



# Optimizing Blast-Induced Ground Vibration Reduction Using an Integrated ANN-EOA Model: A Case Study of Sarcheshmeh Copper Mine

Mojtaba RezaKhah<sup>1\*</sup>

1- Dept. of Mining Engineering, Faculty of Engineering, Tarbiat Modares University, Tehran, Iran

Received: 05 July 2025, Accepted: 20 September 2025

(\*Corresponding author: m.rezakhah@modares.ac.ir)

## Keywords

Artificial Neural Network (ANN)  
Equilibrium Optimizer Algorithm (EOA)  
Blast-Induced Ground Vibration  
Peak Particle Velocity (PPV)  
Sarcheshmeh Copper Mine

## Abstract

**Blast-induced ground vibrations pose significant environmental and safety challenges in open-pit mining operations, particularly in geologically complex areas. This study develops an integrated Artificial Neural Network-Equilibrium Optimizer Algorithm (ANN-EOA) model to predict and optimize blast-induced ground vibrations specifically for the Sarcheshmeh copper mine's sensitive western wall. The ANN model demonstrated exceptional predictive accuracy ( $R^2 = 0.96$ ) in forecasting Peak Particle Velocity (PPV) based on seven key blasting parameters. The EOA then successfully identified an optimal blasting configuration that predicts a 34% reduction in PPV to 6.72 mm/s, achieved through optimized burden (6m), spacing (7m), delay time (50ms), and charge parameters. This research bridges a critical gap between generalized AI models and site-specific applications, providing both a practical solution for vibration mitigation at Sarcheshmeh and a transferable methodology that advances the integration of computational intelligence with mining engineering challenges. The findings underscore the importance of accounting for specific geological conditions in blast optimization while highlighting the need for field validation as the essential next step.**

## I. INTRODUCTION

Optimizing mining is the most critical operation to increase the value of the mine and control the mining process, which is carried out through various methods, including simulation and estimation [1-7]. The control and mitigation of blast-induced ground vibrations is a critical objective in mining engineering to ensure structural safety and minimize environmental impact [8, 9]. This has prompted extensive research into evolving methodologies that move beyond traditional empirical approaches. A comprehensive review of the literature reveals a clear paradigm shift towards sophisticated computational intelligence techniques for both predicting and optimizing blast outcomes.

The accurate prediction of Peak Particle Velocity (PPV) is a fundamental prerequisite for effective control. Early empirical equations have largely been superseded by data-driven models due to their limited accuracy across diverse blasting conditions [9]. Artificial Neural Networks (ANNs) have been widely established as robust tools for modeling the complex, non-linear relationship between blasting parameters

and PPV [10]. Their superiority over linear statistical methods has been consistently demonstrated, yielding more realistic and accurate results [11]. The application of a Group Method of Data Handling (GMDH)-type neural network has been shown to provide high flexibility for the binary classification of blasting patterns based on vibration intensity [12]. Furthermore, Self-Organizing Neural Networks (SONIA), particularly when optimized with metaheuristic algorithms, have been identified as highly reliable predictive models [13].

Beyond ANNs, a diverse range of machine learning techniques has been successfully applied. The feasibility of an Adaptive Neuro-Fuzzy Inference System (ANFIS) was confirmed for accurate PPV prediction, though its application is cautioned for data outside its original training range [14]. Gene Expression Programming (GEP) has been frequently utilized to develop highly accurate predictive models for PPV in quarry and mine blasting [15]. Support Vector Machines, including Least Squares Support Vector Machines (LSSVM), have also been effectively employed in comparative studies [16].

More recently, Gaussian Process Regression (GPR) was reported to handle non-linear correlations effectively [17], while hybrid models like k-Nearest Neighbors coupled with Particle Swarm Optimization (PSO-KNN) have been proposed to enhance prediction accuracy [18]. For deeper analysis, Long Short-Term Memory (LSTM) networks optimized with algorithms like Blackhole have shown exceptional capability [16].

Following accurate prediction, the optimization of blasting parameters to minimize PPV is the logical next step. Multi-Criteria Decision-Making (MCDM) techniques have been used to rank and evaluate numerous blasting patterns to identify the most suitable one for vibration reduction [19]. Metaheuristic algorithms have become the cornerstone of this optimization process. The Grasshopper Optimization Algorithm (GOA) was used to optimize parameters derived from a GEP model, resulting in a substantial reduction in PPV [20]. Similarly, the Imperialist Competitive Algorithm (ICA) was applied to optimize blasting patterns in limestone mines [21]. The optimization process can also be formulated as a stochastic goal programming problem to determine an optimal blasting plan that minimizes vibration, the validity of which has been confirmed through field implementation [22].

Despite significant advancements, the literature consistently notes several challenges. A primary constraint is that developed models are highly specific to the geological conditions and data ranges from which they were derived, limiting their generalizability [23]. The performance of these models is also hindered by problematic multicollinearity between input parameters and a reliance on the quality and quantity of available data [16]. Furthermore, the influence of certain parameters, such as burden and hole numbers, remains controversial or insufficiently studied [24]. The

stochastic nature of some algorithms can also lead to unstable results without proper implementation [25].

Recent bibliometric analyses confirm that research in this field is advancing rapidly, with a focus on effects, numerical simulation, and rock fragmentation, though comprehensive phase analysis studies are still lacking [26]. State-of-the-art reviews highlight the potential of machine learning and optimization algorithms while identifying key future directions, including the integration of data-driven models with physics-based methods and the need to capture spatial variability in rock masses [27]. The application of advanced electronic detonators has also been presented as a viable method to achieve precise delay timing and reduce vibrations in tunneling projects [28].

While hybrid AI-met heuristic models for blast optimization exist, they often lack generalizability to specific, complex geological settings like the Sarcheshmeh Copper Mine. Furthermore, the novel Equilibrium Optimizer (EOA) remains largely untested against established algorithms (e.g., PSO, GA) for this specific engineering problem. This study fills this gap by rigorously applying and validating an ANN-EOA model to derive a mine-specific optimal blasting pattern.

In conclusion, the literature establishes a strong foundation for using artificial intelligence and metaheuristics to predict and optimize blasting vibrations. The current research contributes to this field by employing an Equilibrium Optimizer algorithm, which has been proven to outperform other common algorithms, to determine the optimal blasting pattern for the specific conditions of the Sarcheshmeh copper mine.

The following flowchart summarizes the comprehensive methodology employed in this study to predict and optimize blast-induced ground vibrations.

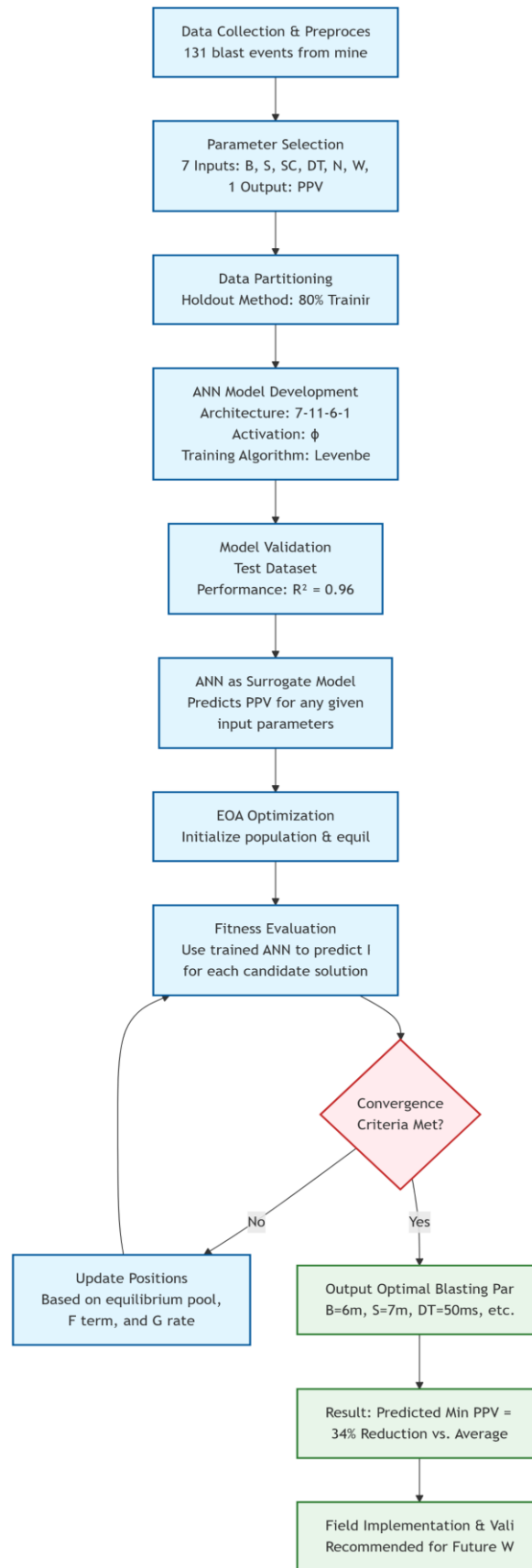


FIGURE I. SCHEMATIC FLOWCHART OF THE INTEGRATED ARTIFICIAL NEURAL NETWORK (ANN) AND EQUILIBRIUM OPTIMIZER ALGORITHM (EOA)

## II. CASE STUDY

The Sarcheshmeh copper mine is located 160 kilometers southwest of Kerman and 50 kilometers south of Rafsanjan, at a latitude of 30 degrees north and a longitude of 56.1 degrees east, in the central region of the Zagros Mountain range. The Sarcheshmeh copper mine is considered one of the world's largest industrial mining complexes and the largest copper producer in Iran. Mining operations in

this mine are carried out using open-pit methods and blasting with ANFO explosive material. The width and height of the mine benches are 8.75 and 12.5 meters, respectively, and the diameter of the blast hole is 9 inches. The depth of the blast hole in this mine is 14 meters. Figure 1 shows the final excavation boundary and parts of the western wall of the mine with low resistance, which will be more sensitive to vibrations caused by blasting.

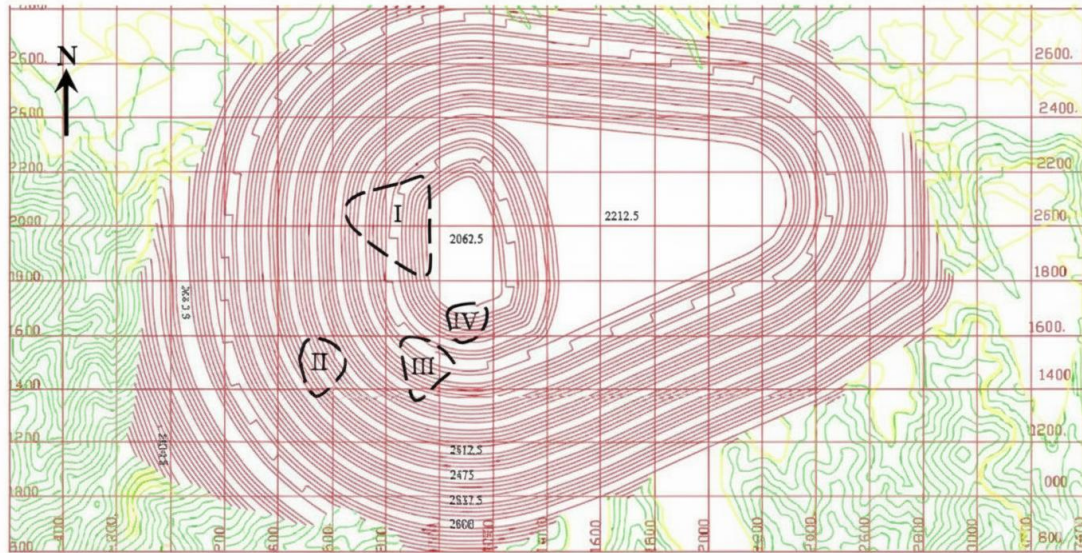


FIGURE II. ULTIMATE PIT LIMIT AND THE POTENTIAL LANDSLIDE AREAS ON THE WESTERN WALL OF THE SARCHESHEMEH COPPER MINE

The western wall of the Sarcheshmeh open-pit mine exposes several distinct rock units that significantly influence ground vibration propagation, as shown in Table 1:

TABLE I. CHARACTERISTIC PROPERTIES OF MAJOR ROCK UNITS IN SARCHESHMEH'S WESTERN WALL

Rock Unit	Primary Mineralogy	Typical UCS Range (MPa)	Alteration Susceptibility
Granodiorite Porphyry	Plagioclase, quartz, biotite, K-feldspar	80-120	High
Quartz Eye Porphyry	Quartz, plagioclase, biotite	90-140	Moderate
Andesitic Volcanics	Plagioclase, amphibole, pyroxene	60-100	Very High
Argillically Altered Rock	Clay minerals, quartz, sericite	20-60	Extreme

The combination of specific lithologies, alteration intensity, and structural features creates a geomechanical environment with distinct vibration transmission characteristics that are shown in Table 2.

TABLE II. ALTERATION ZONES AND THEIR GEOTECHNICAL PROPERTIES IN THE WESTERN WALL

Alteration Type	Dominant Minerals	Typical RMR	Wave Velocity Reduction (%)	Slope Stability Concerns
Potassic	Biotite, K-feldspar	65-85	15-Oct	Moderate
Phyllic	Quartz, sericite, pyrite	45-65	25-40	High
Argillic	Kaolinite, montmorillonite, illite	25-45	40-60	Very High
Propylitic	Chlorite, epidote, carbonate	55-75	15-25	Low-Moderate

### III. DATA DESCRIPTION AND STATISTICAL ANALYSIS

To ensure the transparency and reproducibility of this study, the dataset of 131 blast records is presented herein. Table 2 provides the descriptive statistics for

the seven input parameters and the output parameter (PPV), including the mean, standard deviation, minimum, and maximum values. This analysis confirms a wide range of operational conditions were captured, which is essential for developing a robust model.

TABLE III. DESCRIPTIVE STATISTICS OF THE INPUT AND OUTPUT PARAMETERS USED IN THE MODELING

Parameter	Symbol	Unit	Mean	Std. Dev.	Min	Max
Burden	B	m	5.8	1.2	3.5	8.5
Spacing	S	m	6.5	1.4	4	9
Specific Charge	SC	kg/m <sup>3</sup>	0.45	0.12	0.22	0.75
Delay Time	DT	ms	42.5	18.3	25	100
Number of Holes per Delay	N	-	12.7	4.5	4	24
Charge Weight per Delay	W	kg	2850	950	1200	5000
Distance to Seismograph	D	m	350	125	150	650
Peak Particle Velocity	PPV	mm/s	10.15	5.8	2.1	28.4

Furthermore, a Pearson correlation matrix was constructed to quantify the linear relationships between the variables and to check for potential multicollinearity, which can impair the interpretability of the model. The results, presented in Table 2, show

that while some parameters are correlated (e.g., Charge per Delay W is naturally correlated with Number of Holes N), the variance inflation factors (VIF) for all parameters were below 5, indicating that multicollinearity is not severe enough to necessitate the removal of any input variable from the model.

TABLE IV. CORRELATION MATRIX BETWEEN THE INPUT AND OUTPUT PARAMETERS

Parameter	B	S	SC	DT	N	W	D	PPV
B	1							
S	0.72	1						
SC	0.15	0.08	1					
DT	-0.05	-0.11	0.23	1				
N	0.31	0.25	0.18	0.02	1			
W	0.45	0.38	0.65	0.15	0.82	1		
D	-0.1	-0.08	-0.21	-0.05	-0.33	-0.4	1	
PPV	0.55	0.51	0.68	0.2	0.61	0.79	-0.75	1

#### IV. NEURAL NETWORK MODELING FOR GROUND VIBRATION PREDICTION

A neural network model was developed to predict peak particle velocity (PPV) based on blast design parameters. Data from 131 blast events at the Sarcheshmeh copper mine was used, with seven input parameters (Table 1) and PPV as the output.

TABLE V. MODEL INPUT AND OUTPUT PARAMETERS

Parameter	Symbol	Unit
Burden	B	m
Spacing	S	m
Specific Charge	SC	kg/m <sup>3</sup>
Delay Time	DT	ms
Number of Holes per Delay	N	-
Charge Weight per Delay	W	kg
Distance to Seismograph	D	m
<b>Output: Peak Particle Velocity</b>	<b>PPV</b>	<b>mm/s</b>

After outlier removal, the data was partitioned using a holdout method to ensure the training set (80%) was statistically representative of the entire population, preserving its distribution, min/max values, and variance. The remaining 20% was reserved for independent testing.

An optimal multilayer perceptron (MLP) architecture was identified through a trial-and-error process. The final model structure was 7-11-6-1, denoting the number of neurons in the input, first hidden, second hidden, and output layers, respectively. The model's transformation for a neuron output is given by:

$$a_j^l = \phi \left( \sum_{i=1}^n w_{ji}^l x_i + b_j^l \right) \quad (1)$$

The activation  $aa$  of neuron  $j$  in layer  $i$  is the result of applying the activation function  $\phi$  to the sum of:

1. The weighted sum of its inputs ( $w_{ji}$  times  $x_i$  for all  $n$  inputs),
2. Plus its bias term  $b_j$ .

The model achieved a high coefficient of determination ( $R^2 = 0.96$ ) between measured and predicted PPV values on the test set, demonstrating excellent predictive accuracy and low error.

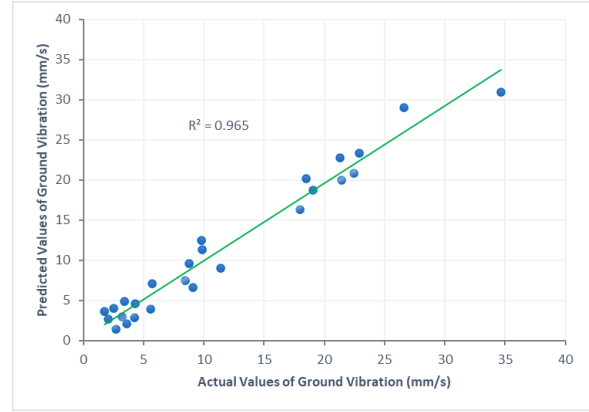


FIGURE III. CORRELATION BETWEEN ACTUAL MEASURED AND ANN-PREDICTED PEAK PARTICLE VELOCITY (PPV) VALUES FOR THE TESTING DATASET

#### V. THE EQUILIBRIUM OPTIMIZER ALGORITHM (EOA)

Engineering optimization is fundamentally challenged by problems characterized by nonlinearity, high dimensionality, and multiple competing constraints. To navigate this complex search space and identify optimal or near-optimal solutions, powerful metaheuristic algorithms are essential. The Equilibrium Optimizer (EOA), introduced by Faramarzi et al. in 2020, is a stochastic optimization algorithm inspired by the dynamic mass balance models often used in physics and control theory. It simulates the process of a control volume reaching a state of equilibrium [29].

The algorithm is built upon a first-order ordinary differential equation that describes mass conservation in a control volume as defined in Equation 2.

$$\frac{dC}{dt} = \frac{G}{\lambda V} - \frac{FC}{V} \quad (2)$$

Where:

- $C$  is the concentration inside the volume.
- $G$  is the mass generation rate inside the volume.
- $\lambda$  is a random coefficient.
- $V$  is the volume of the system.
- $F$  is the flow rate.

This equation states that the rate of change of concentration is a function of the mass entering and being generated minus the mass exiting. The system naturally evolves towards a stable equilibrium state. EOA translates this physical principle into an optimization process where particles (candidate solutions) iteratively update their positions until they converge on the global optimum (the equilibrium state).

The optimization process begins by initializing a population of particles, where each particle's position represents a potential solution with a certain "concentration." These initial concentrations are

generated randomly across the search space to ensure a wide exploration as defined in Equation 3.

$$C_i^{initial} = C_{min} + rand_i \cdot (C_{max} - C_{min}), \quad (3)$$

$$i = 1, 2, \dots, n$$

where:

- $C_i^{initial}$  is the initial concentration (position) of the  $i$ -th particle.
- $C_{min}$  and  $C_{max}$  are the lower and upper bounds of the search space.
- $rand_i$  is a random number uniformly distributed in the interval  $[0, 1]$ .
- $n$  is the number of particles (population size).

A key innovation of EOA is its use of multiple guiding elites instead of a single best solution. This prevents premature convergence and improves global exploration. An equilibrium pool is constructed from the best four particles found so far, plus their average concentration as defined in Equation 4.

$$\vec{C}_{eq, pool} = \{\vec{C}_{eq(1)}, \vec{C}_{eq(2)}, \vec{C}_{eq(3)}, \vec{C}_{eq(4)}, \vec{C}_{eq(ave)}\} \quad (4)$$

During each iteration, every particle selects one guide from this pool at random to update its position.

The core update equation, derived from the analytical solution to the mass balance equation, is used to compute new positions for all particles. It consists of three distinct terms that govern exploration and exploitation as defined in Equation 5.

$$\vec{C}^{new} = \vec{C}_{eq} + (\vec{C}^{old} - \vec{C}_{eq}) \cdot F + \frac{G}{\lambda V} (1 - F) \quad (5)$$

where:

- $\vec{C}^{new}$  is the new concentration (position) of the particle.
- $\vec{C}^{old}$  is the current concentration of the particle.
- $\vec{C}_{eq}$  is an equilibrium concentration vector randomly chosen from the equilibrium pool.
- $F$  is an exponential term that controls the trade-off between exploration and exploitation.
- $G$  is the generation rate vector that enhances local exploitation.
- $\lambda$  is a random vector within the range  $[0, 1]$ .
- $V$  is a unit vector, typically set to 1.

The  $F$  term decays over iterations, shifting the algorithm's focus from global exploration to local exploitation:

$$F = a_1 \cdot \text{sign}(\vec{r} - 0.5) \cdot (e^{-\vec{\lambda} \cdot t} - 1) \quad (6)$$

where:

- $t$  is the current iteration, which decreases as the algorithm progresses.
- $\vec{\lambda}$  are random vectors in  $[0, 1]$ .
- $a_1$  is a constant controlling exploration.
- $(\vec{r} - 0.5)$  introduces random direction.

The generation rate  $\vec{G}$  provides a precise local search mechanism and is defined as in Equation 7.

$$\vec{G} = \vec{G}_{CP} \cdot (\vec{C}_{eq} - \vec{\lambda} \cdot \vec{C}^{old}) \quad (7)$$

$$\vec{G}_{CP} = \begin{cases} 0.5 \cdot r_1 & \text{if } r_2 > GP \\ 0 & \text{otherwise} \end{cases}$$

where:

- $\vec{G}_{CP}$  is the Generation Rate Control Parameter.
- $r_1$  and  $r_2$  are random numbers in  $[0, 1]$ .
- $GP$  is the Generation Probability, a key algorithm parameter that determines how often the generation term is applied.

Results consistently demonstrate that EOA's multi-elite guidance strategy enables it to achieve optimal or near-optimal solutions with high efficiency and strong convergence properties.

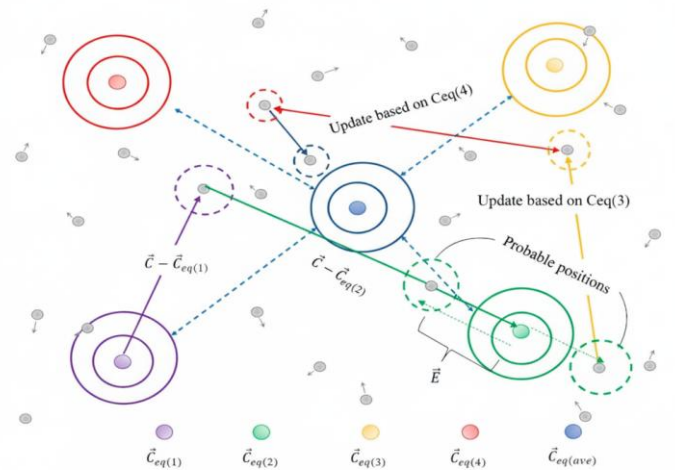


FIGURE IV. CONCEPTUAL DIAGRAM OF THE PARTICLE CONCENTRATION UPDATE MECHANISM IN THE EQUILIBRIUM OPTIMIZER ALGORITHM (EOA), ADAPTED FROM [29]

## VI. DISCUSSION AND RESULTS

Based on empirical experiments on objective functions, Framarzi and et al. considered suitable values for the coefficients  $a_1$ ,  $a_2$ , and  $G_p$  to ensure better algorithm performance as 2, 1, and 0.5, respectively. Although the algorithm developers considered the selectivity of these coefficients based on problem conditions, in this study, using the results of past studies and repeating the algorithm several times with trial and error, the final values of these variables were determined according to Table 1.

TABLE VI. OPTIMAL BLASTING PARAMETERS DETERMINED BY THE EQUILIBRIUM OPTIMIZER ALGORITHM (EOA) FOR MINIMIZING GROUND VIBRATION

500	$Max\_iter$
2	$a_1$
1	$a_2$
0.5	$G_p$

If the value of  $a_1$  is greater than 3, the exploration efficiency of the algorithm is significantly reduced, leading it towards boundary searching. The parameter  $G_p$  indicates the probability of each particle's concentration participation in the update.

If the value of this coefficient is:

- 1 ( $G_p=1$ ), it means that the production rate term is not used in optimization. This indicates a strong potential for exploration.
- 0 ( $G_p=0$ ), it means that the production rate term is used in the process. In this case, the likelihood of stagnation in local optimum increases.
- 510105 ( $G_p=0.5$ ), it indicates a balance between exploration and exploitation phases and can bring the algorithm to a balance between achieving global and local optima.

The optimization process of the algorithm is shown in Figure 4. As can be seen, the EOA algorithm did not converge to a local optimum in the initial steps; instead, it continued exploring the search space to find better solutions over time.

The algorithm's performance, due to having multiple guiding and leading members, as well as particles converging to these points instead of converging to only one best solution, has a lower convergence rate at the beginning of the optimization process compared to other algorithms. However, this feature of the EOA algorithm provides better exploration capability in achieving the best solutions among global optima.

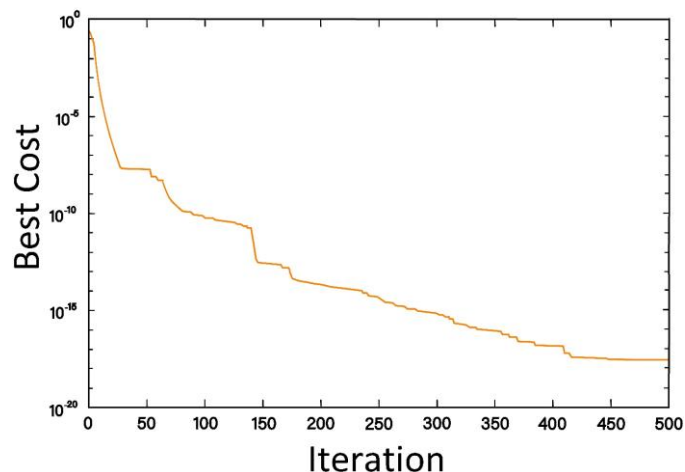


FIGURE V. CONVERGENCE PROFILE OF THE EQUILIBRIUM OPTIMIZER ALGORITHM (EOA) DURING THE OPTIMIZATION PROCESS

The results of the optimization process of the explosion pattern in the Sarcheshmeh copper mine aiming to reduce ground vibration, using the Neural Network-Optimization Algorithm, indicate that the minimum ground vibration resulting from the explosion in this mine is equivalent to 6.72 mm/s. This algorithm successfully predicts a 34% reduction in ground vibration according to the modifications presented in Table 2 compared to the average recorded data.

TABLE VII. EOA OPTIMIZATION RESULTS

Variable	Symbol	Optimal Value
Burden (m)	B	6
Spacing (m)	S	7
Row Delay (ms)	D	50
Specific Charge (Kg/m <sup>3</sup> )	Q	0.183
Maximum Holes per Delay	$N_0$	16
Charge per Delay (Kg)	Q/D	3285
Actual Measured Distance (m)	T	358
Maximum Particle Velocity (mm/s)	PPV	6.72

The optimized pattern requires field validation via a controlled production blast using the recommended parameters, with seismographs measuring the actual PPV. Success is confirmed if the measured vibration is within  $\pm 15\%$  of the predicted 6.72 mm/s without compromising fragmentation or slope stability. This study acknowledges that while the model is statistically validated, this crucial field verification is the essential next step.

## VII. CONCLUSION

This study successfully developed and implemented an integrated ANN-EOA model to derive a novel, optimal blasting pattern specifically designed for the complex geomechanical conditions

of the Sarcheshmeh copper mine's western wall. The model achieved a significant predicted reduction in ground vibration of 34%, lowering the Peak Particle Velocity to 6.72 mm/s through an optimized configuration of burden, spacing, timing, and charge parameters. This work not only provides a practical solution for enhancing operational safety and reducing environmental impact at Sarcheshmeh but also establishes a robust, transferable methodology that effectively bridges advanced computational intelligence with critical mining engineering challenges.

## REFERENCES

- [1] M. Reza khah and E. Moreno, "Open pit mine scheduling model considering blending and stockpiling," in Proceedings of the 28th International Symposium on Mine Planning and Equipment Selection - MPES 2019, Perth, 2019.
- [2] M. Reza khah, "Short-Term Production Planning Optimization in Open-Pit Copper Mines A MILP Model Integrating Comminution Modeling and Feed Quality Control," *Journal of Mining and Environment*, 2025.
- [3] M. Monjezi, S. Moezini, J. K. Hamidi, M. Reza khah, V. Amini and A. Batarbiat, "Determining the Appropriate Rehabilitation Method in Open-Pit Mines using Decision-Making Methods," *Journal of Mining and Environment*, 2025.
- [4] S. Khajevand, Reza khah, M. M. M. and F. A. Manríquez León, "Enhancing Transportation Fleet Efficiency in Open-Pit Mining via Simulation: a Case Study," *Journal of Mining and Environment*, vol. 16, no. 3, pp. 997-1007, 2025.
- [5] M. Mirzahi Kalateh Kazemi, Z. Nabavi, M. Reza khah and A. Masoudi, "Application of XGB-based metaheuristic techniques for prediction time-to-failure of mining machinery," *Systems and Soft Computing*, vol. 5, p. 200061, 1 12 2023.
- [6] M. Mirzahi, M. Reza khah, A. Mousavi and Z. Nabavi, "New MIP model for short-term planning in open-pit mines considering loading machine performance: a case study in Iran," *International Journal of Mining and Mineral Engineering*, pp. 341-364, 2023.
- [7] E. Moreno, F. Ferreira, M. Goycoolea, D. Espinoza, A. Newman and M. Reza khah, "Linear programming approximations for modeling instant-mixing stockpiles," *Application of computers and operations research in the mineral industry-proceedings of the 37th international symposium, APCOM*, vol. 2009, pp. 582-587, 2015.
- [8] S. Tajik, M. Monjezi, M. Reza khah and M. Amiri Hosseini, "Development of a Mathematical Model for Predicting Blast-Induced Fragmentation Considering Elastic Wave Velocities," *JOURNAL OF ROCK MECHANICS*, vol. 7, no. 2, pp. 71-82, 2023.
- [9] Y. Yan, X. Hou and H. Fei, "Review of predicting the blast-induced ground vibrations to reduce impacts on ambient urban communities," *Journal of cleaner production*, vol. 260, p. 121135, 2020.
- [10] A. Al-Bakri and M. Sazid, "Application of Artificial Neural Network (ANN) for Prediction and Optimization of Blast-Induced Impacts," *Mining*, vol. 1, pp. 315-334, 2021.
- [11] K. Behzadafshar, F. Mohebbi, M. Soltani Tehrani, M. Hasanipناه and O. Tabrizi, "Predicting the ground vibration induced by mine blasting using imperialist competitive algorithm," *Engineering Computations*, vol. 35, no. 4, pp. 1774-1787, 2018.
- [12] D. Mohammadi, R. Mikaeil and J. Abdollahi-Sharif, "Implementation of an optimized binary classification by GMDH-type neural network algorithm for predicting the blast produced ground vibration," *Expert Systems*, vol. 37, no. 5, p. e12563, 2020.
- [13] H. Nguyen, X. N. Bui and E. Topal, "Enhancing predictions of blast-induced ground vibration in open-pit mines: Comparing swarm-based optimization algorithms to optimize self-organizing neural networks," *International Journal of Coal Geology*, vol. 275, p. 104294, 2023.
- [14] D. J. Armaghani, E. Momeni, S. V. A. N. K. Abad and M. Khandelwal, "Feasibility of ANFIS model for prediction of ground vibrations resulting from quarry blasting," *Environmental earth sciences*, vol. 74, no. 4, pp. 2845-2860, 2015.
- [15] R. Shirani Faradonbeh, D. Jahed Armaghani, M. Z. Abd Majid, M. Md Tahir, B. Ramesh Murlidhar, M. Monjezi and H. M. Wong, "Prediction of ground vibration due to quarry blasting based on gene expression programming: a new model for peak particle velocity prediction," *International journal of environmental science and technology*, vol. 13, no. 6, pp. 1453-1464, 2016.
- [16] S. Hosseini, J. Khatti, B. Taiwo, Y. Fissaha, K. Grover, H. Ikeda, M. Pushkarna, M. Berhanu and M. Ali, "Assessment of the ground vibration during blasting in mining projects using different computational approaches," *Scientific Reports*, vol. 13, no. 1, p. 18582, 2023.
- [17] Y. Fissaha, H. Ikeda, H. Toriya, N. Owada, T. Adachi and Y. Kawamura, "Evaluation and Prediction of Blast-Induced Ground Vibrations: A Gaussian Process Regression (GPR) Approach," *Mining*, vol. 3, pp. 659-682, 2023.
- [18] X. N. Bui, P. Jaroopattanapong, H. Nguyen, Q. H. Tran and N. Q. Long, "A novel hybrid model for predicting blast-induced ground vibration based on k-nearest neighbors and particle swarm optimization," *Scientific reports*, vol. 9, no. 1, p. 13971, 2019.
- [19] D. Mohammadi, R. Mikaeil and J. Abdollahi Sharif, "Investigating and ranking blasting patterns to reduce ground vibration using soft computing approaches and MCDM technique," *Journal of Mining and Environment*, vol. 11, no. 3, pp. 881-897, 2020.
- [20] P. Bayat, M. Monjezi, A. Mehrdaneh and M. Khandelwal, "Blasting pattern optimization using gene expression programming and grasshopper optimization algorithm to minimise blast-induced ground vibrations," *Engineering with Computers*, vol. 38, no. 4, pp. 3341-3350, 2022.
- [21] A. Rezaeineshat, M. Monjezi, A. Mehrdaneh and M. Khandelwal, "Optimization of blasting design in open pit limestone mines with the aim of reducing ground vibration using robust techniques," *Geomechanics and Geophysics for Geo-Energy and Geo-Resources*, vol. 6, no. 2, p. 40, 2020.
- [22] E. Bakhtavar, J. Abdollahisharif and M. Ahmadi, "Reduction of the undesirable bench-blasting consequences with emphasis on ground vibration using a developed multi-objective stochastic programming," *International Journal of Mining, Reclamation and Environment*, vol. 31, no. 5, pp. 333-345, 2017.
- [23] R. Bhatwadekar, R. Kumar, M. Sabri Sabri, B. Roy, E. Mohamad, D. Kumar and S. Kwon, "Estimating Flyrock Distance Induced Due to Mine Blasting by Extreme Learning Machine Coupled with an Equilibrium Optimizer," *Sustainability*, vol. 15, p. 3265, 2023.
- [24] B. Eleveli and E. Arpaz, "Evaluation of parameters affected on the blast induced ground vibration (BIGV) by using relation diagram method (RDM)," *Acta Montanistica Slovaca*, vol. 15, no. 4, p. 261, 2010.
- [25] C. K. Arthur, V. A. Temeng and Y. Y. Ziggah, "A Self-adaptive differential evolutionary extreme learning machine (SaDE-ELM): a novel approach to blast-induced ground vibration prediction," *SN Applied Sciences*, vol. 2, no. 11, p. 1845, 2020.
- [26] Y. Zhang, H. He, M. Khandelwal, K. Du and J. Zhou, "Knowledge mapping of research progress in blast-induced ground vibration from 1990 to 2022 using CiteSpace-based scientometric analysis," *Environmental Science and Pollution Research*, vol. 40, no. 47, pp. 103534-103555, 2023.

- 
- [27] J. Zhou, Y. Zhang and Y. Qiu, "State-of-the-art review of machine learning and optimization algorithms applications in environmental effects of blasting," *Artificial Intelligence Review*, vol. 57, no. 1, p. 5, 2024.
- [28] K. Iwano, K. Hashiba, J. Nagae and K. Fukui, "Reduction of tunnel blasting induced ground vibrations using advanced electronic detonators," *Tunnelling and Underground Space Technology*, vol. 105, p. 103556, 2020.
- [29] A. Faramarzi, M. Heidarinejad, B. Stephens and S. Mirjalili, "Equilibrium optimizer: A novel optimization algorithm," *Knowledge-based systems*, vol. 191, p. 105190, 2020.
- [30] M. Monjezi, K. Goshtasbi, M. Rezakhah and T. N. Singh, "Design of stable slopes for Songun copper mine," *Mining Technology*, vol. 116, no. 3, pp. 146-152, 2007.

## بهینه‌سازی کاهش ارتعاشات زمین ناشی از انفجار با استفاده از یک مدل یکپارچه ANN-EOA: مطالعه موردی معدن مس سرچشمه

مجتبی رضاخواه<sup>۱\*</sup>:

۱- گروه مهندسی معدن، دانشکده مهندسی، دانشگاه تربیت مدرس، تهران، ایران

دریافت: ۱۴۰۴/۰۴/۱۴؛ پذیرش: ۱۴۰۲/۰۶/۲۹

(<sup>\*</sup>نویسنده مسئول: [m.rezakhah@modares.ac.ir](mailto:m.rezakhah@modares.ac.ir))

ارتعاشات زمین ناشی از انفجار، چالش‌های زیست‌محیطی و ایمنی قابل توجهی در عملیات معادن روباز، به ویژه در مناطق با پیچیدگی زمین‌شناسی ایجاد می‌کنند. این مطالعه یک مدل یکپارچه شبکه عصبی مصنوعی-الگوریتم بهینه‌ساز تعادل (ANN-EOA) را برای پیش‌بینی و بهینه‌سازی ارتعاشات زمین ناشی از انفجار، به‌طور خاص برای دیواره حساس غربی معدن مس سرچشمه توسعه می‌دهد. مدل ANN دقت پیش‌بینی استثنایی (۹۶٪  $R^2 = 0$ ) را در پیش‌بینی سرعت ذره اوج (PPV) بر اساس هفت پارامتر کلیدی آتشفشانی نشان داد. سپس الگوریتم EOA با موفقیت یک پیکربندی بهینه آتشفشانی را شناسایی کرد که پیش‌بینی می‌کند کاهش ۳۴ درصدی در PPV به مقدار ۶.۷۲ میلی‌متر بر ثانیه، از طریق بهینه‌سازی پارامترهای فاصله (۶ متر)، spacing (۷ متر)، زمان تاخیر (۵۰ میلی‌ثانیه) و ماده منفجره حاصل می‌شود. این پژوهش شکاف بحرانی بین مدل‌های هوش مصنوعی تعمیم‌یافته و کاربردهای خاص هر معدن را پل می‌زند و هم یک راه‌حل عملی برای کاهش ارتعاش در سرچشمه ارائه می‌دهد و هم یک روش قابل انتقال که یکپارچه‌سازی هوش محاسباتی با چالش‌های مهندسی معدن را پیش می‌برد. یافته‌ها بر اهمیت در نظر گرفتن شرایط زمین‌شناسی خاص در بهینه‌سازی آتشفشانی تأکید می‌کنند و در عین حال نیاز به اعتبارسنجی میدانی را به عنوان گام ضروری بعدی برجسته می‌سازند.

چکیده

شبکه عصبی مصنوعی (ANN)، الگوریتم بهینه‌ساز تعادل (EOA)، ارتعاشات زمین ناشی از انفجار، سرعت ذره اوج (PPV)، معدن مس سرچشمه

واژگان کلیدی