Journal of Mining and Earth Sciences

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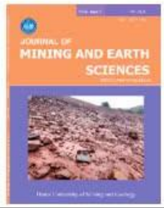

Prediction of flyrock distance in open-pit mines using an optimized artificial neural network with evolution strategies

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ARTICLE INFO

Article history:
Received 14th Nov. 2024
Revised 18th Feb. 2025
Accepted 28th Feb. 2025

Keywords:
Blasting,
Flyrock,
Machine learning,
Safety in mining,
Sustainable development.

ABSTRACT

Blasting is a fundamental technique in open-pit mining, used to break rock and ore. Its effectiveness and the degree of fragmentation significantly affect the efficiency of subsequent processes and the overall mine productivity. However, a major concern is the dangerous impact of flyrock, which poses serious safety risks to personnel and equipment in the vicinity, potentially leading to fatal accidents. This paper presents an advanced machine learning model, named ES-ANN, which combines an Artificial Neural Network (ANN) with Evolution Strategies (ES) to predict flyrock distance in open-pit mines with high accuracy. The ANN model is used to forecast flyrock distances, while the ES technique optimizes the model's weights, enhancing prediction accuracy. To evaluate the improvement of the proposed ES-ANN model, another optimization model based on the Evolutionary Programming (EP) optimization algorithm and ANN (abbreviated as EP-ANN), and a standalone ANN model were developed and compared based on the same datasets. Blasting data from the Ta Phoi copper mine (Lao Cai) was utilized for model training and validation. The results indicated that the ES-ANN model achieved the highest performance with an MAE of 2.095, RMSE of 2.711, and R^2 of 0.952 on the testing dataset (95.2% accuracy) in predicting flyrock distance. Meanwhile, the EP-ANN and standalone ANN models only provided MAE of 5.512 and 7.300, RMSE of 6.692 and 8.938, and R^2 of 0.708 and 0.479, respectively. Compared to the EP and traditional methods, the ES-ANN model offered superior accuracy and reliability, making it an effective tool for forecasting and managing flyrock hazards in open-pit mining, thus enhancing operational safety.

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DOI: 10.46326/JMES.2025.66(2).03

1. Introduction

Open-pit mines commonly use the synchronized drill-and-blast method to break rock and ore, which is essential for subsequent processes such as excavation, transportation, waste disposal, and crushing. This method is necessary due to the high hardness of the rock and ore typically found in open-pit mines. While the effectiveness of blasting for rock fragmentation in open-pit mines is undeniable, it also has significant environmental impacts. These include blast-induced vibrations, air shock waves, flyrock, ground shocks, and air pollution from dust and toxic gases (Bach et al., 2015; Thang et al., 2015). Among these, flyrock is particularly dangerous, posing serious risks to the safety of nearby personnel and equipment, with the potential to cause fatalities.

In recent years, several mining operations have failed to control flyrock during blasting, leading to "rock showers" that have fallen on the homes and properties of local residents. This has endangered the safety of those living in the area and caused damage to buildings, farmland, and other structures (Dong, 2024; Luat, 2024; Nien, 2024; Phong, 2024; Plus, 2024) (Figure 1).

In practice, the Vietnam Ministry of Industry and Trade's regulation QCVN 01:2019/BCT (Trade, 2019) sets the safe flyrock distance at 300 meters for people and 200 meters for equipment during blasting with large-diameter drill holes. For mines with significant elevation differences, the required safe distance increases by 1.5 times. However, in many cases, blasting operations have resulted in flyrock distances far exceeding these safety limits, making it impossible to control or predict the flyrock range, as previously mentioned.

To address this issue, some researchers have proposed empirical formulas to predict flyrock distance caused by blasting, but their accuracy remains limited (Ghasemi et al., 2012; Jahed Armaghani et al., 2016).

With the advancement of science and technology in the era of Industry 4.0, researchers globally have shifted toward more sophisticated models utilizing machine learning and artificial intelligence. These models aim to better understand the relationship between flyrock and blasting parameters, as well as the physical and

Figure 1. Evidence of Flyrock Incidents from Blasting at Open-Pit Quarries (Vietnam) (Law, 2024; Plus, 2024).

mechanical properties of the rock, in order to improve prediction accuracy. Several machine learning models have been developed worldwide to predict flyrock distance. One such model is the Outlier Robust Extreme Learning Machine (ORELM), which was designed to reduce the impact of outliers, thereby providing more stable and accurate predictions (Lu et al., 2020). Additionally, Zhang et al. (2024) developed a Stacked Multiple Kernel Support Vector Machine to predict flyrock distances at the Sugun copper mine in Iran, achieving an accuracy of approximately 99%. Another model worth noting is the Monte Carlo-based regression model, developed by Armaghani et al. (2016), which was used to predict flyrock distance from blasting at the Ulu Tiram quarry in Malaysia, showing an accuracy of 85.5%. Li et al. (2023) also developed a hybrid model combining Harris Hawks Optimization and Multi-strategies-based Support Vector Regression to predict flyrock distances in open-pit mines, with an accuracy of 96.6%.

While these studies demonstrate the high reliability of modern machine learning models in predicting flyrock distances, researchers have also cautioned that the accuracy of these models needs to be carefully reviewed or further tested when applied to different regions. Variations in data characteristics (such as geological conditions, geophysical properties, and rock mechanics) mean that results from one area cannot be generalized to others. As such, these models cannot be directly applied in Vietnam without careful research and adaptation. Therefore, in this study, the authors developed a new machine learning model based on Evolution Strategies Optimization and an Artificial Neural Network (ANN), abbreviated as ES-ANN, and tested its feasibility with appropriate parameters at the Ta Phoi copper mine in Lao Cai, Vietnam. Another optimization model based on the Evolutionary Programming (EP) optimization algorithm and ANN, namely EP-ANN, and a standalone ANN model are also developed to compare with the proposed ES-ANN model in predicting blast-induced flyrock based on the same datasets. The research methodology and results are discussed in the following sections of this paper.

2. Methodology

2.1. Multi-layer perceptron neural network

The MLP (Multi-Layer Perceptron) neural network is a type of neural network with a multi-layer structure. It consists of at least three main layers: the input layer, the hidden layer (which can have multiple hidden layers), and the output layer. MLP is one of the most commonly used neural network types and is widely applied to classification and regression tasks (Khashei et al., 2012; Desai & Shah, 2021; Uncuoglu et al., 2022; Xu et al., 2022; Zhang et al., 2023). In this study, we use an MLP neural network to predict flyrock distance caused by blasting in open-pit mines, which is a regression problem.

The input layer of the MLP neural network is responsible for receiving the initial data and passing this information into the network. The number of neurons in the input layer corresponds to the number of features (input variables) in the data.

In the hidden layer, the neurons apply nonlinear transformations (typically using activation functions such as ReLU, Sigmoid, or Tanh) to learn complex patterns within the data, discovering relationships and rules.

Finally, the MLP provides the final prediction at the output layer, where the number of neurons corresponds to the predicted flyrock distance caused by blasting in open-pit mines. Figure 2 illustrates the structure of the MLP model used to predict flyrock distance from blasting in open-pit mines.

The operating principle of an MLP neural network is as follows: the MLP learns to transform data by updating its weights through the process of backpropagation. This algorithm involves both forward and backward propagation (Naskath et al., 2023).

- Forward propagation: Data is passed through each layer of the network, from the input layer to the output layer. At each layer, the input is multiplied by the weights, a bias is added, and the result is passed through an activation function to produce the layer's output.

- Backward propagation: After the network makes a prediction, a loss function is used to calculate the error between the predicted values and the actual values. This error is then

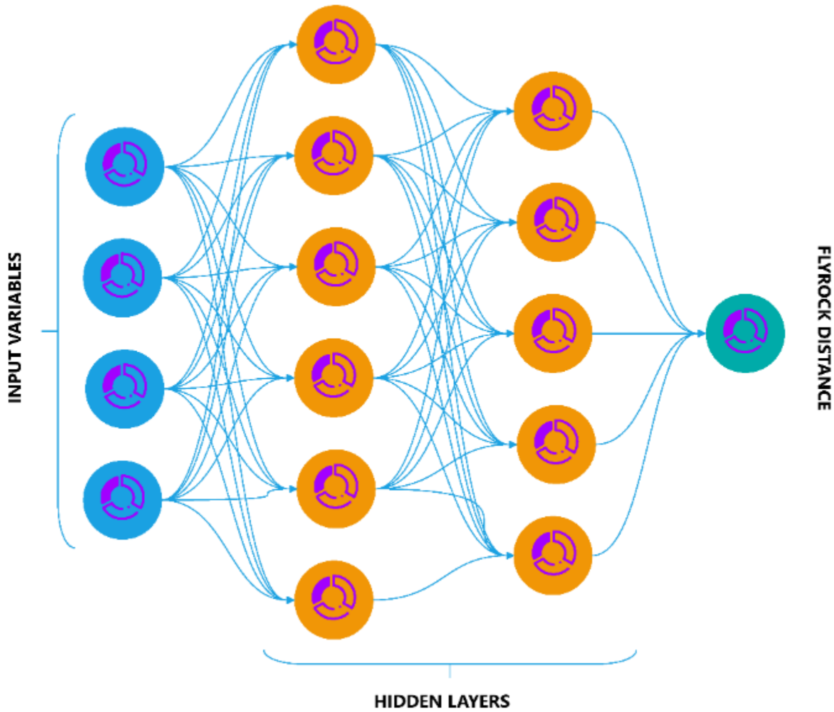


Figure 2. MLP model structure for predicting flyrock distance from blasting in open-pit mines.

propagated backward through the network to update the weights using optimization algorithms such as gradient descent. This process allows the network to self-correct and improve accuracy by minimizing the error.

2.2. Optimization algorithms based on evolutionary techniques

2.2.1. Evolutionary programming (EP)

Evolutionary Programming (EP) is an optimization method based on the principles of natural evolution and is part of the broader family of Evolutionary Algorithms (EAs). It was developed by Fogel (1962) in the 1960s with the original aim of simulating biological evolution to solve complex problems (Fogel, 1964).

The key features of the Evolutionary Programming algorithm include:

1. Simulating the evolutionary process: EP simulates evolution by generating and evolving a population of potential solutions (individuals) to a given problem. These individuals are represented as numerical strings or other suitable data structures for solving the problem.

2. No crossover operation: Unlike Genetic Algorithms (GA), EP does not use crossover between individuals. Instead, it focuses on mutation to introduce diversity within the population.

3. Evaluation and selection: Each individual in the population is evaluated based on a fitness function, which reflects how well that solution meets the problem's objectives. The better-performing individuals have a higher chance of surviving and reproducing in the next generation.

4. Unconstrained optimization: EP is well-suited for unconstrained optimization problems and can be easily applied to complex or discontinuous objective functions.

The basic steps of the Evolutionary Programming algorithm are as follows:

- Step 1: Initialization: Generate a random population of individuals representing potential solutions to the problem.

- Step 2: Mutation: Apply mutations to the individuals to create new solutions.

- Step 3: Evaluation: Measure the fitness of each individual based on the objective function.

- Step 4: Selection: Choose the best individuals to proceed to the next generation.

EP emphasizes exploration of the search space through mutation and is particularly effective for problems with large or complex solution spaces.

2.2.2. Evolutionary strategies (ES)

Evolution Strategies (ES) is an optimization method based on the principles of natural evolution, similar to other evolutionary algorithms (EA) such as Genetic Algorithm (GA) and Evolutionary Programming (EP). ES was developed by Rudolph (2000) to address optimization problems by simulating biological processes.

The key features of Evolution Strategies (ES) include individual representation, mutation, recombination, selection, and self-adaptation of strategy parameters (Hansen et al., 2015). In ES, individuals are typically represented as real-valued vectors, where each value (gene) corresponds to a parameter to be optimized. Each individual consists of two components:

- Genotype: The solution values.
- Strategy parameters: Parameters such as the standard deviation (σ) used during mutation.

Mutation is the primary mechanism in ES. Unlike GA, which focuses on recombination, ES emphasizes small changes in individuals through random mutation (Back, 1996). Mutation usually involves adding a randomly generated value from a normal distribution to both the solution parameters (genotype) and the strategy parameter (σ). This allows ES to self-adapt the degree of change throughout the evolutionary process.

ES can also use recombination, but it is not the main factor as it is in GA. Recombination may occur between individuals to create a new individual by combining solution parameters (genotypes) from two or more parents (Beyer & Arnold, 2001).

Selection in ES is similar to that in GA, but it uses two main types:

- (μ + λ) selection: In this strategy, both the current generation (μ individuals) and the offspring (λ individuals) compete for a place in the next generation. This helps retain some of the better traits from the previous generation.
- (μ, λ) selection: In this strategy, only the λ offspring are evaluated, and the current generation is completely replaced. This is a more aggressive evolutionary strategy, enabling broader exploration of the search space.

In the next step, ES self-adjusts its strategy parameters, such as the mutation standard deviation (σ), which is a defining feature of ES. This enables the algorithm to adapt to the search space and gradually improve optimization as it progresses through generations.

The structure of the Evolution Strategies algorithm involves five basic steps:

1. Initialization: ES generates an initial random population of μ individuals, each with solution parameters and strategy parameters.
2. Mutation: ES mutates the individuals by adding a random value from a normal distribution to the parameters.
3. Recombination (optional): ES performs recombination between individuals to create new individuals.
4. Evaluation: ES calculates the objective function for the newly created individuals.
5. Selection: ES selects the best individuals from both the current and new generations to advance to the next generation (in the μ + λ or μ, λ strategy).

ES is commonly used for continuous optimization problems where the parameters to be optimized are represented as real numbers, such as the problem of predicting flyrock distance in blasting operations, which is addressed in this study. ES combines flexible exploration of the search space (through mutation and self-adaptation) with the ability to exploit the best individuals (through selection). This makes it a powerful tool for optimizing complex problems and is widely used in various engineering and scientific fields.

2.3. Optimizing ANN using optimization algorithms based on Evolutionary Strategies (EP-ANN and ES-ANN)

This paper employs the Multi-Layer Perceptron (MLP) artificial neural network as the primary model for predicting flyrock distance caused by blasting in open-pit mines. The essential components of the MLP model include input parameters, the network structure, and output parameters (flyrock distance).

In an MLP network, neurons are organized into multiple layers and interconnected by weighted links. The goal of training is to optimize these weights to improve the network's ability to accurately predict flyrock distance. In this study, evolutionary strategies are used to optimize the weights of the MLP. Unlike traditional backpropagation, which relies on gradient-based methods, evolutionary strategies apply a generalized search and optimization process based on the rules of each algorithm. Instead of adjusting weights using derivatives and gradients, metaheuristic algorithms perform a guided random search (heuristic) for the optimal weights, following the principles outlined earlier. This method offers an alternative to backpropagation, helping to avoid issues like getting trapped in local minima, which can affect gradient-based training methods.

To apply this process, the MLP network structure must be defined before it can be used to predict flyrock distance. The EP and ES optimization algorithms then generate populations of solutions. Each individual in the search space represents a set of weights and biases in the MLP network. These metaheuristic algorithms typically begin by randomly initializing a population of individuals, each with different weight sets. These weights are integrated into the MLP, and errors are calculated based on output results using loss functions such as RMSE or MSE. The forward propagation process is used to compute the MLP's predictions with the weights from each individual. The error between the predicted and actual values is then calculated, which feeds into the fitness function. Metaheuristic operators, such as selection, crossover, and mutation, are applied to optimize the weight sets according to the optimization principles of each algorithm.

After each optimization cycle, the individuals in the population are updated based on the results of the EP and ES metaheuristic operators. The better-performing individuals are prioritized, allowing the population to evolve toward improved solutions. This iterative process continues until a stopping condition is met, such as reaching the maximum number of iterations or when no further improvement in the fitness function is observed (convergence).

Once optimization is complete, the individual with the best fitness (optimal weight set) is selected as the final result for the MLP network. This weight set is then used in the MLP for future predictions of flyrock distance from blasting. These models are referred to as the hybrid EP-ANN and ES-ANN models in this study. The workflow framework for these hybrid models is shown in Figure 3.

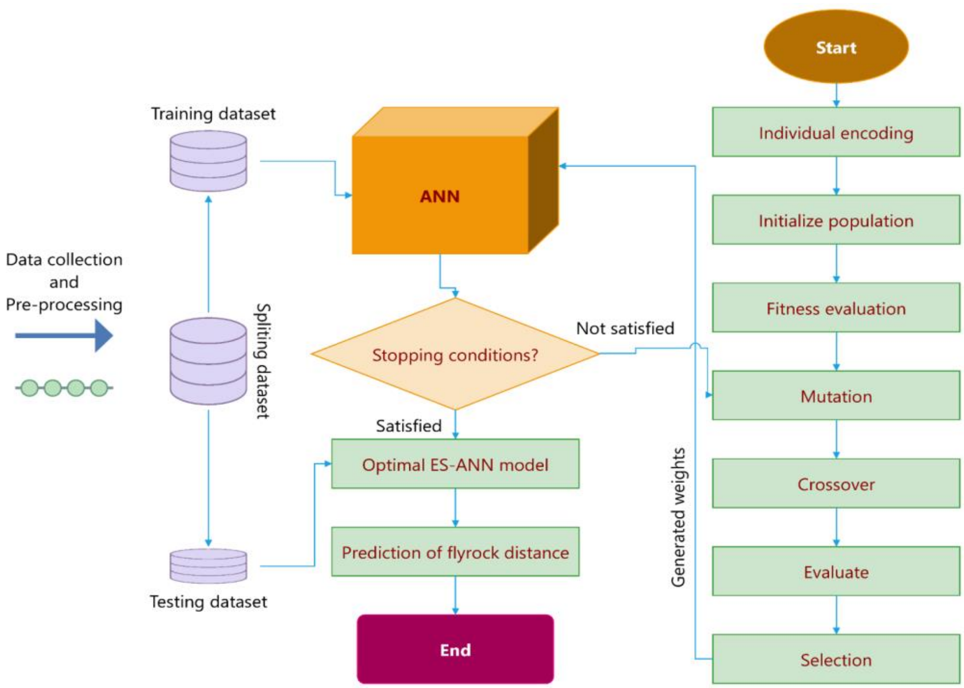


Figure 3. Proposing the ES-ANN and EP-ANN framework for predicting flyrock distance induced by mine blasting.

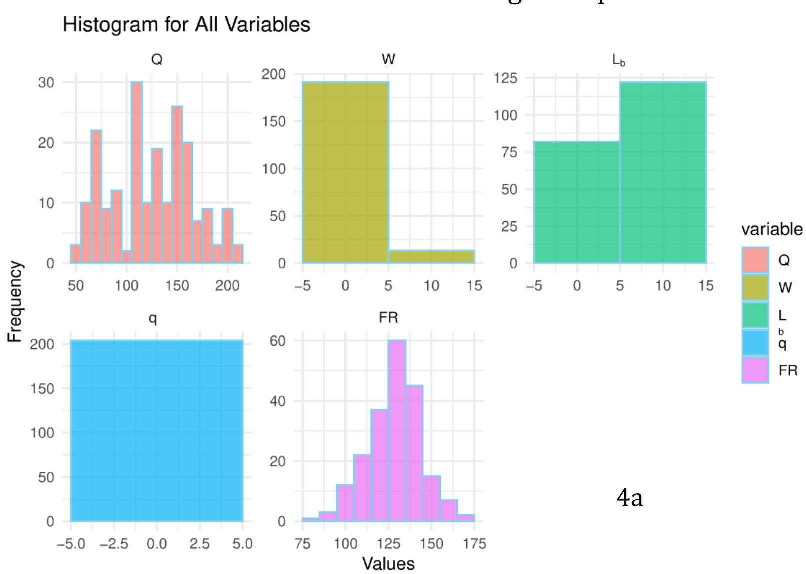
3. Case study

In this study, the Ta Phoi copper mine was selected as the case study, with data collected from 204 blasts and their corresponding blast designs. It's important to clarify that this case study is focused on analyzing the behavior of flyrock generated by blasting and evaluating the potential to predict flyrock distances using machine learning models. This site is not linked to mines that have caused environmental harm, as depicted in Figure 1. The data gathered from the mine's blast designs include key parameters such as the maximum explosive charge per delay (Q), burden (W), stemming (Lb), and specific charge (q), which are analyzed in Figure 4. It should be noted that the selection of these input variables is based on their well-documented influence on flyrock distance in blasting operations, as supported by both empirical studies and practical observations in open-pit mining. In which, Q impacts the energy released in each blast, which can significantly influence the throw of rock fragments. Studies (Raina & Murthy, 2016; Van der Walt & Spiteri, 2020; Chen et al., 2024) have shown that a higher explosive charge correlates with increased flyrock distance, making it a critical factor in predicting flyrock behavior. W affects confinement, which in turn determines the energy available for rock breakage versus flyrock projection. Adequate burden helps manage flyrock distance, as an improper burden can lead to excessive projection of rock fragments (Sawmliana et al., 2020; Nayak et al., 2022; Raina & Bhatawdekar, 2022). Lb is essential for controlling flyrock by containing the blast energy within the borehole. Its effectiveness in absorbing and controlling explosive energy directly impacts flyrock throw, as evidenced in previous studies (Purba, 1992; Armstrong, 1994; Liddell, 2021). Inadequate stemming length often results in excessive flyrock distances. Finally, q is a measure of the energy applied per unit volume of rock, affecting the efficiency and extent of fragmentation. Variations in specific charge influence the distribution of energy between rock breakage and flyrock generation, making it an essential predictor for flyrock distance (cite studies on specific charge in blasting).

Given these factors, the chosen variables are instrumental in controlling and predicting flyrock distances, aligning with both theoretical and practical findings in blasting operations at open-pit mines.

Figure 4a presents the histogram analysis of the dataset, providing insights into the distribution shape of the input and output variables, central tendency, spread, outliers, anomalies, and variability. The results indicate that the variables exhibit non-normal and skewed distributions with a wide range of spread.

Figure 4b illustrates the pairwise relationships between variables, highlighting their distributions and enabling the visual identification of linear or non-linear correlations. This visualization also captures interactions among multiple variables. Observing Figure 4b,



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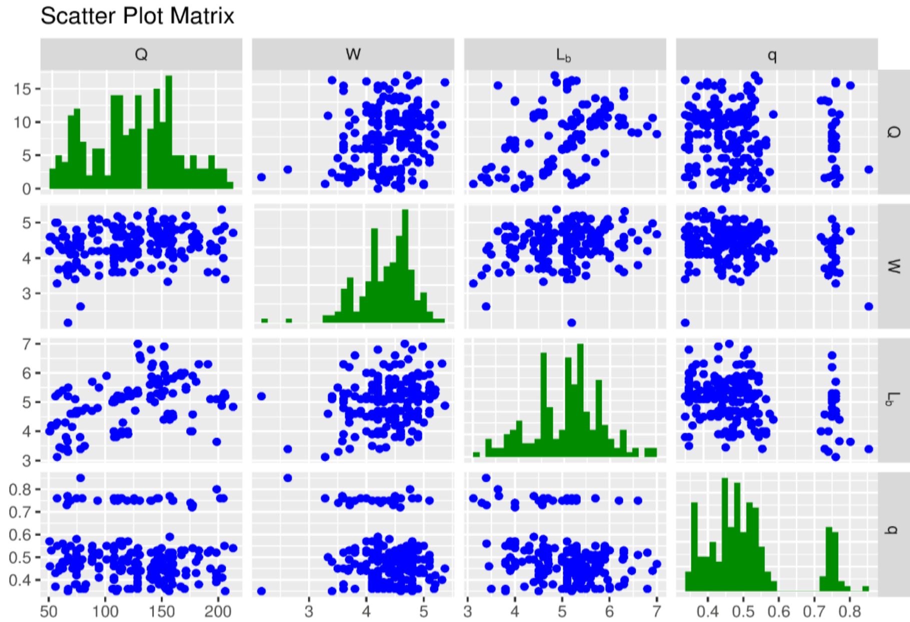

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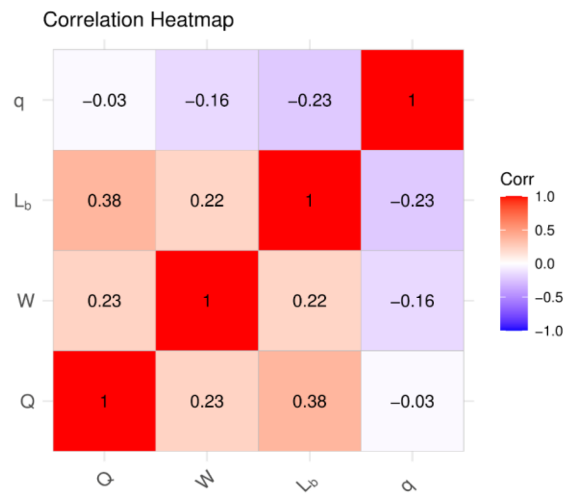

Figure 4. Data analysis of the collected blasting dataset at the Ta Phoi open-pit copper mine. (a) Histogram plot; (b) Scatter plot; (c) Correlation heatmap plot

the distribution of blasting parameters and their relationships is evident, reflecting characteristics of the study area, such as rock hardness, cracks, and the presence of underground water.

Figure 4c analyzes the correlations among input variables to determine the presence of strong relationships. If strong correlations exist, removing one of the correlated variables is recommended to maintain model quality during training. In this study, the correlations among input variables are weak, suggesting that all variables should be retained for predicting flyrock distance.

To determine the flyrock distance from blasting events, unmanned aerial vehicles (UAVs) were used in this study in combination with specialized flyrock behavior analysis software, ProAnalyst. The UAV was configured to fly in areas with wide visibility, ensuring sufficient resolution to detect the flyrock fragments. Before setting up the flight zone for the UAV, a reference object of known size (a ball) was placed on the blast site to serve as a size standard and to calibrate the flyrock distance in the ProAnalyst software. Figure 5 illustrates the process of collecting flyrock data and analyzing the flyrock distance using UAV data.

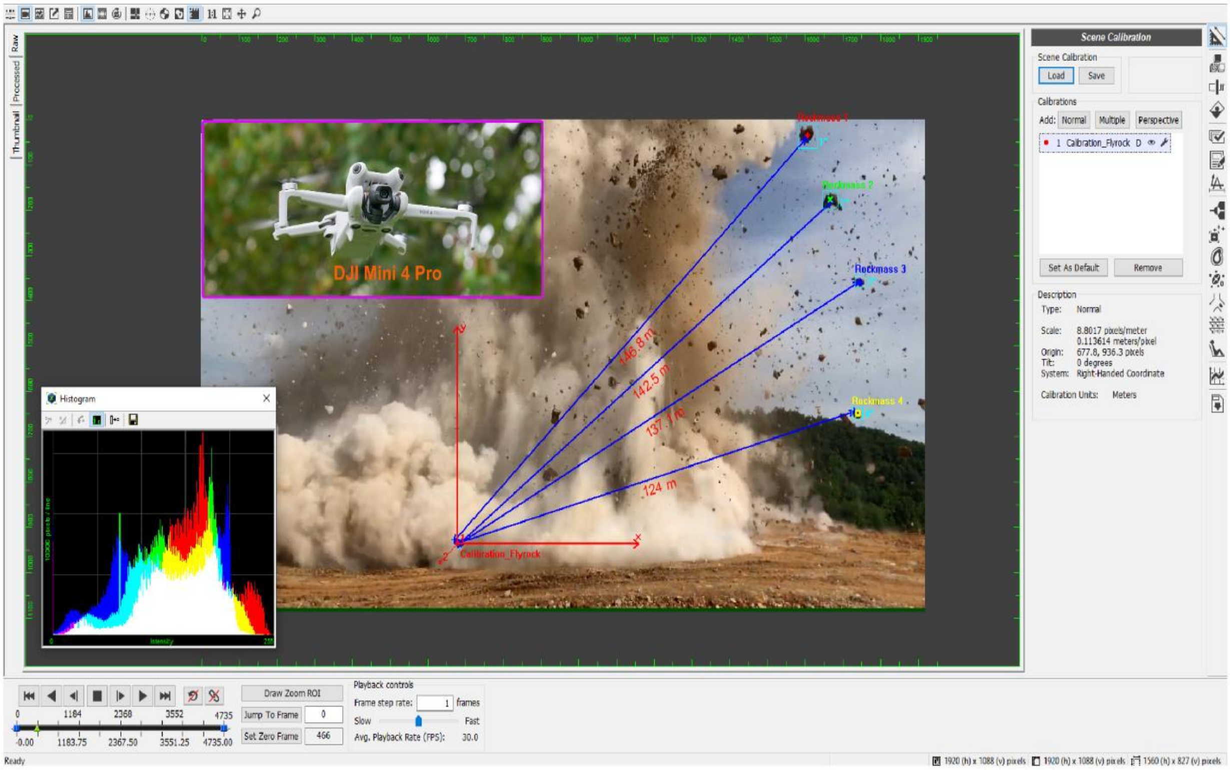

Figure 5. Collecting flyrock data and analyzing the flyrock distance using UAV data.

4. Results and discussion

To predict flyrock distance from blasting at the Ta Phoi copper mine, a dataset of 204 blast events was randomly divided into two parts: 80% for training the model and 20% for testing its performance after training. A 5-fold cross-validation method was employed to validate the machine learning model, utilizing different data segments for training and testing to prevent overfitting.

The framework outlined in Figure 3 was applied to develop the prediction model for flyrock distance at the Ta Phoi copper mine. The main model used for prediction was an ANN, specifically a Multi-Layer Perceptron (MLP), with optimization algorithms applied to fine-tune the network's weights. The ANN structure was predefined before weight optimization began. A simple architecture with one hidden layer containing five neurons was employed for this task, using the ReLU activation function. The Mean Squared Error (MSE) was used as the objective function in this ANN model.

In addition to designing the ANN architecture, appropriate optimization parameters were selected to ensure the algorithms performed at their best. In this study, the EP optimization algorithm used a parameter called "bout_size," which determines the percentage of offspring agents involved in tournament selection, allowing for the evolution of better individuals. Here, bout_size was set to 0.05, meaning that 5% of the offspring participated in the selection process. For the ES algorithm, the parameter "lambda" was used to define the percentage of offspring agents that would evolve into the next generation. In this case, lambda was set to 0.75, meaning 75% of the offspring were selected to evolve into the next generation. The optimization process for both algorithms was conducted with an initial population of 100 and iterated over 1000 epochs. The results of the optimization for the EP-ANN and ES-ANN models are shown in Figure 6.

For the standalone ANN model, the stochastic gradient descent (SGD) algorithm was applied to train the ANN model with the learning rate was selected automatically. The training performance of the ANN model is shown in Figure 6.

The optimization results in Figure 6 demonstrate that the ES-ANN model achieved a much more effective optimization process compared to the EP-ANN model, with the MSE error of the ES-ANN model being significantly lower. Additionally, the gap between the training and testing errors in the ES-ANN model suggests superior performance over the EP-ANN model. While the EP-ANN model appears to converge earlier, its optimization performance is not as strong as that of the ES-ANN model. To further assess the accuracy of both models in predicting flyrock distance at the Ta Phoi copper mine, a test dataset comprising 41 blasts was used to evaluate their performance.

The results in Figure 7 showed that both the training and testing loss of the standalone ANN model decreased over iterations, indicating learning and convergence. The losses stabilize after approximately 800 iterations, suggesting sufficient training. The training and testing loss appear close at convergence, which implies the

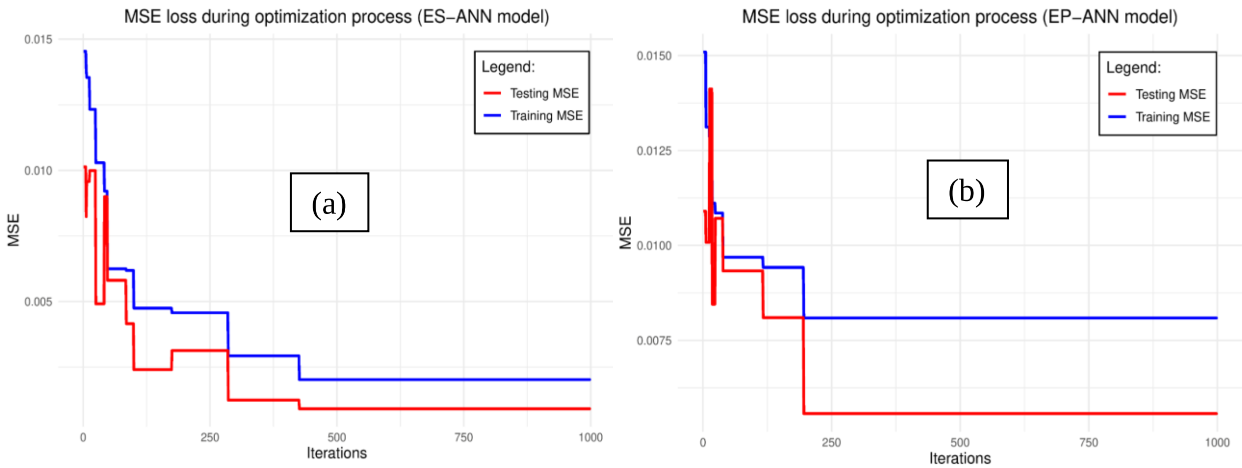

Figure 6. Optimization results of the EP-ANN and ES-ANN models for predicting flyrock distance at the Ta Phoi copper mine. (a) ES-ANN model; (b) EP-ANN model.

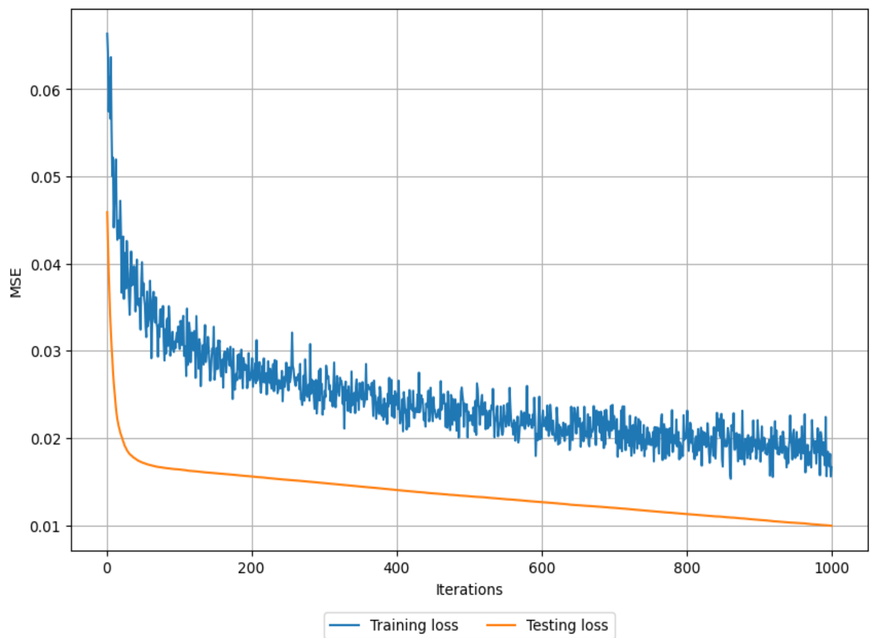

Figure 7. Training performance of the standalone model for predicting flyrock distance at the Ta Phoi copper mine.

model generalizes well and is not overfitting. Overall, the model demonstrates effective learning and a good balance between training and testing performance. The prediction results of these models are displayed in Figure 8.

The predicted flyrock distances generated by the EP-ANN and ES-ANN models for the Ta Phoi copper mine on the test dataset, as shown in Figure 8, revealed that the ES-ANN model's predictions are closer to the actual flyrock distances compared to the EP-ANN and ANN models. This suggests that the ES-ANN model delivers more accurate predictions for flyrock distance at the Ta Phoi copper mine. Although both the EP-ANN and ES-ANN models were optimized, the evolutionary strategy used in the ES-ANN model appears to be more robust and better suited for predicting flyrock distances in this case than the EP-ANN model. Figure 9 presents the regression charts comparing the prediction accuracy of the three models in this study.

The results in Figure 9 show that the regression line of the ES-ANN model (green) tends to be closer to the actual regression line (black). In contrast, the regression line of the EP-ANN model (red) is relatively farther from the actual regression line, and remarkably, the regression line of the ANN model (purple) is fathest from the actual regression. These analyses further suggest that the EP and ES optimization algorithms contributed significantly in improving the accuracy of the ANN model for predicting flyrock distance in this study, and the ES-ANN model appears to be more suitable for predicting flyrock distance from blasting at the Ta Phoi copper mine compared to the EP-ANN and ANN models. To confirm these findings, this study calculated additional performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2) to quantify the accuracy of the models. The computed results are presented in Table 1.

Table 1. Performance of flyrock distance prediction models for the Ta Phoi copper mine.

Model	Training dataset			Testing dataset		
	MAE	RMSE	R^2	MAE	RMSE	R^2
ES-ANN	2.757	4.037	0.935	2.095	2.711	0.952
EP-ANN	5.871	8.064	0.742	5.512	6.692	0.708
ANN	8.322	10.957	0.524	7.300	8.938	0.479

The results in Table 1 demonstrated that the ES-ANN model delivers significantly higher accuracy than the remaining models in predicting flyrock distance at the Ta Phoi copper mine, across both the training and testing datasets. The ES-ANN model's MAE on the training dataset is just 2.757 meters, while the EP-ANN model shows a much higher MAE of 5.781 meters, and the ANN

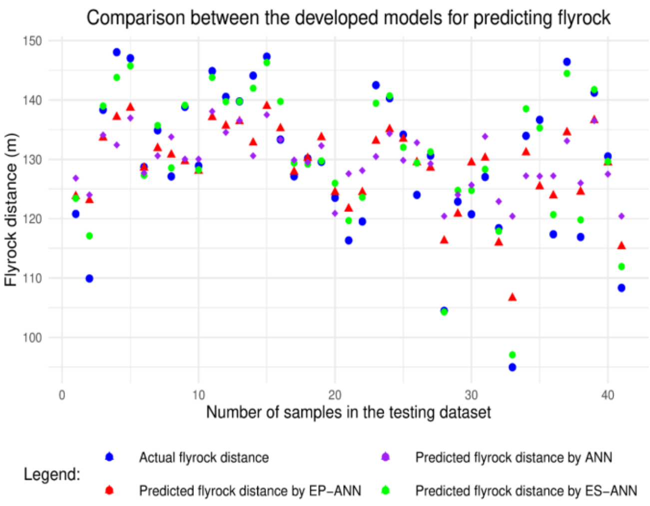

Figure 8. Comparison of accuracy between actual values and predicted values by flyrock distance prediction models.

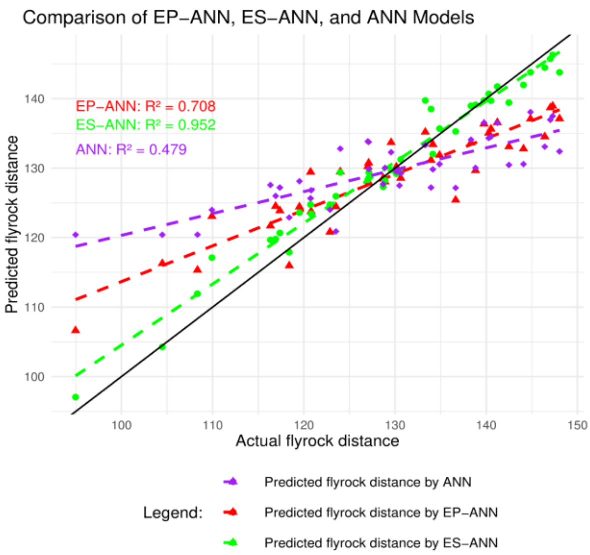

Figure 9. Regression plot comparing the performance of the models based on actual values and predicted values from the developed models.

model shows the highest MAE of 8.322. Similarly, the RMSE for the ES-ANN model on the training data is only 4.037 meters, compared to 8.064 meters for the EP-ANN model and 10.957 meters for the standalone ANN model. Moreover, the ES-ANN model achieved a higher coefficient of determination (R^2) of 0.935 on the training dataset, whereas the EP-ANN model only reached R^2 = 0.742, and the standalone ANN model reached 0.524. The results demonstrated that the optimization algorithms (i.e., EP and ES) significantly enhanced the accuracy of the standalone ANN model in predicting flyrock distance. These patterns were also observed in the testing dataset, confirming that the ES-ANN model is the more accurate choice for predicting flyrock distance at the Ta Phoi copper mine, with an accuracy of approximately 95% in practice. The ES proves to be the most suitable optimization method for this specific case.

5. Conclusion

Predicting flyrock distance during blasting presents a significant challenge for open-pit mines, particularly those in mountainous regions, due to the need to manage the associated risks. This study marks the first domestic effort to apply AI in predicting flyrock distance, demonstrating significantly improved accuracy compared to traditional empirical methods. Three prediction models based on ANN and optimized using the EP and ES algorithms were successfully developed and tested at the Ta Phoi copper mine. The findings show that the ES-ANN model achieved superior accuracy, around 95%, compared to the EP-ANN model and standalone ANN model. While the ES-ANN model holds potential for practical application, further research is necessary to confirm its accuracy in other regions. This study provides a solid foundation for the future development of AI-based models for predicting flyrock distance during blasting operations in open-pit mines across Vietnam.

Acknowledgments

This paper was supported by the Ministry of Education and Training (MOET) in Vietnam under grant number B2023-MDA-04.

Contributions of authors

Hoang Nguyen - conceptualization; methodology, data collection, formal analysis, model development, visualization, validation, writing original draft, writing review & editing; Bao Dinh Tran - data collection, formal analysis, visualization, writing original draft, writing-review & editing; Nam Xuan Bui - data collection, formal analysis, visualization, writing original draft, writing review & editing; An Dinh Nguyen - data collection, formal analysis, visualization; Viet Van Pham - data collection; formal analysis; visualization; writing original draft; writing-review & editing; Hoa Thu Thi Le - data collection, formal analysis, visualization; Thao Quy Le - data collection, formal analysis, visualization; Hoan Ngoc Do - data collection, formal analysis, visualization; Ngoc Tuan Le - data collection, formal analysis, visualization; Thanh Tuan Nguyen - data collection, formal analysis, visualization.

References

Armaghani, D. J., Mahdiyar, A., Hasanipanah, M., Faradonbeh, R. S., Khandelwal, M., & Amnieh, H. B. (2016). Risk Assessment and Prediction of Flyrock Distance by Combined Multiple Regression Analysis and Monte Carlo Simulation of Quarry Blasting. *Rock Mechanics and Rock Engineering*, 49(9), 3631-3641, doi:10.1007/s00603-016-1015-z.

Armstrong, L. W. (1994). The quality of stemming in assessing blasting efficiency. *UNSW Syd*ney,

Bach, N. V., Quyen, L. V., Ninh, L. N., & An, N. D. (2015). Modern Blasting Technology with Large-Diameter Boreholes Applied to Construction Material Quarries in Vietnam. Hanoi. *Natural Science and Technology* (in Vietnamese).

Back, T. (1996). Evolutionary algorithms in theory and practice: evolution strategies, evolutionary programming, Genetic Algorithms. *Oxford University Press.*

Beyer, H. G., & Arnold, D. V. (2001). Theory of evolution strategies-A tutorial: *Springer*.

Chen, Y., Wang, M., Yin, H., & Zhang, T. (2024). Prediction of flyrock distance induced by blasting using particle swarm optimization and multiple regression analysis: an engineering perspective. *Acta Geophysica*, 72(1), 287-301.

Desai, M., & Shah, M. (2021). An anatomization on breast cancer detection and diagnosis employing multi-layer perceptron neural network (MLP) and Convolutional neural network (CNN). *Clinical eHealth*, 4, 1-11.

Dong, L. (2024). Residents are frustrated as companies' blasting operations for stone extraction cause environmental pollution (in Vietnamese). https://laodong.vn/photo/nguoi-dan-buc-xuc-vi-doanh-nghiep-no-min-khai-thac-da-gay-o-nhiem-moi-truong-1355229.ldo. Accessed 04/09/2024.

Fogel, L. (1964). *On the organization of intellect* (Ph. D. thesis). University of California, Los Angeles, CA, USA.

Fogel, L. J. (1962). Autonomous automata. *Industrial research*, 4, 14-19.

Ghasemi, E., Sari, M., & Ataei, M. (2012). Development of an empirical model for predicting the effects of controllable blasting parameters on flyrock distance in surface mines. *International Journal of Rock Mechanics and Mining Sciences*, 52, 163-170.

Hansen, N., Arnold, D. V., & Auger, A. (2015). Evolution strategies. *Springer handbook of computational intelligence*. 871-898.

Jahed Armaghani, D., Tonnizam Mohamad, E., Hajihassani, M., Alavi Nezhad Khalil Abad, S., Marto, A., & Moghaddam, M. (2016). Evaluation and prediction of flyrock resulting from blasting operations using empirical and computational methods. *Engineering with Computers*, 32, 109-121.

Khashei, M., Hamadani, A. Z., & Bijari, M. (2012). A novel hybrid classification model of artificial neural networks and multiple linear regression models. *Expert Systems with Applications*, 39(3), 2606-2620.

Law, P. O. T. (2024). Company's Blasting Operation Sends Rocks Flying into Homes: All Mining Activities Temporarily Suspended (In Vietnamese). https://baovephapluat.vn/kinh-te/do-thi-xay-dung/vu-doanh-nghiep-no-min-lam-da-vang-vao-nha-dan-tam-dung-moi-hoat-dong-khai-thac-mo-155572.html. Accessed 04/09/2024.

Li, C., Zhou, J., Du, K., Armaghani, D. J., & Huang, S. (2023). Prediction of Flyrock Distance in Surface Mining Using a Novel Hybrid Model of Harris Hawks Optimization with Multi-strategies-based Support Vector Regression. *Natural Resources Research*, 32(6), 2995-3023, doi:10.1007/s11053-023-10259-4.

Liddell, K. (2021). Investigation into methods to identify and accurately locate misfired explosive charges following drill and blast operations. *University of Southampton*,

Lu, X., Hasanipanah, M., Brindhadevi, K., Bakhshandeh Amnieh, H., & Khalafi, S. (2020). ORELM: a novel machine learning approach for prediction of flyrock in mine blasting. *Natural Resources Research*, 29, 641-654.

Luat, B. V. P. (2024). The quarry blasting incident that sent rocks into residents' homes: Compensation has been provided (in Vietnamese). https://baovephapluat.vn/van-hoa-xa-hoi/doi-song-xa-hoi/vu-mo-da-no-min-lam-da-vang-vao-nha-dan-da-thuc-hien-den-bu-thiet-hai-155920.html. Accessed 04/09/2024.

Naskath, J., Sivakamasundari, G., & Begum, A. A. S. (2023). A study on different deep learning algorithms used in deep neural nets: MLP SOM and DBN. *Wireless Personal Communications*, 128(4), 2913-2936.

Nayak, N. P., Jain, A., & Mahapatra, S. R. (2022). Application of mine excellence software in flyrock prediction & mitigation. *Materials Today: Proceedings*, 48, 1271-1276.

Nien, T. (2024). The 'nightmare' of residents living near quarry blasting sites (in Vietnamese). https://thanhnien.vn/con-ac-mong-cua-nhung-ho-dan-song-gan-khu-no-min-khai-thac-da-185240706121712204.htm. Accessed 04/09/2024.

Phong, T. (2024). Unannounced quarry blasting leaves dozens of households in fear (in

Vietnamese). https://tienphong.vn/no-min-khai-thac-da-khong-thong-bao-khien-hang-chuc-ho-dan-khiep-via-post1621886.tpo. Accessed 04/09/2024.

Plus, E. (2024). Thanh Hoa: Rocks Fly into Residential Homes During Quarry Blasting (In Vietnamese). https://moitruongplus.com.vn/11/17743/Thanh-Hoa-Da-bay-vao-nha-dan-khi-no-min-khai-thac-mo-da.htm. Accessed 04/09/2024.

Purba, R. D. (1992). Control of blasting in surface mining with reference to flyrock. *UNSW Sydney,*

Raina, A., & Murthy, V. (2016). Prediction of flyrock distance in open pit blasting using surface response analysis. *Geotechnical and Geological Engineering*, 34, 15-28.

Raina, A. K., & Bhatawdekar, R. M. (2022). Blast-induced flyrock: risk evaluation and management. *In Risk, reliability and sustainable remediation in the field of civil and environmental engineering* (pp. 209-247): Elsevier.

Rudolph, G. (2000). Evolution strategies. *Evolutionary computation*, 1, 81-88.

Sawmliana, C., Hembram, P., Singh, R. K., Banerjee, S., Singh, P., & Roy, P. P. (2020). An investigation to assess the cause of accident due to flyrock in an opencast coal mine: a case study. *Journal of The Institution of Engineers* (India): Series D, 101, 15-26.

Thang, D. T., Nam, B. X., & Hieu, T. Q. (2015). Blasting in mining and construction industries. Hanoi. *Science and Technics Publishing House*.

Trade, V. M. O. I. A. (2019). QCVN 01:2019/BCT - National Technical Regulation on Safety in the Production, Testing, *Acceptance, Storage, Transportation, Use, Disposal of Industrial Explosives, and the Storage of Explosive Precursors* (In Vietnamese).

Uncuoglu, E., Citakoglu, H., Latifoglu, L., Bayram, S., Laman, M., Ilkentapar, M., et al. (2022). Comparison of neural network, Gaussian regression, support vector machine, long short-term memory, multi-gene genetic programming, and M5 Trees methods for solving civil engineering problems. *Applied Soft Computing*, 129, 109623.

Van der Walt, J., & Spiteri, W. (2020). A critical analysis of recent research into the prediction of flyrock and related issues resulting from surface blasting activities. *Journal of the Southern African Institute of Mining and Metallurgy,* 120(12), 701-714.

Xu, Y., Li, F., & Asgari, A. (2022). Prediction and optimization of heating and cooling loads in a residential building based on multi-layer perceptron neural network and different optimization algorithms. *Energy*, 240, 122692.

Zhang, J., Li, C., Yin, Y., Zhang, J., & Grzegorzek, M. (2023). Applications of artificial neural networks in microorganism image analysis: a comprehensive review from conventional multilayer perceptron to popular convolutional neural network and potential visual transformer. *Artificial Intelligence Review*, 56(2), 1013-1070.

Zhang, R., Li, Y., Gui, Y., Armaghani, D. J., & Yari, M. (2024). A stacked multiple kernel support vector machine for blast induced flyrock prediction. *Geohazard Mechanics*, 2(1), 37-48, doi:https://doi.org/10.1016/j.ghm.2024.01.002.