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Prediction of blast-induced flyrock by using neural-imperialist competitive method (Case Study: Sungun Copper Mine)

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Original scientific paper

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Abstract

This research focuses on conducting studies that predict the distance of blast-induced flyrock, which is an undesirable environmental phenomenon in open-pit mines. While there are experimental methods available for predicting blast-induced flyrock, the complex process of assessing the distance of flyrock has reduced the efficiency of these approaches. This study employs artificial intelligence methods and statistical techniques to forecast the flyrock distance in the Sungun copper mine. Thus, an Artificial Neural Network (ANN-MLP) and a new hybrid model of Artificial Neural Network (ANN) optimized by the Imperialist Competitive Algorithm (ICA), known as (ICA-ANN), are used to predict the flyrock distance, considering crucial parameters such as the number of holes, hole spacing, burden, total charge, specific drilling, charge per hole and specific charge. The results showed that the Artificial Neural Network, with RMSE, MAE, and R^2 error values of 9.31 m, 7.10 m, and 0.81, respectively, was able to predict the flyrock distance well compared to the measured data in the test phase. However, the implementation of the imperialist competitive algorithm optimizer in the neural network enhanced the prediction of the flyrock distance, yielding RMSE, MAE, and R^2 values of 5.66 m, 4.60 m, and 0.89, respectively. Finally, by performing sensitivity analysis on the input parameters of the flyrock distance, it was determined that the amount of explosive consumption and the number of holes have the greatest impact on the blast-induced flyrock distance.

Keywords:
flyrock distance; blast; artificial neural network; imperialist competitive algorithm; Sungun copper mine

1. Introduction

Mining blasting operations involve the design of a blast pattern and the implementation of methods to produce fragmented rocks with desired fragmentation using explosives placed within the specified holes. An effective and desired blasting operation not only results in proper rock fragmentation, but also substantially reduces undesirable and unanticipated environmental issues caused by blasting, such as ground vibrations and flyrock (**Esfandiari, 2021**). Therefore, it is necessary to study the factors and parameters influencing these phenomena to achieve a desirable blast operation. Flyrock is one of the unexpected occurrences in open-pit mine blasting. The flyrock phenomenon is the term used to describe the uncontrolled movement of fragmented pieces of rock that occur during the blasting operation. This phenomenon is a major cause of damage to structures, equipment, and personnel and poses significant hazards in mining operations (**Faraji Asl, 2016**). The blasting pattern is typically designed using empirical methods. These methods only consider a limited number of parameters, which can lead to less desirable results. Through analysis of the results, including fragmentation investigation, geometric shape, bench height, displacement, the status of the remaining rock mass, ground vibrations, and correction of controllable parameters, it is possible to design an appropriate blasting pattern (**Rashtbar Alouig, 2019**). So far, different theoretical and empirical models have been proposed to predict the blasting pattern in open-pit mines. According to studies, these models are not accurate enough, and the reason could be the lack of simultaneous consideration of influential variables. To solve this problem, an appropriate option is to use advanced computational methods, such as evolutionary algorithms. Prediction and optimization of blasting operations using fuzzy methods and metaheuristic algorithms can be effective in reducing drilling volume and eliminating the deficiencies of previous

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methods (**Shirani Faradonbeh, 2016**). Several studies have been conducted to predict the blasting pattern using artificial neural networks and optimizing it using various approaches. **Esfandiar (2018)** proposed an optimized blasting pattern for the Angoran lead-zinc mine. This was achieved by utilizing neuro-fuzzy inference methods and support vector machines and compared their performance in predicting flyrock. The results showed that the Support Vector Machine (SVM) outperforms neural-fuzzy inference methods in predicting the appropriate blasting pattern. Ultimately, by using the cosine domain method, sensitivity analysis was performed on the parameters, revealing that the specific charge parameter and sub-drilling had the highest and lowest impact on the blasting pattern. **Saghatforoush et al. (2016)** developed an optimal blasting pattern for optimizing flyrock and fragmentation rock using a neural network and the Ant Colony Optimization (ACO) algorithm. They considered 97 blasting operations in the Delkan iron mine in Iran and evaluated input data such as burden, depth of hole, hole spacing, specific charge, and stemming length. Based on their evaluation, they determined that the proposed blasting pattern is the most effective in minimizing flyrock distance and optimizing fragmentation. **Koopialipoor et al. (2018)** attempted to provide an optimal blasting pattern by employing three hybrid intelligence models: genetic algorithm (GA), particle swarm optimization (PSO), and imperialist competitive algorithm (ICA). From their findings, the Neural Network Prediction Model (ANN-PSO) achieved superior performance by selecting the input parameters such as the burden-to-spacing ratio, hole diameter, specific charge, stemming length, and hole depth. Between these parameters, hole diameter was found to be one of the most significant input parameters in flyrock. **Nguyen et al. (2019)** proposed a method for predicting blast-induced flyrock based on ANN models and their optimization, called the EANNs model (a set of ANN models), to predict flyrock due to blast. They evaluated their proposed method using 210 data points from blasting operations. The proposed EANN approach outperformed the ANN approach with a similar structure and was able to predict the flyrock distance effectively. **Lu et al. (2020)** developed machine learning algorithms including the extreme learning machine (ELM) and outlier robust ELM (ORELM) to forecast the distance of flyrock that results from blasting. They collected and employed data from three granite mines in Malaysia. Their findings revealed that the machine learning models had superior performance compared to both ANN and multivariate regression models. **Rahimdel et al. (2020)** proposed the most proper drilling and blasting pattern for Sangan Iron Mine, Iran, based on the TOPSIS and PROMETHEE methods. Firstly, they used the AHP method in a fuzzy environment to calculate the importance of various mining operations features, including backbreak, flyrock, specific charge, and specific drilling. Finally, they proposed a drilling pattern with a 5 m spacing, a 4 m burden, a 10 m hole depth, and a 15 cm hole diameter. **Nikafshan Rad et al. (2020)** presented an optimized blasting pattern for reducing flyrock by utilizing a combination of recurrent neural network (RFNN) and genetic algorithm (GA). The mine under study in their research was the Shour River Dam mine, and they considered 70 datasets from blast field operation, including four input parameters such as spacing, burden, stemming length, and specific charge. Their results showed that the predictive model they considered had high accuracy and was significantly superior to the nonlinear regression model. They identified the specific charge as the influential parameter on the flyrock resulting from the blast by performing a sensitivity analysis of the input parameters. **Shakeri et al. (2022)** investigated the accuracy of different models such as ANN, LMR, ICA, and ANFIS, in trying to predict the blast-induced flyrock distance. Their results demonstrated that the neural network model, which had a low error value and R^2 above yielded more accurate results compared to the measured data. Furthermore, the ICA imperialist competitive model yielded superior outcomes in comparison to the ANFIS model. **Zangoei et al. (2022)** attempted to reduce flyrock in the proposed blast pattern using artificial intelligence techniques and employing the Imperialist Competitive Algorithm (ICA). They optimized a three-layer ANN neural network and implemented the ICA algorithm to predict the flyrock distance accurately with a high R^2 value. **Ding et al. (2023)** aimed to develop an accurate model for predicting flyrock based on data collected from three granite mines located in Malaysia. The study employed four methods: the least-squares support vector machine (LSSVM), the convolutional forward neural network (CFNN), and three optimization algorithms. These were the Whale Optimization Algorithm (WOA), the Artificial Bee Colony (ABC), and the Gravitational Search Algorithm (GSA). Their findings demonstrated that all proposed models, employing the examined algorithms, were able to efficiently predict flyrock. Out of all the models, the LSSVM-WOA model outperformed the others and provided more accurate predictions of flyrock values. **Zhang et al. (2024)** developed a flyrock prediction model using a stacked multiple kernel support vector machine (stacked MK-SVM). Their suggested model demonstrated superior performance, achieving an RMSE of 1.73 and 1.74, MAE of 0.58 and 1.08, and VAF of 98.95 and 99.25 throughout the training and testing phases, respectively.

Based on previous literature reviews and valuable research studies using artificial intelligence and machine learning techniques to predict flyrock, several studies have developed hybrid models, incorporating meta-heuristic algorithms to enhance the predictive accuracy of machine learning models and optimize their performance. For instance, the ANN has some limitations, such as the slow rate of learning and getting trapped in local minima. Meta-heuristics can fix this problem by improving the ANN's model parameters over and over again using a self-defined update scheme. Some studies, like **Kalaivaani et al. (2020)**, **Murlidhar et al. (2021)** and **Hasanipanah et al. (2022)**, use particle swarm optimization (PSO), the Harris Hawks optimization (HHO) and adaptive dynamical harmony search algorithm (HS) to develop hybrid ANN models. Given the uncertainty surrounding mine blast results, it is impossible to predict the explosion's outcome, such as the resulting flyrock, with absolute certainty. Therefore, the use of predictive blast models based on metaheuristic algorithms to optimize these predicted models can have an effect on the efficiency and optimization of the blast pattern in mines. This paper presents a hybrid ICA-ANN predictive model for flyrock prediction in the Sungun copper mine, Iran. The population-based evolutionary algorithm ICA draws inspiration from the sociopolitical evolution of humans. Engineers have successfully applied this algorithm to various optimization problems. Using ICA, it is possible to improve the limitations of the ANN and provide a hybrid model for predicting flyrock.

2. Materials and Methods

2.1. *Case study - Sungun Copper Mine*

The Sungun copper mine is located in the East Azerbaijan Province, Iran, about 73 kilometers northwest of Ahar city. Its specific geographical coordinates are 46 degrees east longitude and 38 degrees north latitude. **Figure 1** depicts the specific geographical location of the mine. This mine, located at an approximate elevation of 2390 meters above sea level, is part of the globally recognized Alpine-Himalayan copper belt. The main minerals it produces are copper and molybdenum. The mine has an overall reserve of approximately 796 million tons, a proven reserve of about 388 million tons, and a copper grade of 0.67%. This mine also extracts valuable metals such as gold and silver, in addition to copper. The mining extraction process involves the use of an open pit. The working steps have a slope of 63 degrees and a height of 12.5 meters. The mine's overall slope is 37 degrees. **Table 1** presents the geometrical and geological specifications of the mine.

In the Sungun copper mine, the blast process involved bench blasting with a free face using ANFO as the principal explosive in the blast holes. The initial blasting operation system used a detonating cord to join the caps. The primary blasting pattern took on a triangular shape, and the proportion of burden to spacing varied based on the attributes of the blast blocks within different segments of the mine. Flyrock was one of the unwanted consequences of the blasting operation in this mine. Thus, the present work aimed to predict the flyrock distance using a metaheuristic algorithm.

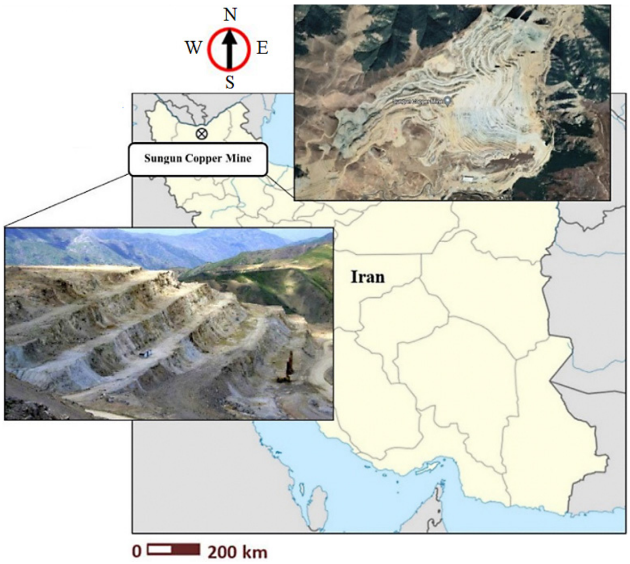

Figure 1: Sungun copper mine location on map

Table 1: Geological and geometric characteristics of Sungun copper mine

Geological/geometric features	Value
Total mine reserve	796 million tons
Proven reserve	388 million tons
Medium grade	0.67 percent
Working bench height	M 12.5
Working bench slope	68°
Mine general slope	37°
Ramp width	30m
Ramp slope	5°
Mine age	About 32 years

2.2. *Databases*

After collecting the data, the input and output parameters were determined. The data on 308 blasts and flyrock rates from each blast in the Sungun copper mine were recorded and measured in the period from April 2018 to December 2018. **Figure 2** presents the box plots of the used data. As can be seen, the initial data related to specific drilling (SD), total charge (TC), specific charge (SC), and charge per hole (CPH) have outliers and should be removed from the database to prevent modelling deviation.

The Z-Score statistic was employed to eliminate outliers from the data. Z-Score, or standard score, is a statistical metric that quantifies the deviation of a data point from the mean of a dataset, measured in standard deviations. It is used to evaluate whether a specific data point is normal or an outlier compared to the rest of the data. The formula for this evaluation is as follows (**Aggarwal et al., 2019**):

$$Z = \frac{x - \mu}{\sigma} \quad (1)$$

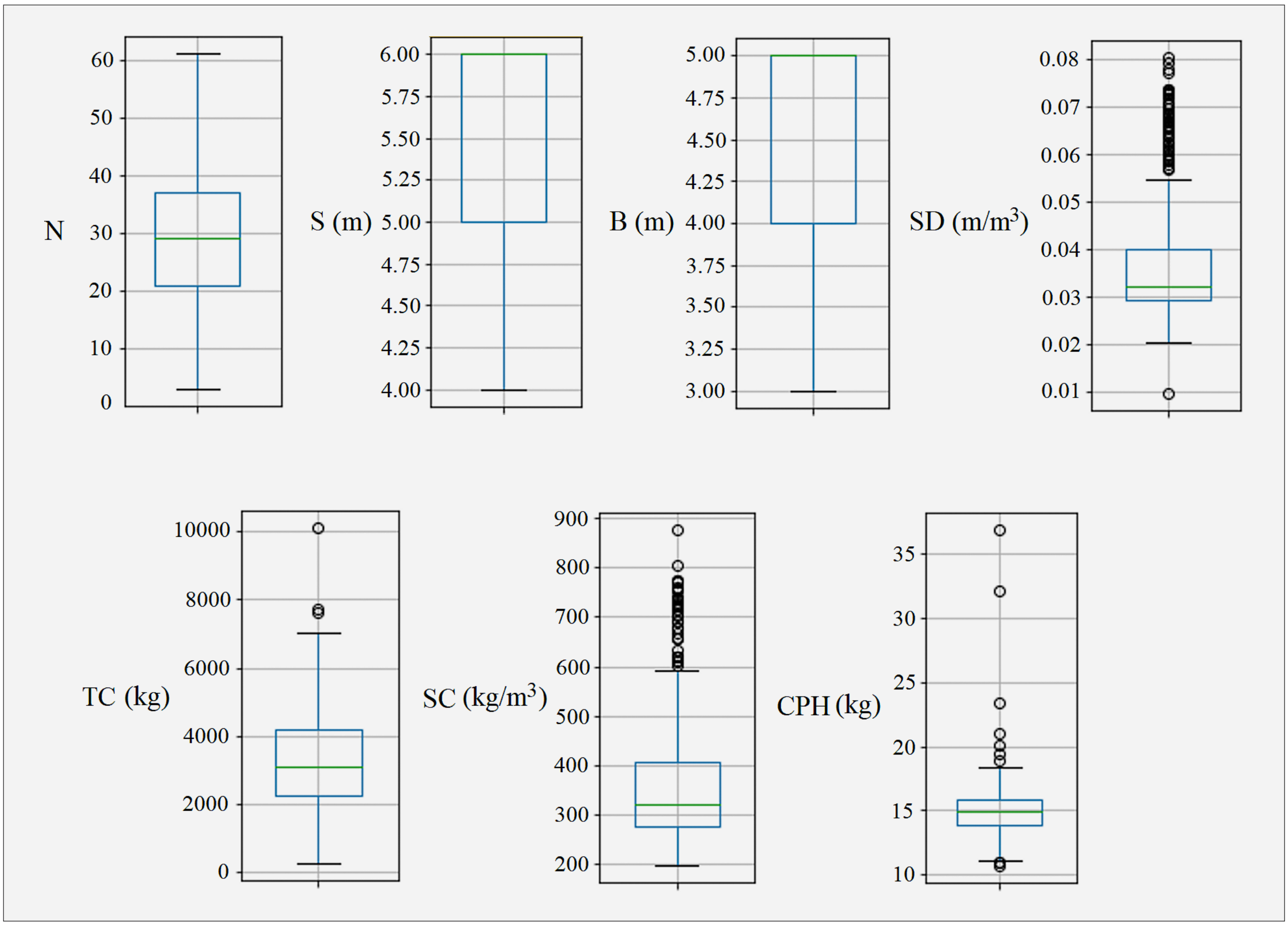

Figure 2: Box plot of input parameters

where σ shows the standard deviation of the data and μ denotes the mean of the data. Data that are more than 3 standard deviations away from the mean of their respective column were removed from the data (**Aggarwal et al., 2019**). Ultimately, 205 data series were used in this study after removing outliers. The statistical characteristics of the data after removing outliers are presented in **Table 2**.

The data collection is split into two parts: training and testing. During the training stage, 80% of the total data is used to train the model. The remaining 20% is randomly selected for testing. The prediction of flyrock was determined using three evaluation criteria: the root mean square error (RMSE), the mean absolute error (MAP), and the square of the correlation coefficient (R^2). The best model is characterized by an RMSE that is near zero and an R^2 value that approaches one. The following equations represent the previously mentioned (**Esmaeilzadeh et al., 2022**):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{i,pred} - X_{i,meas})^2} \quad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|X_{i,meas} - X_{i,pred}\right| \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(X_{i,meas} - X_{i,pred})^2}{\sum_{i=1}^{N}(X_{i,meas} - \bar{X})^2} \quad (4)$$

where $X_{i,\ meas}$, and $X_{i,pred}$ represent the measured and predicted data, respectively, and N denotes the total number of data.

2-3- *Artificial Neural Networks (ANNs)*

Pitts and McCulloch first presented ANNs in 1943. Artificial neural networks (ANNs) are an advanced method for precisely analyzing modelling issues, and identifying optimal solutions (**Guido et al., 2022**). Artificial neural networks are composed of a large number of artificial neurons. The number of neurons used in an artificial neural network depends on the task at hand (**Nguyen and Bui, 2019**). Neurons are commonly arranged in a layer or vector, where the output of one layer serves as the input for the next layer, as well as the next one (**Zinno et al., 2022**). There are different ways to connect neurons to each other to form a neural network. The feedforward method is one of the most common and simplest methods. This type of network earns its name as each layer's neurons transmit their output to the subsequent layer, a process that persists until it reaches the

Table 2: Modified input parameters, output, and their statistical characteristics

Parameters	Type of parameter	Unit	Symbol	Number	Maximum	Minimum	Mean	Standard deviation
Number of holes	Input	Loop	N	205	61	3	29.84	10.84
Spacing	Input	m	S	205	6	4	5.52	0.84
Burden	Input	m	B	205	3	3	4.52	0.84
Specific drilling	Input	m^3	SD	205	0.08	0.02	0.04	0.01
Total charge	Input	Kg	TC	205	7000	270	3225	1375
Specific charge	Input	Kg/m^3	SC	205	875.45	203.19	38.540	15.750
Charge per hole	Input	Kg	CPH	205	23.34	10.71	14.69	1.60
Flyrock	Output	m	FR	205	140	40	18.28	18.28

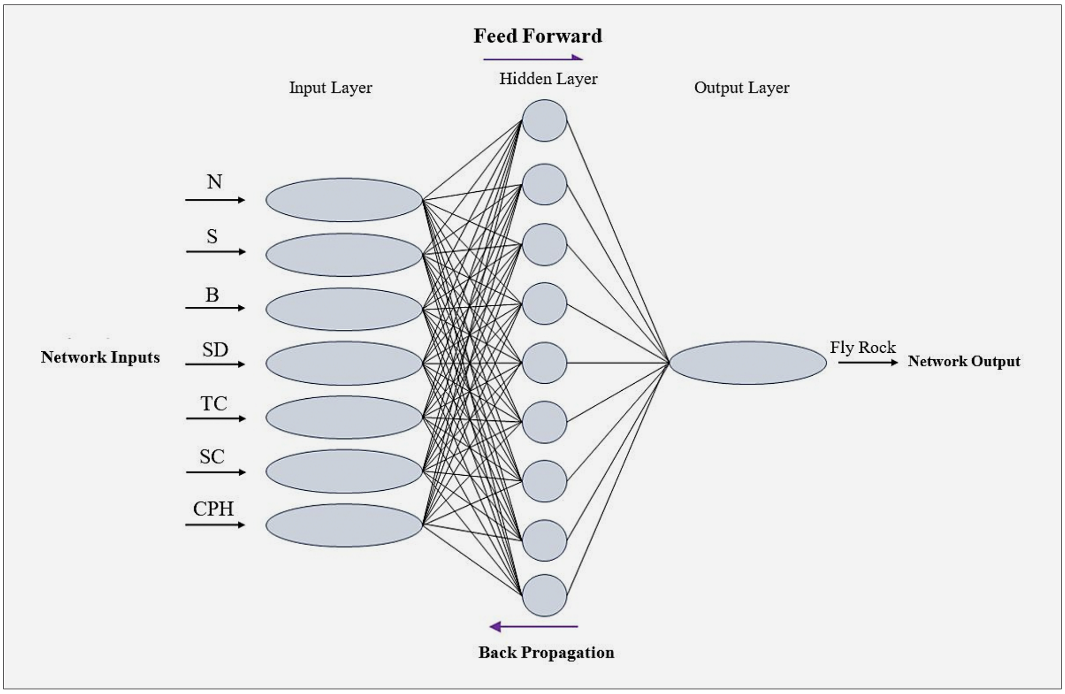

Figure 3: The basic framework of the ANN

final output. The accuracy of the output in neural networks is highly dependent on the training technique and the datasets used for training (**Astarita et al., 2023**). Studies have shown that a neural network with up to two hidden layers and sufficient neurons is capable of solving complicated engineering problems. Experimentation typically determines the number of hidden layers and the neurons that comprise those layers, depending on the complexity of the issue at hand. Opting for a low number of neurons can lead to the network losing its capacity for generalization and struggling to approximate complex mappings. Conversely, employing too many neurons results in an increase in the network's adjustable elements, widening the statistical population for training and weight balancing (**Monjezi et al., 2006**). **Figure 3** illustrates the overall architecture of an artificial neural network. Artificial neural networks function by assigning an arbitrary weight to each input variable within the range of 0 to 1. Then this weight is multiplied by the input value, and the sum of these values reaches the neurons located in the hidden layer with a value called bias, which is in fact the weight of the neuron, and usually its value is equal to one; it is added, and a transfer function acts on it in the neuron (step, linear, or sigmoid). Weight is assigned to this value again and it is transferred to the next neuron in the next hidden layer or output layer. In this way, the values obtained from all the neurons of the hidden layer are added and the training stage is completed. The obtained output values are compared with the actual measured values, and from their difference, the mean square error is calculated. This error is adjusted with a post-propagation algorithm in the return path. Modifying the weight values initiates a new training phase. This process is repeated until the network stop criteria (the number of training steps) is defined or is satisfied by the desired error rate. In this way, the network is trained and tested with other data whose output is not given to the network. By comparing the results obtained from the network and the actual measured results, the network performance is measured.

2.4. Imperialist competitive metaheuristic algorithm (ICA)

Lucas and Atashpaz presented the ACI in 2007, drawing inspiration from socio-political processes (**Atashpaz-Gargari and Lucas, 2007**). The high speed of convergence and greater ability to search for optimization are the advantages of this method (**Shakeri et al., 2022**). According to **Figure 4**, which illustrates the algorithm's process, the initial stage is the initial determination of empires (including countries) as a random population (**Alzoubi et al., 2017**). In the following, some powerful cities are considered imperialists, and the rest are colonies, according to the function of cost in the generated population. Each imperial power distributes colonies among itself based on its prowess. Following the transfer of colonies to their respective imperialist nations, these empires enter a competitive phase. As a result, the dominant empires annex their colonies, ousting the weaker ones. In this competition between imperialist governments trying to integrate newcomers and revolutionary events (sudden changes in the positions of some countries), the colonies' influence grows, changing the way empires and their colonies interact with each other. This cycle concludes when only one empire remains, leading to the collapse of all weaker empires (**Shakeri et al., 2022**).

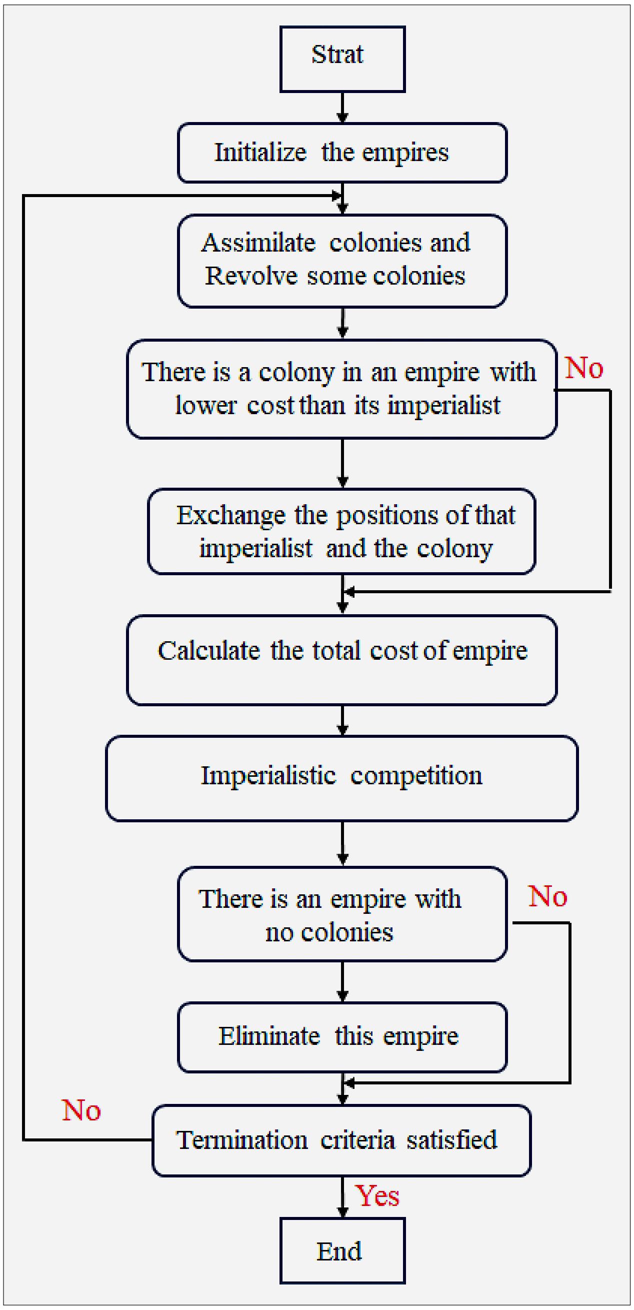

Figure 4: Flowchart of the ICA

3. Development of flyrock distance prediction models

3.1. Preparation of optimal neural network model

In order to achieve a highly efficient network, the random research optimizer algorithms and the optimal and combined hyperparameters of different hidden layers and neuron numbers were tested. Ultimately, a neural network consisting of two hidden layers, each containing five neurons and utilizing sigmoid transfer functions, was identified as the most optimal network. The study's assessment errors, derived from equations (2) to (4) and compared against measurement values, serve as the primary consideration for determining the optimal neural network. This paper used MatLab software to predict flyrock distance using both prediction models. **Table 3** presents the specifications of the best network.

Figure 5 shows the predicted values in the superior neural network model against the measurement data for the training and testing phases. The selected neural network demonstrates a high ability to predict the measured values. The ANN-MLP model demonstrated superior results with an R^2 value of 0.86, MAE value of 4.84 m, and RMSE value of 6.61 m during the training phase. It achieved an R^2 value of 0.81, a MAE value of 9.31 m, and an RMSE value of 7.10 m during the testing phase.

Figure 6 presents a comparison between the predicted values and the measured values obtained from the flyrock distance resulting from the superior neural network model (ANN-MLP) for the testing phase. It is evident that the neural network outperforms the measured values in predicting the flyrock distance.

One of the basic evaluations after modelling is to determine the sensitivity of the flyrock distance as an output function to the input parameters. To ascertain the influence degrees of input parameters on the flyrock, the relevancy factor (RF) is analysed (**Mehrdanesh et al., 2018**). A notable variance between the model's estimated values and the measured values suggests a heightened influence of the omitted parameter on the outcomes (**Oakley and O'Hagan, 2004**). The RF values can be calculated by:

Table 3: The optimal values of ANN parameters for generation flyrock

Optimal model	Number of hidden layers	Number of neurons per layer	Iterations	Data classification	RMSE (m)	MAE (m)	R^2
ANN-MLP	2	5	1000	20	9.31	7.10	0.81

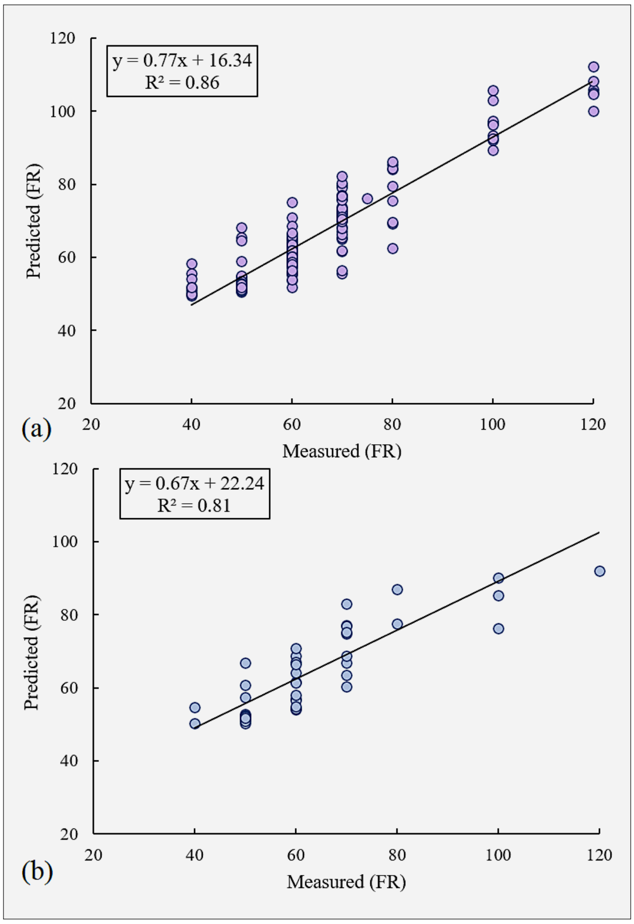

Figure 5: Correlation between measured and predicted values of flyrock distance obtained from ANN-MLP, a: Training phase b: Testing phase.

$$r(p_l, MMP) = \frac{\sum_{i=1}^{N}(p_{l,i} - \overline{p}_l)(MMP_i - \overline{MMP})}{\sqrt{\sum_{i=1}^{N}(p_{l,i} - \overline{p}_l)^2 \sum_{i=1}^{N}(MMP_i - \overline{MMP})^2}} \quad (5)$$

Here, $p_{l,i}$ and p_l are the i^{th} value and the average value of the l^{th} input variable, respectively, MMP_i and MMP are the i^{th} value and the average value of the predicted

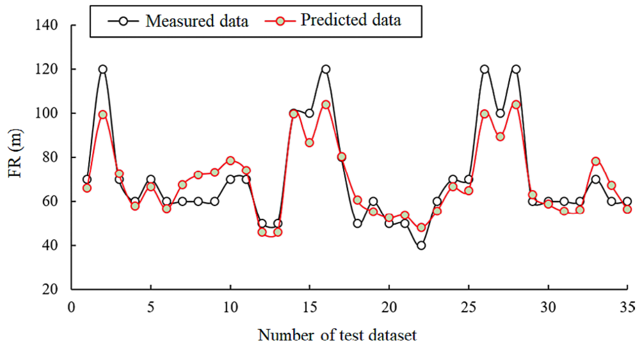

Figure 6: Measured flyrock vs. predicted flyrock by ANN-MLP model for testing phase

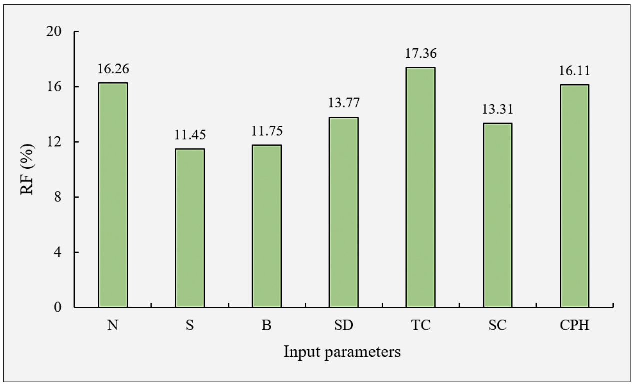

Figure 7: Sensitivity analysis of input parameters on flyrock distance

output, respectively. **Figure 7** shows the effectiveness of the input parameters on the objective function (flyrock distance). It is observed that the specific charge (SC), the total charge (TC), and the number of holes (N) have the greatest impact on the flyrock (FR) with 17.41%, 16.51%, and 16.26% respectively. This result is consistent with previous research conducted by various researchers such as **Armaghani et al. (2014)**, and **Yari et al. (2023)**. Also, the space (S) has the lowest sensitivity of 11.45% on the flyrock distance (**Yari et al., 2023**). This suggests that attention to the specific charge, total

Table 4: Control parameters of imperialistic competition algorithm

Variable name	Control values #1	Control values #2	Control values #3	Control values #4
Number of populations	20	15	20	25
Assimilation coefficient	1.5	2	1.5	2
Imperialistic competition	10	15	20	25
Revolution rate	0.1	0.2	0.2	0.1
Iterations	1000	1000	1000	1000
The R^2 value of the testing phase	0.89	0.86	0.84	0.82

charge, and number of holes is essential for having an efficient explosion pattern in the studied mine.

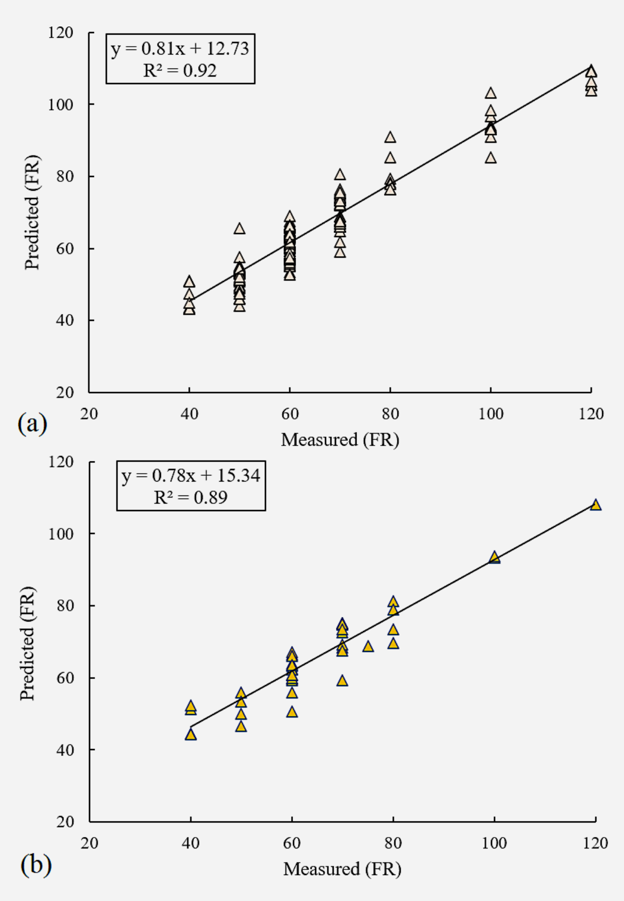

Figure 8: Correlation between measured and predicted values of flyrock distance obtained from ICA-ANN, a: Training phase b: Testing phase.

3.2. Optimization with the meta-heuristic algorithm of imperialistic competition

The imperialistic competition optimization algorithm has been employed to enhance the efficiency of the neural network. This algorithm requires an objective function. A neural network has been used to determine the objective function. In fact, the neural network is responsible for simulating the objective function. The imperialistic competition algorithm's main foundations are assimilation policy, imperialistic competition, and revolution. Therefore, it's crucial to determine the hyperparameter values of the imperialistic competition algorithm through its implementation and the application of the trial-and-error method. After doing numerous iterations, the algorithm yielded the values of the control parameters, as shown in **Table 4**. To get the best results from ANN trained by ICA, it is critical to find the optimum network architecture. ICA can only adjust an ANN's weights and biases to minimize learning error and cannot determine the optimal network architecture. Therefore, the superior neural network obtained from the previous section was chosen as the objective function for ICA.

Figure 8 displays the graphs comparing the predicted flyrock using the hybrid neural network-competition imperialistic (ICA-ANN) technique to the measured flyrock for both the training and testing datasets. The hybrid models of ANN have shown an increase in the R^2 value and a reduction in the RMSE and MAE errors, resulting in values of 5.36 m, 4.37 m, and 0.92 for the training phase and 5.66 m, 4.60 m, and 0.89 for the testing phase, respectively.

Figure 9 displays the Taylor diagram, which compares the measured and predicted data during the testing

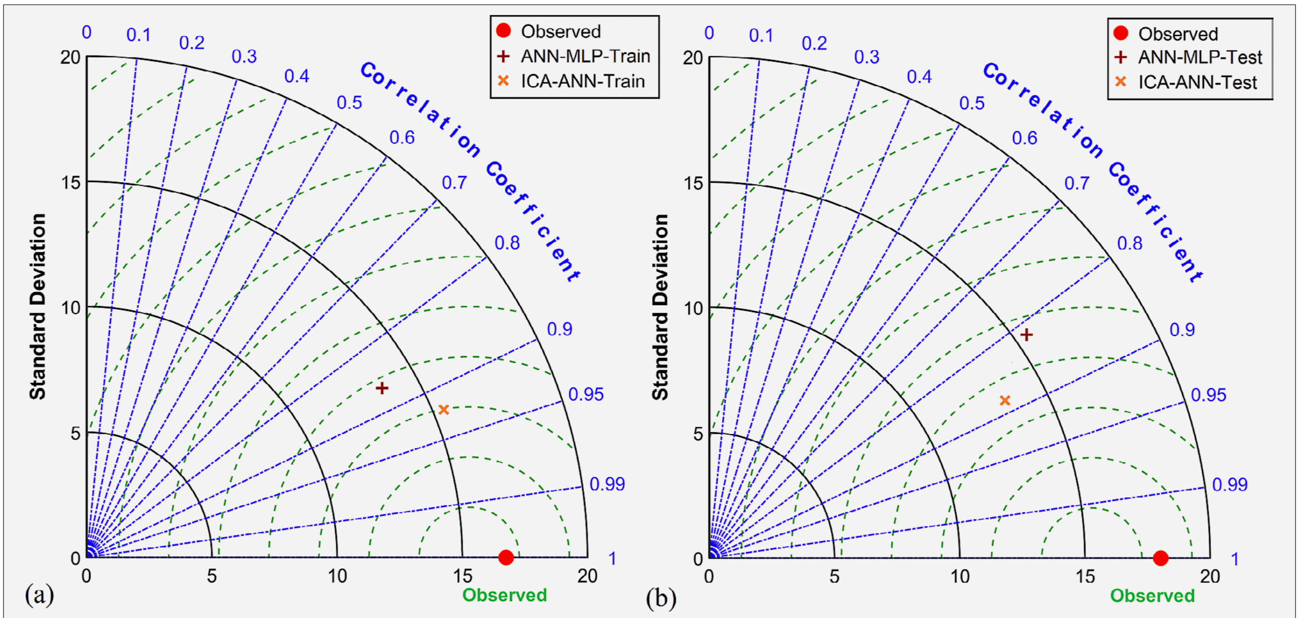

Figure 9: Taylor diagram for assessing the accuracy of the models, a: Training phase b: Testing phase.

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Table 5: Comparison of some of the values predicted by the hybrid model prediction versus measured data in the testing phase

Blast pattern	B (m)	N	SD (m/m^3)	TC (kg)	Flyrock distance, measured (m)	Flyrock distance, ANN-MLP (m)	Flyrock distance, ICA-ANN (m)
1	5	32	0.032	4400	60	54.09	59.71
2	3	19	0.059	2000	50	66.85	49.99
3	5	49	0.039	3200	80	77.60	69.61
4	3	20	0.034	3000	100	76.23	93.29
5	3	33	0.062	5000	80	86./92	73.41
6	3	12	0.039	1580	70	66.83	72.70
7	5	25	0.033	2400	60	56.93	62.45
8	5	28	0.031	2270	40	50.18	44.56
9	3	18	0.064	2010	70	60.38	68.46
10	5	16	0.031	1730	50	52.43	55.95
11	5	45	0.028	2750	40	54.79	52.24
12	5	44	0.030	5100	70	83.10	75.07
13	5	36	0.027	4530	70	74.85	72.84
14	5	27	0.030	3000	50	50.92	53.39
15	5	25	0./031	3480	60	68.84	64
16	5	41	0.028	3500	60	70.84	62.23
17	3	23	0.073	2160	60	54.21	63.98
18	3	14	0.054	2100	120	91.94	108.24
19	5	27	0.034	3390	100	85.25	93.77
20	5	41	0.031	5000	60	58.06	60.86
21	5	12	0.027	1600	60	54.21	64.98
	Mean				67.14	66.45	67.70

and training phases, offering a comprehensive evaluation of all the models under study. The Taylor diagram incorporates three evaluation metrics: root mean square error, standard deviation, and correlation coefficient. These metrics measure the concordance between predictions and measurements The x-axis and y-axis of this diagram illustrate the standard deviation; the arcs depict RMSE values. The closer a model's prediction results to the experimental results (reference), the higher its accuracy and efficiency. As per the Taylor diagram, the hybrid neural network model with ICA-ANN exhibits superior performance compared to ANN-MLP in both training and testing phases.

Table 5 provides some of the data used to compare the two models in flyrock prediction. The hybrid imperialistic neural-competition model (ICA-ANN) predicts flyrock values that are closer to the measured flyrock distance data than ANN-MLP.

4. Conclusions

Blasting is the prevailing approach to rock fragmentation in the mining industry. The process of blasting generates flyrock, which is a significant and challenging activity that requires careful evaluation in order to minimize the associated risks. Empirical methods and relationships for predicting flyrock when using some input parameters and affecting it, have a performance with a high error. As a result, modern soft computing methods, such as meta-heuristic algorithms, can be useful in accurately and efficiently predicting the flyrock distance. This study aimed to develop neural network predictive models to predict the flyrock distance using the ANN-MLP and imperialist competitive algorithm (ICA). After testing different neural network models, the superior p neural network was selected with RMSE, MAE, and R^2 error values of 9.31 m, 7.10 m, and 0.81, respectively. Therefore, the selected ANN-MLP model utilized a combination of the imperialistic competition algorithm (ICA-ANN). By performing different iterations and selecting the appropriate hyperparameters for the ICA with a population of 20, an assimilation coefficient of 1.5, an imperialist competition of 10, and a revolution rate of 0.1, the neural network model was finally optimized, and the hybrid neural-imperialist competitive model with high capability predicted the flyrock distance with RMSE, MAE, and R^2 values of 5.66 meters, 4.60 meters, and 0.89, respectively, in the testing phase. It was determined by performing a sensitivity analysis on the parameters affecting the flyrock distance that the amount of total charge (TC) used and the number of holes (N) have the greatest impact with 17.36% and 16.26%, respectively, and spacing (S) with 11.45% has the least impact during flyrock (FR) caused by blast patterns. Considering the high accuracy of the suggested developed model in predicting flyrock in mining operations, studying the proposed prediction model on ground vibration and air blast and employing other meta-heuristic optimization algorithms to find the best prediction model and replace these methods with the field methods could be recommended for future studies.

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SAŽETAK

Predviđanje udaljenosti odbacivanja minirane stijenske mase korištenjem algoritma imperijalističke konkurencije (studija slučaja: rudnik bakra Sungun)

U ovome istraživanju provedena je studija koja procjenjuje udaljenosti odbacivanja minirane stijenske mase, a to je nepoželjna pojava u okolišu površinskih kopova. Iako postoje dostupne eksperimentalne metode za predviđanje udaljenosti odbacivanja minirane stijenske mase, njihova je učinkovitost smanjena zbog složenosti procesa procjene. Ova studija koristi se metodama umjetne inteligencije i statističke tehnike za predviđanje udaljenosti odbacivanja minirane stijenske mase u rudniku bakra Sungun. Stoga se umjetna neuronska mreža (ANN-MLP) i novi hibridni model umjetne neuronske mreže (ANN) optimiziran algoritmom imperijalističke konkurencije (ICA), poznatim kao (ICA-ANN), koriste za predviđanje udaljenosti odbacivanja minirane stijenske mase uzimajući u obzir ključne parametre kao što su broj bušotina, razmak između bušotina, izbojnica, ukupna količina eksploziva, specifičnosti bušenja, eksplozivno punjenje po bušotini i specifična potrošnja eksploziva. Rezultati su pokazali da je umjetna neuronska mreža, s RMSE od 9,31 m, MAE od 7,10 m i R^2 od 0,81, bila u stanju dobro predvidjeti duljinu odbacivanja u usporedbi s izmjerenim podatcima u ispitnoj fazi. Međutim, implementacija algoritma imperijalističke konkurencije u neuronskoj mreži poboljšala je predviđanje udaljenosti odbacivanja, uz vrijednosti RMSE od 5,66 m, MAE od 4,60 m i R^2 od 0,89. Analizom osjetljivosti na ulazne parametre duljine odbacivanja utvrđeno je da količina utroška eksploziva i broj bušotina imaju najveći utjecaj na udaljenost odbacivanja minirane stijenske mase.

Ključne riječi:
udaljenost odbacivanja minirane stijenske mase, miniranje, umjetna neuronska mreža, algoritam imperijalističke konkurencije, rudnik bakra Sungun

Authors' contribution

Jalil Hanifehnia (1) (PhD, Islamic Azad University Ahar): participated in all work stages, such as sample presentation, experimental tests, data analysis, writing and editing the article, and all project costs. **Akbar Esmaeilzadeh (2)** (Associate Professor, Urmia University of Technology): shared contributions throughout the whole process and data analyses. **Reza Mikaeil (3)** (Assistant Professor, Urmia University of Technology): supervised the project and contributed to the writing and editing of the paper. **Solat Atalou (4)** (Assistant Professor, Islamic Azad University Ahar): reviewed and edited the paper.