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# Mine-to-crusher policy: Planning of mine blasting patterns for environmentally friendly and optimum fragmentation using Monte Carlo simulation-based multi-objective grey wolf optimization approach

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ABSTRACT

The quality of rock fragmentation intensively affects downstream operations and operational costs. Besides, Environmental side effects are inevitable due to mine blasting despite improvements in blasting consequences such as fly-rock and back-break. This study concentrates on optimizing mine blasting patterns for environmentally friendly mineral production and minimizing operational costs by achieving environmental-oriented and economic objectives-based on a new framework using artificial intelligence techniques. A gene expression programming (GEP) based on Monte Carlo simulations (MCs) denoted that rock size distribution can be modeled and predicted without any uncertainty. Four main objectives involving operational costs, back-break, fly-rock, and toe volume were highlighted for minimizing in the optimization framework. The multi-objective model was implemented by applying it to a running mine and solved using the grey wolf optimization algorithm. As optimizing, 17 optimal blasting plans were achieved to implement in the different rock types. The multi-objective model was able to reduce mine to crusher cost as well as undesirable blasting consequences considerable favourite of mining managers.

## 1. Introduction

The mining industry as an interdisciplinary activity exploited affordable minerals including gold, copper, coal, and others, in a challenging space through surface or underground mining. A set of mining operations, including drilling, blasting, loading, hauling, crushing, and grinding, are linked together to break rock mass into valuable minerals. All these steps are accompanied by energy and cost, in which the most consuming activity in terms of energy is the crushing and grinding in the world (Park and Kim, 2020).

Energy consumption of rock-breakage operation is about 30–60% of the total mine energy. Hence, energy consumption and mine productivity depend on these operations. Researchers are looking to improve each mining operation by improving rock-breakage during the blasting, crushing, and milling phase. The implementation of this activity has taken a toll on the mine-to-mill (MTM) that has been introduced to the world for over a decade. This concept was firstly tested by Julius Kruttschnitt Mineral Research Center (JKMRC) (Nielsen and Malvik, 1999). Many studies have focused on various aspects of the challenging MTM approach by examining the influence of mining operation, the energy consumption of milling, fragment rocks monitoring, and computer tools (software and hardware) associated with muck-pile fragmentation (Adel et al., 2005; Calibration, 2000; Jansen et al., 2009; Nageshwaraniyer et al., 2018; Valery et al., 2007; Willis, 2013; Xingwana, 2016).

The common goal of most studies is to improve the mill performance. Nevertheless, many researchers have studied the performance of other operations, such as drilling and blasting, which the investigating the performance of this operation is directly related to blast-induced rock fragmentation (Erkayaoglu and Dessureault, 2019). Park and Kim (2020) monitored the drilling operation in a mine to explore the rock fragmentation to implement the MTM optimization. They collected representative penetration rate data to investigate the effect of fragmentation on comminution energy consumption. Their obtained results showed that efficiency prediction models can be used to study the energy consumption and efficiency of crushing and grinding rock-breakage processes. Nageshwaraniyer et al.(2018) implemented the spectral imaging-based tracking way to present an economic analysis model to

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predict the cost savings incurred in the MTC process. They monitored a large-scale copper mine and used an ore tracking method. They concluded that the technique could accurately analyze rock fragmentation and improve mining economics. Erkayaoglu and Dessureault (2019) focused on data warehousing and data mining of MTM operations to improve the performance of drilling and blasting works. They monitored blasting operations using a data-driven framework and used a random forest and adaptive boosting algorithm to discover blasting parameters. They stated that this approach is capable to control and analyze the drilling and blasting operation in the implementation of the MTM concept. Grundstrom et al. (2001) monitored the drilling and blasting operations and analyzed the blast-induced rock fragmentation to investigate the fragmentation impact on the downstream operations, especially throughput of semi autogenous (sag) mill. They resulted that optimization of blasting and drilling operation is valuable way to improve the performance of downstream operations. They increased the sag mill throughput using fragment optimization. Jansen et al. (2009) tracked the ore fragment due to mine blasting to estimate the plant performance. They structured an MTC optimization for monitoring the concentrator and stockpile. They used radio-frequency identification (RFID) tracer technology to track coarser ores. Their achieved results indicated that metallurgists can accurately find out the size and grade of material by ore tracking. Zhang et al. (2020) presented an artificial intelligence technique for estimating capital cost of mining projects. They used the methahuristic optimization algorithms to increase model accuracy. In another study, Guo et al. (2021) developed an artificial neural network model to forecast capital cost in open-pit mining. They concluded that the artificial intelligence technique are applicable approach for predicting operational costs. Table 1 summarizes some of the mine-to-mill studies with their application in various sectors of the operations and downstream process and their relationships with mine-to-mill projects. As it can be found, the impact of the blasting work in mine-to-mill optimization has been highlighted as a critical factor in most studies.

The main aim of MTM is to increase the efficiency of the operations and improve energy consumption by optimizing the blasting activity. The reason is that after the bench blasting, a series of microcracks extended in the fragmented rocks, which causes a significant productivity increase and reduction in energy consumption of crushing and grinding (Michaux and Djordjevic, 2005). MTM projects focus on two main research: 1) optimizing the fragmentation due to blasting, and 2) monitoring and controlling fragmentation. The present study follows the first category and investigates the effect on downstream operations, mainly crushing, to blasting pattern optimization.

It should be noted that more than 80% of explosion energy is wasted due to adverse consequences, such as blast vibration, air blast, fly-rock, toe problem, back-break, dust dispersion, etc., and the rest is used effectively to fragment and displace the rock mass (Bakhtavar et al., 2021a; 2021b, Hosseini et al., 2022a). Particle size distribution (PSD) of rock fragmentation is one of the crucial components of blasting operation because this not only affects downstream operations' efficiency but also the cost required process variation (Bahrami et al., 2011). Notably, paying attention to a sustainable environment addresses solving blast-induced adverse consequences require significant spending ($). The mining activities have emphasized sustainable development issues by reducing and minimizing the environmental side effects from the operations based on green mining and climate-smart mining (Wang et al., 2021). These strategies are two eco-friendly policies to modify conventional mining practices. In Green mining strategy, the implement of green technologies enhances the environmental efficiency of a mine over its lifecycle (Jiskani et al., 2021a). However, Climate-smart mining strategy highlights a sustainable mineral supply chain to provide clean energy manufacturers while the footprint of climate pollution and material may be reduced (Jiskani et al., 2021b). In mining literature that emphasizes green and climate-smart practices, Jiskani et al. (2021a) follows a hybrid technique based on grey clustering and fuzzy analytical hierarchy process to highlighting green and climate-smart mining strategies. Identifying the pollutant agents due to coal mining was performed by Luo et al. (2021). Green and climate-smart mining in surface mines was addressed by Jiskani et al. (2022) using a combination framework based on fuzzy Delphi technique and fuzzy decision system.

In the literature of environmental side analysing, Hosseini et al. (2022b) addressed an fuzzy cognitive map (FCM)-based artificial neural network (ANN) for predicting flyrock induced by bench blasting in surface mines. They used reliability information to eliminate uncertainty in fly-rock prediction. Dehghani and Pourzafar (2021) developed a gene expression programming model to predict blast-induced fly-rock using 318 blasting data in the Sungun copper mine. They used the most influential parameters, such as burden, stemming, powder factor, spacing, and charge length in the model to optimize the blasting pattern using a cuckoo optimization algorithm to minimize fly-rock. Zhou et al. (2019) integrated an artificial neural network and particle swarm optimization to predict and optimize fly-rock due to bench blasting. Their ANN model predicted target with acceptable accuracy. They suggested a new blasting pattern and reduced the fly-rock by 34 m. Monjezi et al. (2012) attempted to predict blast-induced fly-rock and back-break in a surface mine using a new neuro-genetic model. Shirani Faradonbeh et al. (2015) developed a genetic programming (GP) model to predict back-break produced due to mine blasting using 175 blasting rounds. They used stemming, stiffness ratio, spacing, powder factor, and burden as parameters affecting back-break. Sadeghi et al. (2020) used an artificial neural network and decision tree to predict the toe volume due to bench blasting using 100 blasting data of a limestone mine. They considered six effective parameters including spacing, stemming, hole depth, burden, sub-drilling, and powder factor to develop the models. Then, they optimized the blasting pattern to minimize blast nuisances using imperialism competitive algorithm, which reduced the amount of toe to 288 $m^3$ (49.35% decrease). Numerous other scholars have also conducted studies concerning produced back-break and fly-rock due to mine blasting, which Table 2 is presented by reviewing their studies.

From the literature, it can be concluded that by utilizing artificial intelligent methods and metaheuristic algorithms, blasting patterns can be optimized and consequences can also be effectively controlled. Therefore, this study simultaneously considers the effect of blasting consequences, mine-to-crusher (MTC) costs, and the cost required for restitution for the damage caused due to blasting. In this research, rock fragmentation due to mine blasting is monitored during downstream operations. A gene expression programming (GEP) method as an intelligent approach is developed to predict the distribution of rock fragmentation. It is believed that this method is first time applied to model PSD due to mine blasting. Then, the effect of fragmentation on MTC processes is investigated to calculate the cost of these activities i.e., loading, hauling, crushing, secondary blasting, hydraulic hammer, bulldozing and grading, loader, secondary crushing, additional loading, additional hauling, and compensation due to blasting consequences (flyrock, backbreak, and toe problem). Here, the main goal is to determine the operational cost of a real surface mine. It should be noted, that blasting results in mines are associated with uncertainty; therefore, PSD simulation has also been performed to eliminate the uncertainties using the Monte Carlo simulation (MCs) technique. Then, a multiple nonlinear regression (MNLR) model was presented to model the MTC cots. To consider the blasting consequences and its costs, three important adverse consequences were measured, including toe volume, back-break and fly-rock. The Bayesian regularized neural networks (BRNN)-based model was developed to estimate the mentioned blast-induced consequences. Finally, a multi-objective optimization model was applied to simultaneously optimize the total MTC cost, back break, toe volume, and fly rock. To solve the model, a multi-objective grey wolf optimization algorithm (MOGWO) was also coded and implemented. As the MOGWO algorithm has the advantages of simplicity in principle, fast seeking speed, high search precision, and easy to realize, it is more easily combined with practical engineering problems. Therefore, this algorithm

**Table 1**
Mine to mill optimization studies.

| NO. | Reeference | Year | Drilling | Blasting | Mechanical crushing | Loading | Hauling | Crushing | Milling | Additional operations[a] | Environmental side effects[b] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Kanchibotla, S.S. et al. (1998) | 1998 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 2 | Eloranta, J. (1999) | 1999 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | |
| 3 | Kanchibotla, S.S. et al. (1999) | 1999 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 4 | Herbst, J.A. & Blust, S.L. (2000) | 2000 | | ✓ | | | | ✓ | ✓ | | |
| 5 | Grundstrom, C. et al. (2001) | 2001 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 6 | Paley, N. & Kojovic, T. (2001) | 2001 | ✓ | ✓ | | | | ✓ | ✓ | | |
| 7 | Eloranta, J. (2001) | 2001 | | ✓ | | | | ✓ | ✓ | | |
| 8 | Strohmayr, S. & Valery, W. (2001) | 2001 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 9 | Valery, W. et al. (2001) | 2001 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 10 | Scott, A. et al. (2002) | 2002 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| 11 | Valery, W. & Jankovic, A. (2002) | 2002 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 12 | Eloranta, J. (2003) | 2003 | ✓ | | | | | ✓ | ✓ | | |
| 13 | Kanchibotla, S.S. (2003) | 2003 | ✓ | ✓ | | | | ✓ | ✓ | | |
| 14 | Workman, L. & Eloranta, J. (2003) | 2003 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 15 | Kose, H. et al. (2005) | 2005 | | ✓ | ✓ | ✓ | ✓ | | | | |
| 16 | Palangio, T.W. et al. (2005) | 2005 | | ✓ | | ✓ | ✓ | ✓ | | | |
| 17 | Bye, A. (2006) | 2006 | ✓ | ✓ | | ✓ | | | ✓ | | |
| 18 | Adel, G. et al. (2006) | 2006 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 19 | Esen, S. et al. (2007) | 2007 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 20 | Dance, A. et al. (2007) | 2007 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 21 | Hikita, D.H. (2008) | 2008 | ✓ | ✓ | | | | ✓ | ✓ | | |
| 22 | Ndibalema, A. (2008) | 2008 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | |
| 23 | Mwansa, S. et al. (2010) | 2010 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 24 | Rybinski, E. et al. (2011) | 2011 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 25 | Choudhary, B.S. (2013) | 2012 | | ✓ | ✓ | ✓ | ✓ | | | | |
| 26 | Beyglou, A.H. (2012) | 2012 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| 27 | Schofield, N. et al. (2012) | 2012 | ✓ | | | | | | | | |
| 28 | Eloranta, J. (2013) | 2013 | ✓ | ✓ | | | | | ✓ | | |
| 29 | Taji, M. et al. (2013) | 2013 | ✓ | ✓ | | ✓ | | | | | |
| 30 | Schofield, N. et al. (2013) | 2013 | | | | | | | | | |
| 31 | Eloranta, J. (2014) | 2014 | ✓ | ✓ | ✓ | | | | ✓ | | |
| 32 | Nadolski, S. et al. (2014) | 2014 | | | ✓ | | | ✓ | ✓ | | |
| 33 | Carrasco, C. et al. (2016) | 2015 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 34 | Kanchibotla, S.S. et al. (2015) | 2015 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 35 | Silva, A.C. et al. (2015) | 2015 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 36 | Rosa, D.L. et al. (2015) | 2015 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 37 | Murr, D. et al. (2015) | 2015 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 38 | Ballantyne, G.R. et al. (2015) | 2015 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 39 | Perälä, A. et al. (2015) | 2015 | | | | ✓ | ✓ | ✓ | ✓ | | |
| 40 | Awuah-Offei, K. (2016) | 2016 | | | | ✓ | ✓ | | | | |
| 41 | Valery, W. et al. (2016) | 2016 | ✓ | ✓ | ✓ | | | | ✓ | | |
| 42 | Ebrahimi, E. et al. (2016) | 2016 | ✓ | ✓ | | ✓ | | ✓ | | | |
| 43 | Beyglou, A. et al. (2017) | 2017 | | ✓ | | ✓ | ✓ | ✓ | | | |
| 44 | Zhang, Z. (2017) | 2017 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 45 | Jug, J. et al. (2017) | 2017 | ✓ | ✓ | | | | ✓ | | | |
| 46 | Esen, S. (2017) | 2017 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 47 | Khademian and Bagherpour, 2017 | 2017 | | ✓ | ✓ | | | | | | |
| 48 | Kanchibotla, S.S. et al. (2018) | 2018 | ✓ | ✓ | ✓ | | | ✓ | ✓ | | |
| 49 | Nageshwaraniyer, S.S. et al. (2018) | 2018 | | ✓ | ✓ | | | ✓ | ✓ | | |
| 50 | Klein, B. et al. (2018) | 2018 | | | ✓ | | | ✓ | ✓ | | |
| 51 | Johnson, C. (2018) | 2018 | ✓ | ✓ | ✓ | | | | | | |
| 52 | Valery, W. et al. (2019) | 2019 | ✓ | ✓ | ✓ | | | | ✓ | | |
| 53 | Rafeeian, N. et al. (2019) | 2019 | | ✓ | | | | | | | |
| 54 | Zhang, Z.X. & Luukkanen, S. (2021) | 2021 | ✓ | ✓ | | | | ✓ | ✓ | | |
| 55 | Gyamfi, S. & Afum, BO. (2021) | 2021 | ✓ | | | | | | | | |
| 56 | Kinyua et al. (2022) | 2022 | | | | | | | ✓ | | |
| 57 | | 2022 | | | | | | | ✓ | | |

(continued on next page)

**Table 1** (*continued*)

| NO. | Reeference | Year | Drilling | Blasting | Mechanical crushing | Loading | Hauling | Crushing | Milling | Additional operations[a] | Environmental side effects[b] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Luukkanen, S. et al. (2022) | | | | | | | | | | |
| 58 | Faramarzi, F. et al. (2022a) | 2022 | ✓ | | | | | | | | |
| 59 | Faramarzi, F. et al. (2022b) | 2022 | | | | | | | ✓ | | |
| 60 | Smith, F. et al. (2022) | 2022 | | | | | | | ✓ | | |
| | Total | | 35 | 47 | 33 | 13 | 10 | 40 | 45 | 0 | 0 |
| | Current research | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ |

[a] Loading, hauling, loader, crushing, drilling and blasting.
[b] Back-break, flyrock, peak particle velocity, air-over pressure, dust emission, gas emission, and toe problem (in the case study back-break, flyrock, and toe problem were widest).

**Table 2**
A summary of the literature review in the field of environmental side effects.

| References | Year | Technique | Inputs | Output | Number of dataset | $R^2$ |
|---|---|---|---|---|---|---|
| Monjezi and Dehghani (2008) | 2008 | ANN | B, CLR, PF, S/B, ST/B, N | Back-break | 300 | – |
| Monjezi et al. (2009a) | 2009 | ANN | UCS, SD, WC, B, S, ST, D, BH, PF, Cd | Back-break | 97 | 0.9 |
| Monjezi et al. (2010b) | 2010 | FIS | B, S, ST, SD, PF, L, Cd, RD | Back-break | – | 0.95 |
| Monjezi et al. (2012) | 2012 | GA-ANN | D, L, B, S, ST, PF, SD, Cd, RMR | Back-break | 195 | 0.96 |
| Mohammadnejad et al. (2013) | 2013 | SVM | B, S, L, SD, ST, PF | Back-break | 193 | 0.92 |
| Sayadi et al. (2013) | 2013 | ANN | B, S, L, ST, PF, SD | Back-break | 103 | 0.87 |
| Monjezi et al. (2013) | 2013 | ANN | B, S, ST, N, PF, DPM, SD, RF | Back-break | – | 0.86 |
| Esmaeili et al. (2014) | 2014 | ANN, ANFIS | SR, ST, PF, RD, N, CLR, S/B | Back-break | 42 | ANN = 0.92<br>ANFIS=0.96 |
| Shirani Faradonbeh et al. (2015) | 2015 | GP | B, S, ST, PF, SR | Back-break | 175 | 0.98 |
| Ebrahimi et al. (2016) | 2016 | ANN | B, S, ST, L, PF | Back-break | 34 | 0.77 |
| Ebrahimi et al. (2016) | 2016 | ANN-ABC | B, S, ST, L, PF | Back-break | 34 | 0.77 |
| Monjezi et al. (2011) | 2011 | ANN-GA | B, S, ST, PF, SD | Flyrock | 234 | ANN-GA=0.933 |
| Monjezi et al. (2012) | 2012 | GA-ANN | D, L, B, S, ST, PF, SD, Cd, RMR | Flyrock | 195 | 0.98 |
| Amini et al. (2012) | 2012 | ANN, SVM | L, D, B, S, ST, PF, SD | Flyrock | 245 | ANN = 0.85<br>SVM = 0.94 |
| Ghasemi et al. (2012) | 2012 | MCs | B, S, ST, PF, MC, D, L | Flyrock | 150 | 0.834 |
| Khandelwal & Monjezi (2013) | 2013 | SVM | L, S, B, ST, PF, SD | Flyrock | 234 | 0.95 |
| Armaghani et al. (2014) | 2014 | ANN-PSO | D, L, Cd, S, B, ST, PF, RD, J, N | Flyrock | 44 | 0.93 |
| Trivedi et al. (2014) | 2014 | ANN | B, PF, ST, UCS, RQD | Flyrock | – | 0.98 |
| Ghasemi et al. (2014) | 2014 | ANN, FIS | B, S, ST, PF, Cd, L | Flyrock | 230 | ANN=0.935<br>FIS=0.955 |
| Armaghani et al. (2015) | 2015 | ANN, ANFIS | B, S, ST, PF, Cd | Flyrock | 166 | ANN=0.83<br>ANFIS=0.96 |
| Yari et al. (2016) | 2016 | ANN | B, S, ST, PF, SD, Cd, D, n | Flyrock | 334 | 0.97 |
| Saghatforoush et al. (2016) | 2016 | ANN-ACO | B, S, ST, PF, L | Flyrock | 97 | 0.99 |
| Faradonbeh et al. (2016) | 2016 | GP, GEP | B, S, L, ST, PF | Flyrock | 97 | GP=0.935<br>GEP=0.991 |
| Armaghani et al. (2016) | 2016 | MCs | B, S, L, ST, PF | Flyrock | 62 | 0.855 |
| Asl et al. (2018) | 2018 | ANN-FA | B, S, L, ST, PF | Flyrock | 200 | 0.93 |
| Hudaverdi & Akyildiz (2019) | 2019 | LMR | B, S, BH, PF, D, B/S | Flyrock | – | 0.843 |
| Monjezi et al. (2009b) | 2009 | FIS | B, S, ST, SD, PF, L, RD | Rock fragmentation | 415 | 0.96 |
| Monjezi et al. (2010b) | 2010 | ANN | D, L, B/S, ST, N, PF, MC | Rock fragmentation | 250 | 0.98 |
| Bahrami et al. (2011) | 2011 | ANN | B, S, ST, SD, PF, L, MC, BI, D | Rock fragmentation | 220 | 0.97 |
| Sayadi et al. (2013) | 2013 | ANN | B, S, L, SD, SC | Rock fragmentation | 103 | 0.85 |
| Karami & Afiuni-Zadeh (2013) | 2013 | ANFIS | B, PF, UCS, S/B, N, ST/B, MC | Rock fragmentation | 30 | 0.83 |
| Shams et al. (2015) | 2015 | FIS, LMR | B, S, D, PF, ST | Rock fragmentation | 185 | FIS=0.922<br>LMR=0.738 |
| Ebrahimi et al. (2016) | 2016 | ANN-ABC | B, S, ST, L, PF | Rock fragmentation | 34 | 0.78 |
| Hasanipanah et al. (2016) | 2016 | RES, NLMR | B, MC, PF, S/B, ST/B, H/B, N, D, B/D | Rock fragmentation | 52 | RES=0.866<br>NLMR=0.777 |
| Asl et al. (2018) | 2018 | ANN-FA | B, S, L, ST, PF | Rock fragmentation | 200 | 0.94 |

B: burden, S: spacing, ST: stemming, PF: powder factor, Cd: charge per delay, N: number of rows, J: sub drilling, L: hole depths, SD: specific drilling, SR: stiffness ratio, RD: rock density, BH: bench height, RF: rock factor, WC: water content, DPM: delay per meter, Q: linear charge concentration, CLR: last row charge per total charge ratio, D: hole diameter, RMR: rock mass rating, UCS: uniaxial compressive strength, n: number of holes, MC: mean charge per blast hole, BI: Blastability index, SC: specific charge, ANN: artificial neural network, FIS: fuzzy inference system, GA: genetic algorithm, SVM: support vector machine, ANFIS: adaptive neuro-fuzzy inference system, GP: genetic programming, ABC: artificial bee colony algorithm, MCs: Monte Carlo simulation, PSO: particle swarm optimization, ACO: ant colony optimization, GEP: gene expression programming, FA: firefly algorithm, LMR: linear multiple regression, NLMR: non-linear multiple regression, RES: rock engineering system.

was selected among a wide range of optimization algorithms.

The organisation of this study is as follows: Section 2 explains the main tools used in this research based on GEP, BRNN, MCs, and MOGWO. In Section 3, the theoretical frame of mining-to-crushing cost is investigated. Section 4 briefly introduces a real large-scale Pb–Zn mine. Section 4 presented the obtained results and discussion in a separate Sub-section. Finally, Section 6 addresses the conclusions.

## 2. Research methodology

This study focuses on multi-objective optimization to optimize the blasting patterns design parameters to obtain the minimum value of mine-to-crusher (MTC) costs as well as three adverse blasting consequences, such as toe volume, fly-rock, and back-break. To reach these goals, the required data was collected from a large-scale lead-zinc mine named Anguran. Fig. 1 highlights the research framework steps in detail.

### 2.1. *Particle size distribution processing*

Several ways have been introduced to predict rock fragmentation, such as uncontrollable techniques dependent on mechanical and physical characteristics of rocks and controllable methods based on design parameters, including measurement of fragmented rocks and size distribution prediction (Singh and Narendrula, 2010). Fig. 2 summarize the controllable and uncontrollable methods to predict the PSD. Direct and indirect methods are classified into a group of controllable methods. The base of the direct method is sieve analysis to calculate the fragmentation content, which has high accuracy but has not been applied recently due to cost and time-consuming (Sudhakar et al., 2006). Whereas indirect techniques, including empirical, visual, and image analysis methods, provide a trade-off between the test's accuracy and the time and cost value. Visual methods calculate the PSD with lower accuracy. Various experimental methods introduce different equations for predicting the PSD of the fragmented rocks. These methods do not provide the properties and geometries of the rock. However, they are used as the most effective and fastest ways to obtain blast-induced rock fragmentation (Lopez Jimeno et al., 1995; Siddiqui et al., 2009; Thornton et al., 2001). Notably, image analysis is the most accurate method in determining the PSD of the fragmented rocks. A commonly used image analysis software packages include Gold-Size, WipFrag, and Split-Desktop. The accurate value of PSD can be determined using the captured images from blast-induced fragmentation (Babaeian et al., 2019).

In recent years, the image analysis method has been widely implemented to predict blast-induced PSD as an acceptable-competence technique in mining operations. Thurley (2011) managed three-dimensional (3D) information related to rock fragmentation to

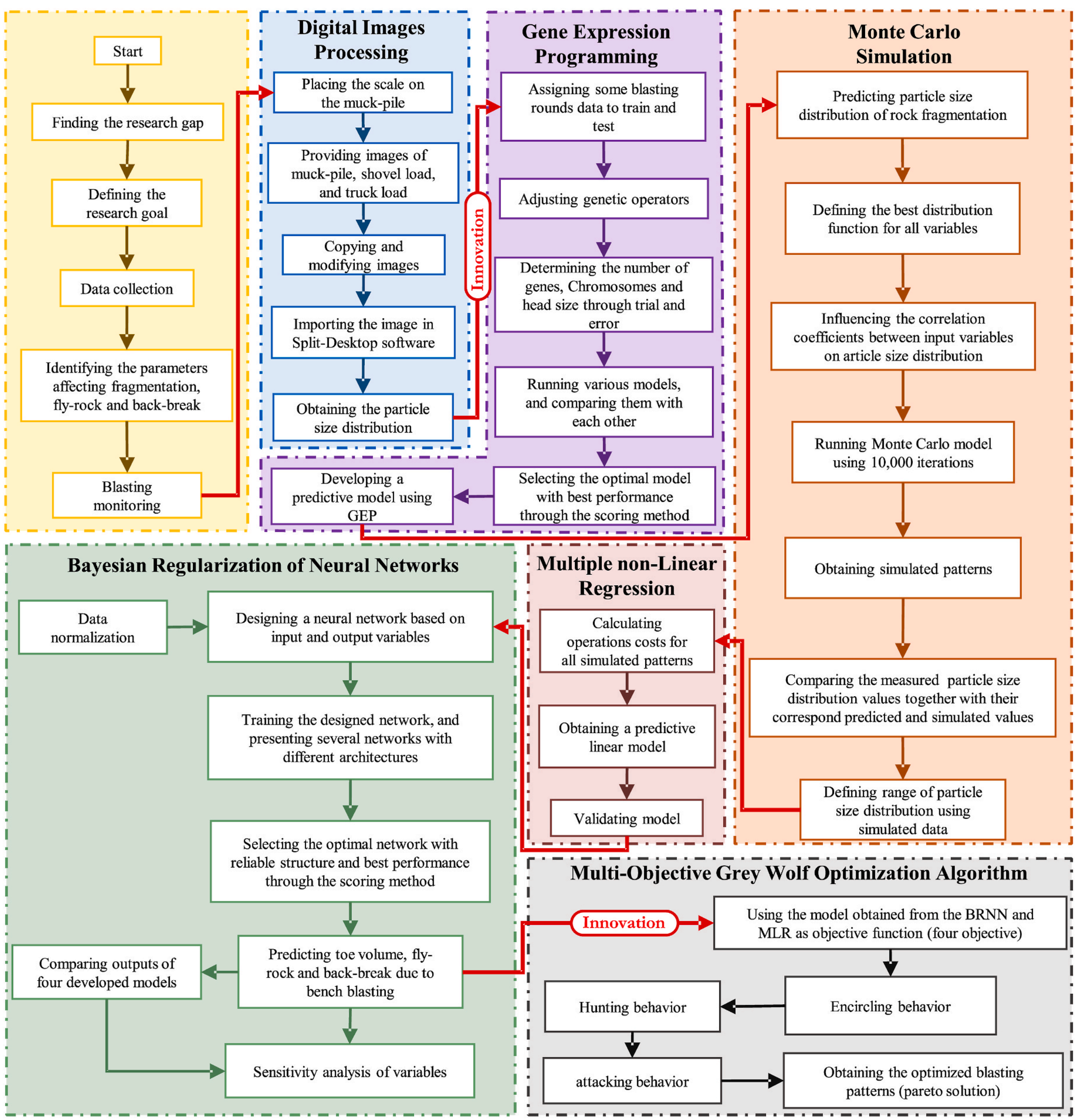


**Fig. 1.** A framework of research for MTC implementation.

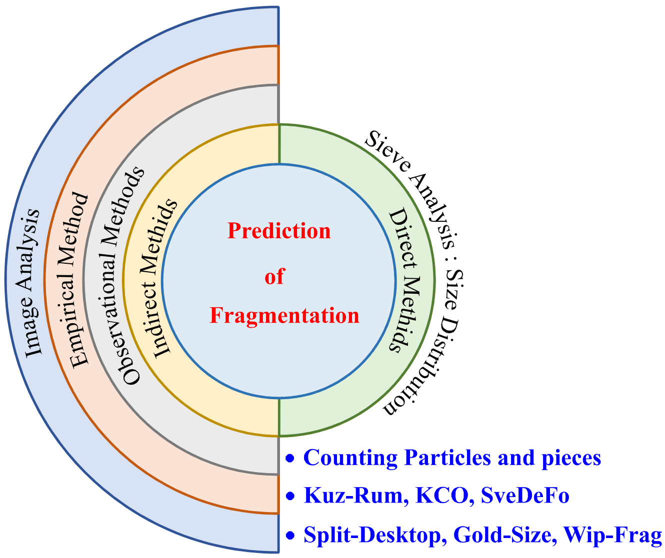


**Fig. 2.** Main methods of rock fragmentation prediction.

measure the granular particles of limestone on a conveyer belt to investigate and analyze the automatic control of the fragmentation process. Their results were developed concerning fragmentation quality and energy consumption efficiency. Al-Thyabat and Miles (2006) estimated the PSD due to blasting utilizing image analysis technique and watershed algorithm. Other researchers have been studied rock fragmentation due to bench blasting using Gold-Size software (Hosseini and Namvar, 2017), WipFrag software (Nanda and Pal, 2020) to compare the PSD of fragmentation using the mentioned software and experimental studies (Sereshki et al., 2016), and propose a novel fragmentation model through image processing (Tavakol Elahi and Hosseini, 2017).

### 2.2. Multi-objective grey wolf optimization

Multi-objective grey wolf optimization (MOGWO) algorithm as a new multi-objective evolutionary algorithm proposed by Mirjalili et al. (2016). This algorithm is known for fast convergence and easy implementation. MOGWO has been widely used in recent years and has shown excellent performance, which has made it more practical than the other similar algorithms. To defeat quickly falling into the local optimal and weak stability, a new solution for population initialization is proposed to improve the exploration of the initial population. Besides, to increase the strength of the algorithm, a nonlinear adjustment procedure of the control parameter is applied to improve the global exploitation. Notably, to circumvent the local optimum, an increased search approach is introduced to increase the exploration of the leaders.

In nature, Grey Wolves are classified into a group known as Canidae, and among them, are placed in the highest food chain (apex predators). This algorithm simulates the social leadership and group hunting of grey wolves (usually 5–12 wolves), which are divided into four main categories during hunting:

1) Alpha ($\alpha$) is the main leader of the group. The gender of the Alpha wolf can be both male and female, which is responsible for the final decisions of the group, and the rest of the members followed the commands. Given this fact, the Alpha wolf is also known as the prevailing wolf.
2) Beta ($\beta$) is the successor to the Alpha wolf and obeys the final commands to be implemented by other wolves.
3) Delta ($\delta$) is involved in several responsibilities, including charge hunting, and guarding.
4) Omega ($\omega$) completes the group and is responsible for maintaining the internal structure and hierarchy. These wolves have the lowest rank in the group.

There is an intense hierarchy among all categories. Notably, one of the essential parts of the life of grey wolves is their hunting method, which mathematical modeling of the GWO algorithm is developed based on them. The hunting of wolves includes three steps. 1) the First step of hunting is encircling behavior. Grey wolves surround the prey to hunt it, and this behavior can be mathematically simulated through Eqs. (1) and (2):

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}\cdot\vec{D} \tag{2}$$

where $\vec{A}$ and $\vec{D}$ are the coefficient vectors; $t$ is the current iteration; $\vec{X}_p$ indicates the position vectors of the prey; $\vec{X}$ is the current position vector of a grey wolf (Fig. 3). The vectors $\vec{A}$ and $\vec{C}$ are determined as follows:

$$\vec{A} = 2\vec{a}\cdot\vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2\cdot\vec{r}_2 \tag{4}$$

where $\vec{r}_1$, $\vec{r}_2$ are random vectors in [0,1], elements of $\vec{a}$ are linearly changed from 2 to 0, which is defined as:

$$\vec{a} = 2 - t\cdot\frac{2}{Iteration_{max}} \tag{5}$$

2) In the second step, hunting behavior is taken into consideration. The omega wolves update their positions according to higher-level grey wolves ($\alpha$, $\beta$, and $\delta$) as follows (Fig. 4):

$$\vec{D}_\alpha = \left|\vec{C}_1\vec{X}_\alpha(t) - \vec{X}(t)\right| \tag{6}$$

$$\vec{D}_\beta = \left|\vec{C}_2\vec{X}_\beta(t) - \vec{X}(t)\right| \tag{7}$$

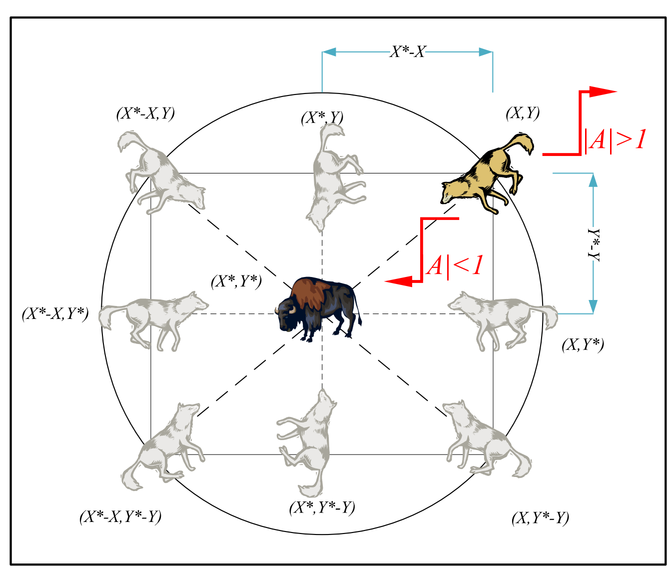


**Fig. 3.** Search agents position updating mechanism and effects of A on it (based on Mirjalili et al., 2016).

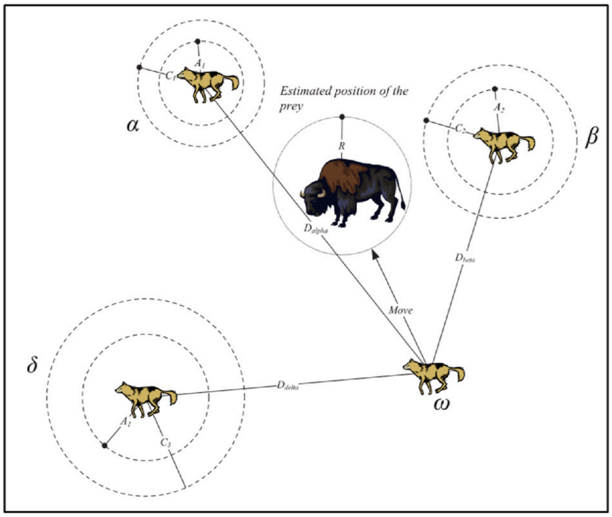


**Fig. 4.** The position update process of the grey wolf algorithm (based on Mirjalili et al., 2016).

$$\vec{D}_\delta = \left| \vec{C}_3 \vec{X}_\delta(t) - \vec{X}(t) \right| \tag{8}$$

$$\vec{D}_1 = \vec{X}_\alpha - \vec{A}_1 \left( \vec{D}_\alpha \right) \tag{9}$$

$$\vec{D}_2 = \vec{X}_\beta - \vec{A}_2 \left( \vec{D}_\beta \right) \tag{10}$$

$$\vec{D}_3 = \vec{X}_\delta - \vec{A}_3 \left( \vec{D}_\delta \right) \tag{11}$$

$$\vec{X}(t+1) = \left( \vec{X}_1 + \vec{X}_2 + \vec{X}_3 \right) \Big/ 3 \tag{12}$$

3) The third step of hunting is attacking behavior (the final hunting behavior). The main target of this behavior is to detect the optimized position of the prey. To this concept, the attacking behavior of the grey wolves is specified by the value of $|A|$. They can only attack the prey while $|A| \leq 1$. Therefore, the optimization of the GWO will be obtained when the criterion is attained.

## 3. Case Study and data collection

In this research, a large-scale lead and zinc mine namely Anguran was investigated. The Anguran mine is about 135 km southwest of Zanjan city (northwest Iran) and is located at an altitude of approximately 2950 m above sea level, in the Oroumieh-Poldokhtar zone and Zagros belt (Fig. 5). Exploiting operation of the Anguran open-pit mine practically has been started since 1940. In the Anguran, more than one

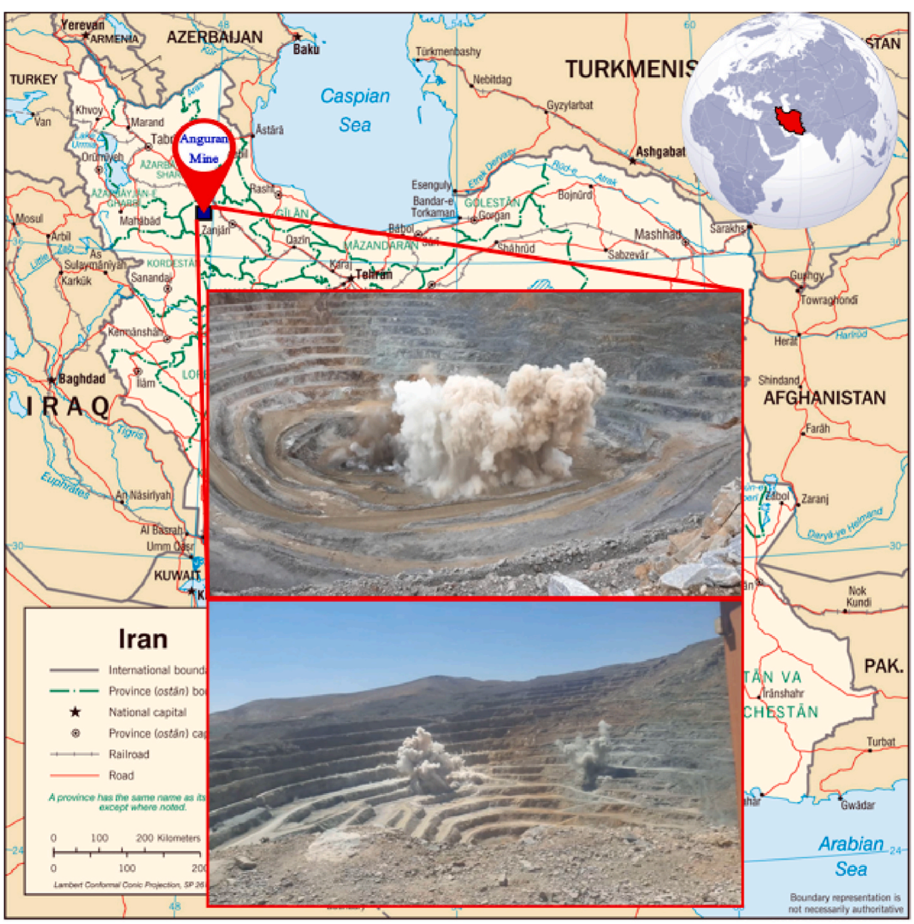


**Fig. 5.** Location of Anguran mine and bench blasting.

million tons of ore arebeing extracted annually. Therefore, this mine has been identified as one of the biggest and oldest Pb–Zn open-pit mines in the Middle East. The mine contains the zinc-lead ore resource of about 17.6 million tons (28.3% zinc and 4.4% lead).

Fragmentation measurements are a bit more complicated than other blasting consequences such as flyrock, backbreak, dust emission, and ground vibration. As mentioned in Section 1, the determination of PSD due to blasting was implemented using the digital image processing technique in this study. This method is superior compared to the traditional sieve analysis method due to its accuracy, rapidity, and economy. First, the muck-pile was carefully analyzed, and then a sufficient number of digital images of the rock fragmentation were taken from the blast site. It should be noted that the rocks on the surface of the muck-pile do not represent the PSD (Herbst and Blust, 2000). Hence, the rocks inside the truck and shovel bucket were also imaged to obtain a very accurate value for the rock size distribution. The 80 % passing size of rocks ($d_{80}$) represented the fragmentation quality. The quantity of $d_{80}$is one of the most essential and effective parameters determining the quality of haulage and efficiency of crushing operation; High equipment performance is directly related to lower the $d_{80}$. In this study, Split-Desktop version 4.0 was used to analyze digital images captured from the fragmented rocks to get the particle size distributions. The back-break, toe volume and fly-rock were accurately measured in the Anguran mine. The back-break causes severe damage to the pit walls. This problem is being seriously studied because there has been a huge failure (25 million tons rock slide) in pit slope mine 2006 (Fig. 6), making production planning difficult. Notably, fly-rock also makes a significant impact on the efficiency of loading and hauling operations.

The descriptive statistics of the input variables and objectives are tabulated in Table 3. A dataset of 1032 blasting works is collected to obtain an acceptable result.

Given that industrial activities are important to reduce operating costs, it is most important to compare them with other objectives. Therefore, operational cost related to each performed blasting pattern is calculated. Each operation including drilling, blasting, bench cleaning, loading, hauling, crushing, loader working, hydraulic hammer, secondary blasting, additional secondary crushing and the cost of compensating adverse consequences are considered in the cost

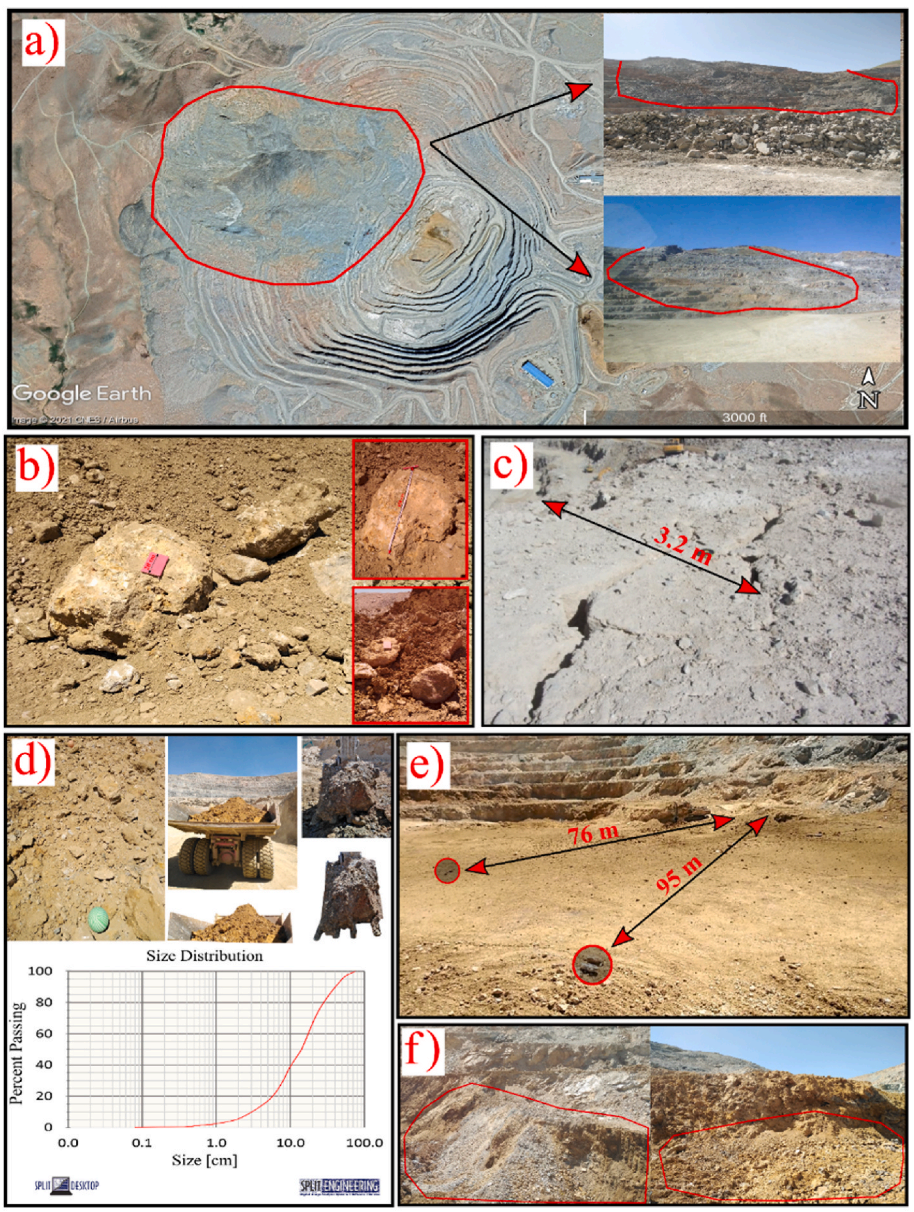


**Fig. 6.** a) Wall failure, b) boulders produced from blasting, c) back-break, d) fragmentation images and size distribution, e) fly-rock, and f) toe problem.

**Table 3**
Descriptive statistics of the measured effective parameters and targets.

| Parameters | Sign | | Unit | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|---|---|
| Inputs | Number of holes | n | – | 10.00 | 180.00 | 73.96 | 35.79 |
| | Hole length | L | m | 6.50 | 12.50 | 10.65 | 0.87 |
| | Burden | B | m | 3.80 | 4.20 | 4.13 | 0.11 |
| | Spacing | S | m | 4.80 | 5.00 | 4.95 | 0.08 |
| | Hole slope | HA | degree | 80.00 | 90.00 | 85.19 | 3.20 |
| | Stemming | St | m | 2.00 | 4.90 | 3.44 | 0.63 |
| | Blasted rock per hole | BRH | ton | 41.87 | 788.42 | 392.37 | 163.65 |
| | Powder factor | Pf | $Kg/m^3$ | 0.11 | 0.56 | 0.33 | 0.09 |
| | Charge per delay | CD | Kg | 55.36 | 274.61 | 165.42 | 41.25 |
| Targets | Fragmentation | $d_{80}$ | cm | 12.01 | 43.53 | 22.98 | 5.00 |
| | Back-break | BB | m | 2.5 | 9.5 | 5.84 | 0.86 |
| | Fly-rock | Fr | m | 59 | 329 | 114.5 | 17.71 |
| | Toe volume | TV | $m^3$ | 117.38 | 355.17 | 227.43 | 21.94 |

**Table 4**
Descriptive statistics of costs.

| Operations Cost | Notation | Unit | Min | Max | Ave | Std |
|---|---|---|---|---|---|---|
| Drilling | DC | $ per blast | 182 | 6062 | 1992 | 964 |
| Blasting | BC | $ per blast | 95 | 10913 | 2419 | 1360 |
| Loading | LC | $ per blast | 933 | 31703 | 10202 | 4951 |
| Hauling | HC | $ per blast | 2614 | 88850 | 28591 | 13875 |
| Crushing | CC | $ per blast | 0 | 176496 | 31308 | 37823 |
| Secondary Blasting | SBC | $ per blast | 0 | 64 | 25 | 7 |
| Hydraulic Hammer | HHC | $ per blast | 0 | 219 | 84 | 31 |
| Bulldozing and Grading | BC | $ per blast | 23 | 2088 | 105 | 103 |
| Loader | LC | $ per blast | 59 | 1031 | 222 | 91 |
| Secondary Crushing | SCC | $ per blast | 0 | 44124 | 8544 | 9615 |
| Additional Loading | ALC | $ per blast | 0 | 467 | 29 | 28 |
| Additional Hauling | AHC | $ per blast | 0 | 224 | 67 | 33 |
| Compensation | CC | $ per blast | 0 | 6774 | 347 | 415 |
| Total Cost[a] | TC | $ per blast | 5888 | 351785 | 83935 | 53209 |

[a] Summation of DC, BC, LC, HC, CC, SBC, HHC, BC, LC, SCC, ALC, AHC, an CC.

calculation. Descriptive statistics of MTC costs are reported in Table 4.

## 4. Result and discussion

In this section, obtained results of this study are presented.

### 4.1. GEP-based fragmentation model

A total of nine variables were employed which influence d80 based on the researchers' pre-investigations and available data. These parameters are the number of holes, hole length (m), burden (m), spacing (m), hole slope (degree), stemming (m), blasted rock per hole (ton), powder factor ($Kg/m^3$), and charge per delay (Kg). These variables are blasting pattern-related parameters that can be changed (controllable parameters).

The abovementioned parameters (collected from the blasting operations) and fragmentation database of the Anguran lead-zinc mine is entered into the organized GEP to estimate d80 utilizing the developed method. According to the notions introduced in GEP and general setting and genetic operators, a model for estimating d80 is developed in the present research. d80 is considered to be a function of the controllable blasting and uncontrollable parameters as below:

$$d_{80} = f(n, L, B, S, HA, St, BRH, Pf, CD) \tag{13}$$

where n, L, B, S, HA, St, BRH, Pf and CD are independent variables and d80 is a dependent variable.

Firstly, the data gathered from the Anguran mine involving 1032 blasting rounds, is divided into two principal divisions: training and validating part and approximately 723 datasets (70% of the whole datasets) were randomly selected and assigned to the training category of the model, and the rest (309 blasting data, 30 % of the dataset) was considered for the validating category of the GEP model. For this work, GeneXproTools 5.0, a powerful tool and one of the most famous software was used to find an appropriate mathematical equation.

Since several parameters have various influences on the performance and accuracy of the obtained model; hence, various GEP models were structured, and several evaluation indicators were implemented, including the coefficient of determination, root-mean-square error, mean absolute error, value account for, and accuracy denoted $R^2$, *RMSE*, *MAE*, *VAF*, and *Acc*, respectively. The mentioned statistical indices as models comparison were applied to determine the most desirable equation to predict $d_{80}$, which can be calculated from Eqs. (14)-(18), respectively (Hosseini et al., 2022a):

$$R^2 = 1 - \left( \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (P_i - \overline{P}_i)^2} \right) \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2} \tag{15}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |O_i - P_i| \tag{16}$$

$$VAF = 100 \cdot \left( 1 - \frac{var(O_i - P_i)}{var(O_i)} \right) \tag{17}$$

$$Acc = 100 - \frac{100}{n} \cdot \sum_{i}^{n} \frac{2 \times |O_i - P_i|}{|O_i| - |P_i|} \tag{18}$$

where $O_i$ and $P_i$ are measured and predicted values respectively, $\overline{P}_i$ is the average of the predicted values, and $n$ is the number of data sets.

Evaluation indices values of $R^2$, *RMSE*, *MAE*, *VAF*, and Acc were as (0.97, 0.7841, 0.0288, 97.639, 97.48156) and (0.981, 0.6335, 0.0644, 98.127, 97.67523) for training and validating part of model 1, respectively. The best chromosome was achieved, which relates to generation No. 2552. In Eqs. (19)-(25) obtained sub-ETs for six genes of model 1. The Obtained results revealed the development of a high-accuracy mathematical model that predicts the value of the d80 acceptable.

$$Gen1 = L + \left(\frac{HA + n + [n \cdot B]}{[B \cdot 84.9402]}\right)^2 \tag{19}$$

$$Gen2 = \frac{-7.4493 \cdot B - BRH \cdot (S - [-7.4493 \cdot L])}{BRH \cdot B \cdot St^3} \tag{20}$$

$$Gen3 = \frac{([-2.7268 \cdot n] - n - S + 8.0769) \cdot 9.9475}{-1339.8028} \tag{21}$$

$$Gen4 = \sqrt{n - Sin\left(\frac{41.7303 + [2 \cdot HA] + [48.8982]}{4.35}\right)} \tag{22}$$

$$Gen5 = [2 \cdot St] + Sin\left([2 \cdot B]^2 + Pf + B + 2.8827 + St\right) \tag{23}$$

$$Gen6 = -6.7457 + Sin(S) + St + \sqrt{CD} \tag{24}$$

$$d_{80} = Gen1 + Gen2 + Gen3 + Gen4 + Gen5 + Gen6 \tag{25}$$

### 4.2. Random-probabilistic model for fragmentation simulation

In this section, attention is paid to the uncertainty of the blasting results. MC simulation was used to solve the blast-induced rock fragmentation uncertainty. The implementation structure of MCs techniques is detailed in five main steps. First, the $d_{80}$ data and effective parameters (n, L, B, S, HA, St, BRH, Pf, and CD) were identified, and their values were collected from various benches with different geomechanical properties in at Anguran mine, and the initial analyses are completed for each.

Second, the best distribution functions were fitted for each input simulation through *@RISK* software as an MS-Excel plug-in feature. Table 5 listed the best probability distribution functions of all variables and their minimum and maximum values, which are assessed (stochastically) using continuous probability distribution (CPD).

Third, a predictive model that was developed utilizing the GEP method (Equation (19)–(25)) was imported into the simulation framework.

Fourth, the Spearman's rho correlation as consideration of relationships among input parameters was taken in the simulation process (Table 6), relationships between variables deeply affect the simulation results. As can be recorded in Table 6, a correlation among the independent variables is calculated, which, according to formulas, returned each independent variable as a function of the other. The correlation coefficient between the burden and spacing with a direct relationship is highest among another one, whereas the relationship between the hole slope and blasted rock per hole is the lowest of all.

Fifth, several simulations were performed to develop the MCs model and obtain a statistical representation for the amount of $d_{80}$ phenomenon through the Latin hypercube sampling method. This simulation was repeated up to 100,000 trials. Sixth, the $d_{80}$ ranges were achieved.

According to the statistical outcomes of the $d_{80}$ simulation applying MCs, the best distribution function attained from the results of 100,000 iterations is 'Inverse Gaussian,' given in Fig. 7.

Comparing actual and resulting values from the 'Inverse Gaussian' distribution function indicated that the data experienced a negligible difference; therefore, the probability distribution considered for the simulated quantities fits most appropriately. Furthermore, different percentages of the fragmentation were calculated in various ranges; The maximum, minimum, and average simulated values of $d_{80}$ are achieved as 49.409, 6.723, and 23.045, respectively. The attained outcomes reveal that with engineering confidence (95%), the values of d80 will not be less than 14.6 and not exceed 33.1 cm. Notably, the maximum d80 value is predicted more than approximately 44.89 cm, and the d80 chance to 1 chance in 100,000 or 0.01% of occurrence would be 44.89 cm.

**Table 5**
Best fitted probability distribution functions on input variables used in MC modeling.

| Model Input | Range | Best Distribution Function |
|---|---|---|
| n | 10-180 | BetaGeneral (2.2691, 5.7662, 6.6444, 245.14) |
| L | 6.5–12.5 | ExtvalueMin (10.984, 0.56598) |
| B | 3.8–4.2 | Triang (3.78064, 4.2, 4.2) |
| S | 4.8–5 | Triang (4.75407, 5, 5) |
| HA | 80-90 | Uniform (79.99, 90.01) |
| St | 2–4.9 | Triang (1.93, 3.1, 5.165) |
| BRH | 41.9–788.4 | Kumaraswamy (2.2005, 4.9359, 11.543, 954.79) |
| Pf | 0.11–0.56 | Dagum (0.08678, 0.3131, 8.7041, 0.3003) |
| CD | 55.4–274.6 | Weibull (4.6046, 181.77, RiskShift (−0.67122)) |

### 4.3. BRNN-based model for predicting the toe volume, back-break and fly-rock

BRNN is a type of artificial neural network in which the hidden nodes are stopping criteria to limit intricacy in modeling. As described in Sub-Section 3.3, too many or too few neurons can lead to problems in the learning process. Hence, we considered the range of 2–11 for the number of hidden nodes in BRNN architecture and the tenfold cross-validation resampling technique to avoid mentioned problems. Finally, various BRNN is designed with different architecture, and only one structure is selected as the best BRNN architecture. The obtained results indicated that the $R^2$ value were (0.983, 0.982, 0.979), (0.998,0.996,0.998), and (0.913,0.924,0.915) for training, validating and testing fly-rock, back-break, and toe volume model, respectively.

### 4.4. MOGWO for optimization of blasting operation

The developed MOP was organized with four objective functions developed precisely to minimize MTC costs, fly-rock, toe volume, and back-break simultaneously. Primary investigations showed that the blast-induced consequences caused different problems in the studied mine. As the mine suffered a huge failure (25 million tons rock slide) in 2006 and adversely impacted mining operations. Since the engineering team has been seriously seeking to reduce the consequences and elimination of additional costs to compensate for the damage caused. Therefore, the main goal of this project is to reduce MTC costs. However, the consequences due to mine blasting also create unintended costs. The BRNN related to BB, TV, and FR is used as an objective function. Nevertheless, the objective function of MTC cost is obtained based on MNLR is below:

$$\begin{aligned} MTC = & -145100431.95 - \left(1309032.95 \times L^2\right) + \left(62947086.81 \times B^2\right) \\ & + \left(16620759.58 \times S^2\right) + \left(0.32^{HA}\right) - \left(1757825396.48 \times \sqrt{St}\right) \\ & + \left(9.19 \times BRH^2\right) + \left(144317646.17 \times Pf^2\right) + \left(1339.99 \times CD^2\right) \\ & + \left(136061482.85 \times d_{80}\right) \end{aligned} \tag{26}$$

Hence, this section presents the results obtained by multi-objective optimization for simultaneous minimization of four objective functions TC, FR, TV, and BB presented in Section 5. The main parameters of MOGWO applied for this problem include the number of GreyWolves of 150, maximum iteration of 500, archive size of 85, $\alpha$ of 0.1, $\beta$ of 4, and $\delta$ of 2. Using these parameters, the MOGWO started finding the Pareto solutions in the space capsule, and MOGWO obtained numerous non-dominated solutions for MTC. The best of them have been tabulated in Table 7. Figs. 8 and 9 illustrate the 2D and 3D objectives front identified by MOGWO for the MTC in a search space.

According to results achieved by MOGWO, 17 non-dominant solutions for Anguran mine were obtained (Table 6). All the obtained solutions (patterns) can be implemented in the Anguran mine and each of them can be effective in reducing one or all of the effective objectives. Hence, optimal patterns were provided to the engineering team to

**Table 6**
Spearman's rho correlation of model inputs.

| | n | L | B | S | HA | St | BRH | Pf | CD |
|---|---|---|---|---|---|---|---|---|---|
| n | 1 | | | | | | | | |
| L | 0.075* | 1 | | | | | | | |
| B | −0.158** | −0.132** | 1 | | | | | | |
| S | −0.147** | −0.153** | 0.686** | 1 | | | | | |
| HA | 0.012 | 0.012 | 0.025 | −0.007 | 1 | | | | |
| St | 0.017 | 0.401** | −0.096** | −0.085** | 0.041 | 1 | | | |
| BRH | −0.151** | 0.461** | 0.031 | 0.029 | 0.008 | 0.361** | 1 | | |
| Pf | −0.246** | 0.118** | −0.047 | −0.011 | −0.021 | −0.033 | 0.489** | 1 | |
| CD | 0.165** | 0.166** | −0.261** | −0.251** | −0.027 | −0.263** | 0.125** | 0.388** | 1 |

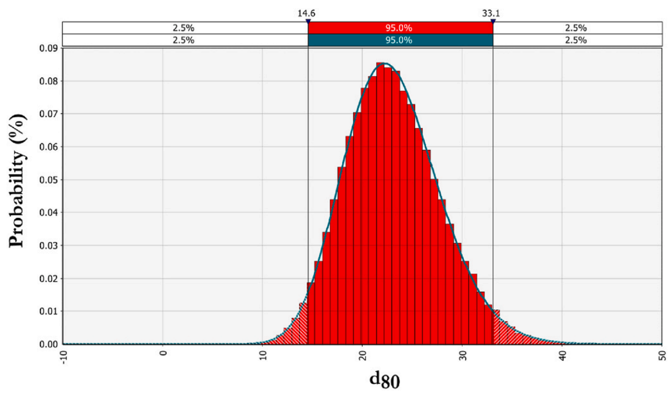


**Fig. 7.** Best distribution functions of $d_{80}$ using MC.

decide on them to implement the appropriate patterns. For example, the engineering team may conclude performing a pattern with the simultaneously minimum fly-rock and back-break, therefore, solution #4 is the best pattern, while still, costs are acceptable. The cost of implementing this pattern from the phase of drilling to crushing is equal to 55235 $ per blast, which is very reasonable compared to its average value (83935 $ per blast).

## 5. Conclusions

Mine blast-induced distribution of rock fragmentation as one of the desirable blast outcomes has effect significantly on downstream operations costs of the mining industry. Rock blasting has resulted in several desirable outcomes such as fly-rock, toe problem, and back-break outcoming significant destructive effects on the ecosystem and surrounding environments. An economic-oriented policy of rock fragmentation can reduce the additional costs due to undesirable rock fragmentation on blast downstream operations. Furthermore, an environment-oriented plan of undesirable blasting consequences is capable of decreasing the adverse impacts of fly-rock, toe problems, and back-break on the environment and mine area.

Due to the lack of a policy to solve the problem of simultaneously minimizing operational mining costs as well as an adverse environmental side related to mine blasting from an economical and environmentally viewpoint, the current research structured a multi-objective policy based on gene expression programming, artificial neural networks, and multi-objective grey wolf optimization algorithm. Based on obtained results, the flyrock model yielded a $R^2$ value of 0.983 and this value were 0.998 and 0.913 for back-break and toe volume, respectively. In can be concluded that the artificial intelligence technique is accurately capable of model environmental side effects. Moreover, the GEP model attained the $R^2$ of 0.97 in the modeling rock fragmentation produced by bench blasting. The developed model proposed the Pareto set associated with an optimum blasting plan, minimizes blasting downstream operations (from mine to crusher) and undesirable blasting consequences. The remarkable advantages of the model are its soft computing base, its multi-objective base using metaheuristic algorithms, and considering uncertainties in the blast-induced rock size distribution using simulation levels of Monte Carlo. Based on these advantages, the

**Table 7**
Obtained results from MOGWO step of the methodology.

| Solutions | Parameters | | | | | | Objectives | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | L | B | S | HA | St | CD | TC | Fr | BB | TV |
| 1 | 11.4 | 3.0 | 4.4 | 85.0 | 1.6 | 121.0 | 50193.6 | 45.5 | 1.1 | 180.6 |
| 2 | 10.8 | 3.0 | 4.3 | 85.0 | 1.6 | 123.5 | 50802.0 | 42.7 | 0.9 | 182.7 |
| 3 | 12.4 | 3.1 | 5.2 | 85.0 | 1.7 | 132.0 | 54429.6 | 63.4 | 2.6 | 164.4 |
| 4 | 10.8 | 3.0 | 4.5 | 87.2 | 1.6 | 121.9 | 55234.7 | 45.0 | 1.0 | 178.6 |
| 5 | 11.1 | 3.1 | 5.0 | 85.0 | 1.6 | 122.3 | 54124.9 | 55.7 | 1.9 | 168.7 |
| 6 | 10.9 | 3.0 | 4.7 | 85.7 | 1.6 | 141.3 | 53416.6 | 51.8 | 1.6 | 174.0 |
| 7 | 10.8 | 3.1 | 5.1 | 85.0 | 1.7 | 124.5 | 54836.8 | 61.4 | 2.3 | 166.9 |
| 8 | 11.4 | 3.1 | 5.1 | 85.1 | 1.7 | 123.1 | 55229.0 | 59.2 | 2.2 | 166.2 |
| 9 | 12.9 | 3.1 | 4.8 | 85.8 | 1.7 | 142.9 | 55140.7 | 54.8 | 1.8 | 171.6 |
| 10 | 11.6 | 3.0 | 5.4 | 85.0 | 1.6 | 128.7 | 55350.2 | 61.9 | 2.5 | 160.9 |
| 11 | 13.1 | 4.9 | 6.0 | 88.7 | 2.1 | 139.1 | 97822.9 | 136.0 | 7.9 | 141.5 |
| 12 | 12.8 | 4.9 | 6.0 | 89.9 | 2.1 | 156.1 | 99303.9 | 133.2 | 7.8 | 141.6 |
| 13 | 13.0 | 4.7 | 6.0 | 87.7 | 2.1 | 138.6 | 92283.7 | 130.9 | 7.6 | 142.1 |
| 14 | 12.7 | 3.2 | 5.8 | 86.0 | 1.7 | 166.4 | 63529.8 | 69.9. | 3.5 | 152.0 |
| 15 | 13.2 | 4.7 | 6.0 | 88.1 | 2.1 | 136.7 | 92597.0 | 130.8 | 7.6 | 142.2 |
| 16 | 13.4 | 4.8 | 6.0 | 88.3 | 2.1 | 197.9 | 94895.6 | 134.6 | 7.8 | 141.8 |
| 17 | 13.4 | 4.7 | 6.0 | 87.1 | 2.1 | 207.7 | 91044.3 | 131.8 | 7.6 | 142.1 |
| Original mean value | 10.6 | 4.1 | 4.9 | 85.2 | 3.4 | 165.4 | 83934.7 | 114.5 | 5.84 | 170.52 |
| Optimized mean value | 9.9 | 3.7 | 5.3 | 86.5 | 1.8 | 128.4 | 68837.4 | 82.9 | 4.0 | 159.9 |
| Difference (%) | 7.4 | 11.1 | 7.3 | 1.5 | 47.5 | 22.3 | 18.0 | 27.6 | 31.8 | 6.2 |
| | Dec | Dec | Inc | Inc | Dec | Dec | Dec | Dec | Dec | Dec |

Dec: Decrement, Inc: Increment

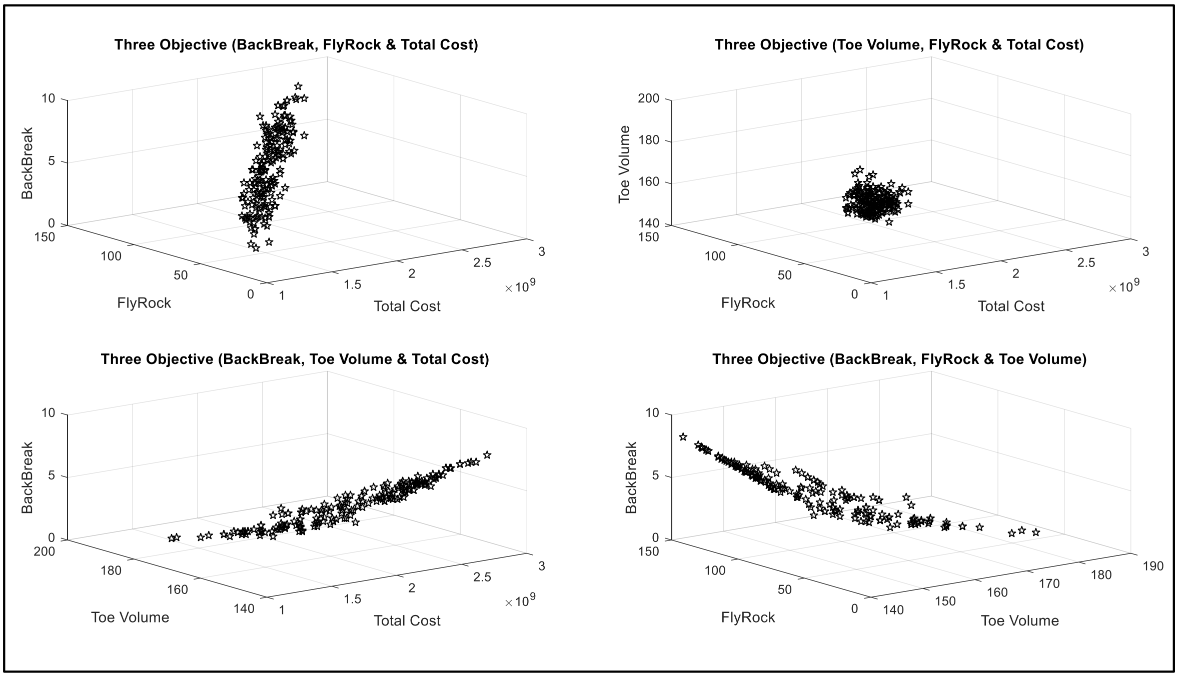


**Fig. 8.** 3D objective front with respect to MOGWO algorithm for MTC: (TC, FR, BB), (TC, TV, BB), (TC, FR, TV), and (TP, FR, BB) fronts.

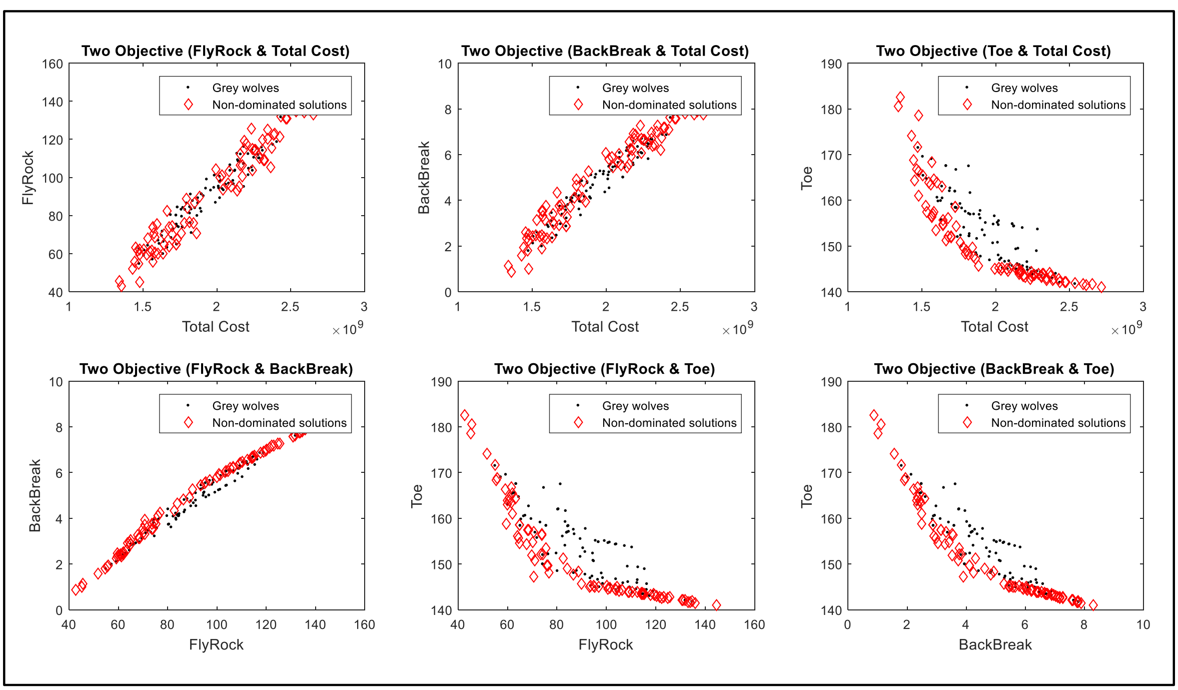


**Fig. 9.** 2D objective front with respect to MOGWO algorithm for MTC: (TC, FR), (TC, BB), (TC, TP), (FR, BB), (FR, TP), and (BB, TP) fronts.

model is capable of considering actual circumstances, which can yield the best achievable plan. The literature did not consider the objective of "environmental side effects due to mine blasting," despite its essential effect on the ecosystem and additional costs, but instead examined only economic issues and the impact of rock fragmentation on downstream operations separately. For future directions, it is recommended to consider milling cost in the calculations process and to import geo-mechanical properties in the developed cost function. The proposed framework can be applied in mining engineering fields, where fragmentation is undesirable and incurs a lot of costs to the project. As the current study faced some limitations, the two main further works are recommended. First, the operations considered can be expanded to milling process in the to include a more comprehensive cost data with more monitored operations. Second, other consequences due to bench blasting should be measured and considered in the optimization process to increase the correspondence of the results with the real-world problems.

## Author statement

**Shahab Hosseini**: Writing - Original Draft, Visualization, Software, Formal analysis **Amin Mousavi**: Conceptualization, Methodology,

Supervision, Writing - Review & Editing **Masoud Monjezi**: Methodology, Writing - Review & Editing, Supervision. **Manoj Khandelwal**: Writing- Reviewing and Editing, Conceptualization.

## Declaration of competing interest

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

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