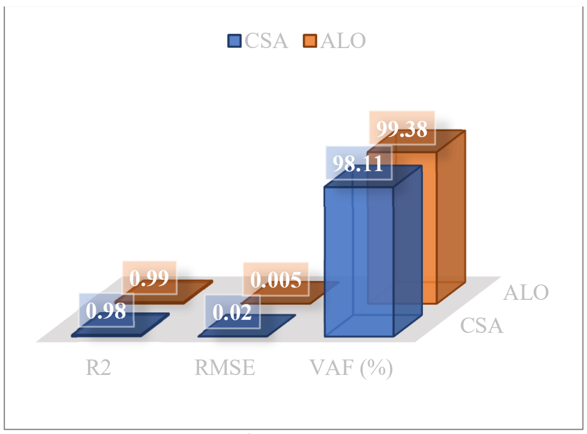

Figure 12. R^2, RMSE, and VAF.

5. Limitations and Future Works

This investigation into the prediction of rock fragmentation in mining through algorithmic approaches has produced encouraging outcomes; however, it is crucial to acknowledge certain limitations that may influence the broader applicability and practical utility of our results. A significant limitation is the dependence on a constrained dataset, which may not capture the full range of geological variations and mining conditions present in different locales. This restricted perspective could result in models that excel in specific contexts but may falter when faced with varied environments or unforeseen geological characteristics. Furthermore, the algorithms utilized in our research work may possess intrinsic biases stemming from the training data. Should the training dataset fail to adequately reflect the complexities of actual scenarios, the models' predictive precision could be adversely affected. This limitation highlights the necessity of validating our results across a variety of mining sites and conditions to ensure their robustness and dependability. The inherently dynamic characteristics of mining operations, which encompass variations in equipment, methodologies, and environmental conditions, can significantly hinder the effectiveness of our models. As mining practices progress, it is essential for forthcoming research to be flexible and responsive to these developments, thereby ensuring that predictive models remain pertinent and insightful. To mitigate these challenges, future investigations should aim to incorporate a wider array of data sources such as geological surveys, real-time monitoring systems, and historical performance metrics from diverse mining operations. By integrating varied datasets, researchers can improve the precision of their models, and extend their applicability across multiple contexts. Furthermore, the exploration of sophisticated machine learning techniques including ensemble methods and deep learning may lead to the development of more resilient models that can effectively capture intricate relationships within the data. In summary, although our preliminary results are promising, it is essential to consider them with a degree of skepticism and analytical rigor. Recognizing the constraints of our research and striving to broaden the parameters of subsequent investigations will enable us to create more thorough and efficient predictive models for rock fragmentation in the mining sector, thereby enhancing operational effectiveness and resource management within the industry. Future research initiatives stand to gain considerably from an in-depth analysis of a variety of datasets, which would offer a more comprehensive view of the multiple factors that affect blasting outcomes. By utilizing a broader spectrum of data sources, researchers can uncover patterns and relationships that might remain obscured when working with a restricted dataset. Furthermore, the inclusion of additional geological parameters—such as rock type, mineral composition, and structural characteristics—together with operational factors like blast design, timing, and equipment utilized, could yield a more holistic understanding of the interactions between these elements and their impact on blasting results. This multi-faceted methodology would not only deepen the overall understanding of the blasting process, but also support the formulation of more effective and customized blasting strategies. By investigating the relationship between geological conditions and operational methodologies, researchers could reveal insights that enhance safety, efficiency, and cost-effectiveness in blasting operations.

6. Conclusions

Typically, rock fragmentation serves as a key metric in the mining sector to assess the impact of blasting. Nevertheless, the notion of optimal fragmentation is largely contingent upon the characteristics of downstream processe such as mucking equipment, processing facilities, and mining objectives. In reality, fragmentation significantly influences the expenses associated with drilling and blasting, as well as the economic viability of subsequent operations. Accurate prediction of rock fragmentation is vital for the optimization of blasting procedures. This fragmentation is contingent upon multiple variables, such as the properties of the rock mass, the design of the blast, and the characteristics of the blasting.

In this work, a database primarily established from field data for predicting rock fragmentation in the mines of Anguran and Sarcheshmeh. Datasets including burden (m), spacing(m), poweder factor (kg/m^3), stemming(m) as the input parameters and fragmentation (cm) as an output parameter. Datasets were analyzed by the Ant Lion Optimizer (ALO) and Crow Search Algorithm (CSA) approaches. In this research work, coefficient of determination (R^2), Variance Accounted For (VAF), and Root Mean Square Error (RMSE) were used to evaluate the accuracy of predictive models. With this regard, Ant Lion Optimizer (ALO) and Crow Search Algorithm (CSA) were applied to the database. Results showed that these parameters for Ant Lion Optimizer (ALO) R^2 = 0.99, RMSE = 0.005, VAF (%) = 99.38, and for Crow Search Algorithm (CSA) R^2 = 0.98, RMSE = 0.02, VAF (%) =98.11, respectively. Finally, it can be concluded that predictive models lead to acceptable results, while ALO contributes to a more precise and realistic outcome.

Conflict of interest

The authors declare no competing interests.

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پیش‌بینی خردشدگی سنگ با استفاده از الگوریتم بهینه‌سازی شیر مورچه و الگوریتم جستجوی کلاغ

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کلمات کلیدی

قطعه قطعه سازی
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چکیده

به طور کلی خردشدگی سنگ به عنوان یک شاخص مهم در فرآیند استخراج و بهره‌برداری معادن و به‌منظور ارزیابی عملیات انفجار در نظر گرفته می‌شود. در این تحقیق، با استفاده از داده‌های میدانی، یک پایگاه داده جامع از پارامترهای انفجار به منظور پیش‌بینی خردشدگی سنگ در معادن سرب و روی انگوران و مس سرچشمه تهیه و جمع‌آوری شد. پارامترهای ورودی مدل‌سازی‌ها شامل بارسنگ، فاصله‌داری چال‌ها، خرج ویژه، گل‌گذاری و پارامتر خروجی میزان خردشدگی سنگ (ماده معدنی و باطله) بود. برای مدل‌سازی و تحلیل داده ها از الگوریتم بهینه‌سازی شیر مورچه و الگوریتم جستجوی کلاغ بهره گرفته شد. برای ارزیابی دقت مدل‌های پیش‌بینی‌کننده، از ضریب تعیین (R2)، شمول واریانس (VAF) و خطای جذر میانگین مربعات (RMSE) استفاده شد. نتایج مدل‌ها و تحلیل‌ها نشان داد که برای الگوریتم بهینه‌سازی شیر مورچه، $R^2 = 0.99$، $RMSE = 0.005$، و $VAF (\%) = 99.38$، و برای الگوریتم جستجوی کلاغ ، $R^2 = 0.98$، $RMSE = 0.02$، و $VAF (\%) = 98.11$ بود. در نهایت، یافته‌ها نشان داد که مدل‌های پیش‌بینی‌کننده نتایج رضایت‌بخشی داشته و الگوریتم بهینه‌سازی شیر مورچه از دقت بالاتری در پیش‌بینی‌ها برخوردار می‌باشد.

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