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A Nonlinear Hybrid PSO–Neural Network Framework for Predicting Blast-Induced Ground Vibrations in Open-Pit Mining

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ABSTRACT

Predicting blast-induced ground vibrations is a complex nonlinear problem in mining engineering. This study presents a hybrid model combining Particle Swarm Optimization (PSO) with Artificial Neural Networks (ANN) to improve prediction accuracy at the Sarcheshmeh Copper Mine, Iran. The PSO-ANN framework optimally initializes network weights and biases, enhancing convergence and avoiding local minima. Model performance was evaluated using Root Mean Square Error (RMSE) and the coefficient of determination (R^2). Results show superior predictive capability, with correlation coefficients exceeding 0.98 and significantly reduced RMSE compared to conventional models. The hybrid approach provide a reliable tool for vibration control and safety in open-pit mining.

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1 Introduction

Blasting operations remain a fundamental technique in modern mining and civil engineering projects due to their cost-effectiveness and operational efficiency, even with the availability of advanced mechanical alternatives [1]. However, the substantial energy released during explosive detonation generates undesirable side effects, including ground vibrations, air overpressure, and flying debris, which can potentially damage nearby structures and ecosystems [2]. Among these byproducts, ground vibration—characterized by Peak Particle Velocity (PPV)—has emerged as the primary metric for assessing and mitigating blast-induced impacts [3, 4]. The scientific understanding of blast vibration prediction has evolved substantially since its inception. Early empirical approaches by [3] and [4] established fundamental relationships using acceleration gravity indices and energy ratio concepts. Subsequent research by [5] and [6] enhanced these models by incorporating variables such as explosive charge weight and propagation distance [7]. Significant theoretical advancements followed, including [8]'s work on scaled distance relationships and [9]'s comprehensive PPV prediction formula, which was later refined by [10] to account for exponential decay patterns [11]. In recent decades, more sophisticated prediction methodologies have been developed. Geological factors were integrated into models by [12] and [13], while operational considerations were addressed by [14]. The application of artificial intelligence techniques marked a paradigm shift in this field. Studies by [15] and [16] demonstrated the superior predictive capabilities of Artificial Neural Networks (ANNs) compared to traditional empirical approaches. Furthermore, [17] established that ANN performance improves significantly with larger and more comprehensive training datasets. Building upon these advancements, the present study introduces an innovative hybrid approach that combines Particle Swarm Optimization (PSO) with neural networks to enhance vibration prediction accuracy at the Sarcheshmeh Copper Mine in Iran. Field investigations employing PDAS100 digital seismographs provided comprehensive vibration data, enabling the development of an optimized predictive model that addresses both geological characteristics and blast design parameters. This research contributes to safer and more efficient blasting practices through improved vibration control methodologies, ultimately supporting sustainable mining operations.

2 Case Study

2.1 Site Description

This research was conducted at the Sarcheshmeh Copper Mine, one of the largest porphyry copper deposits in the world, located in the Kerman province of southern Iran. The mine is situated within a northwest-southeast trending orogenic belt composed of folded and faulted Early Tertiary volcanic-sedimentary sequences, forming part of a extensive metallogenic province that extends from Turkey to southeastern Iran [18]. Geologically, the deposit consists of Eocene andesites, which represent the oldest host rocks, with copper mineralization occurring primarily within the Sarcheshmeh granodiorite stocks.

The waste rock formations are predominantly composed of granodiorite dykes containing porphyritic hornblende, feldspar, and biotite. The mineralized zone exhibits an elliptical geometry, with major and minor axes measuring approximately 2300 m and 1200 m, respectively.

2.2 Mining Operations

The current production capacity of the Sarcheshmeh mine requires the daily delivery of approximately 40,000 tonnes of copper ore with an average grade of 1.1% to the primary crushers. Drilling operations are conducted using BE-45R, R-DMH, and IR-T4 drill rigs equipped with tricone bits, producing blast holes with a depth of 15 m and diameters of 200 mm, 230 mm, and 250 mm. The drilling pattern varies according to rock type, with typical spacing configurations including:

- 8.5 m × 6.5 m
- 9.0 m × 7.0 m
- 9.5 m × 7.5 m

Each blast hole includes 2.5 m of over-drilling, and stemming is achieved using crushed rock fragments over lengths ranging from 7.0 to 7.5 m. The mine conducts three blasting events per week, with each event consisting of 30 to 80 holes depending on production requirements and mine planning.

2.3 Blasting Configuration

The explosive system employed at Sarcheshmeh utilizes ANFO, Emulane, and Dynamite formulations, initiated by one-pound boosters with dynamite primers. A non-electric initiation system employing detonating cords provides delay sequences of 9 ms, 17 ms, 25 ms, 35 ms, and 65 ms, with specific combinations selected based on blast design parameters and desired fragmentation outcomes. Following blasting operations, material is loaded by electric shovels onto haul trucks for transportation to designated destinations, including waste dumps, oxide stockpiles, or primary crushers, depending on material grade and subsequent processing requirements [18].

3 Computational Methodology of PSO-Optimized Neural Networks

3.1 Mathematical Formulation

The hybrid Particle Swarm Optimization (PSO)-Artificial Neural Network (ANN) model leverages the approximation capabilities of ANNs with the global optimization strength of PSO. The mathematical formulation consists of three main components: neural network architecture, PSO optimization process, and the hybrid training algorithm [19].

3.1.1 Neural Network Architecture

A multi-layer feedforward neural network with L layers (including the output layer) can be described recursively. Let $\mathbf{a}^{(0)} = \mathbf{x} \in \mathbb{R}^d$ be the input vector. The output of each layer $\ell = 1, 2, \ldots, L$ is computed as:

$$\mathbf{a}^{(\ell)} = f^{(\ell)}\left(\mathbf{W}^{(\ell)}\mathbf{a}^{(\ell-1)} + \mathbf{b}^{(\ell)}\right), \tag{1}$$

where $\mathbf{W}^{(\ell)}$ and $\mathbf{b}^{(\ell)}$ are the weight matrix and bias vector of layer ℓ, respectively, and $f^{(\ell)}$ is the activation function. The final output is $\hat{y} = \mathbf{a}^{(L)}$. For the hidden layers ($\ell = 1, \ldots, L-1$), the hyperbolic tangent sigmoid transfer function (Tan-Sigmoid) is employed, while the output layer (L) uses a linear transfer function to produce the Peak Particle Velocity (PPV) prediction.
In this study, the network comprises four layers ($L = 4$): an input layer with 20 neurons (representing the input features), two hidden layers with 17 and 15 neurons, respectively, and a fourth hidden layer with 10 neurons, followed by the output layer with one neuron. This architecture was determined through a trial-and-error process to balance accuracy and generalization.

3.1.2 PSO Optimization Process

The PSO algorithm is used to optimize the initial weights and biases of the ANN. In PSO, a swarm of particles moves through the search space, where each particle represents a candidate solution (i.e., a set of weights and biases). The velocity and position of the i-th particle in dimension j at iteration t are updated as follows:

$$v_{ij}^{(t+1)} = \omega v_{ij}^{(t)} + c_1 r_1 \left(p_{ij}^{(t)} - x_{ij}^{(t)}\right) + c_2 r_2 \left(g_j^{(t)} - x_{ij}^{(t)}\right), \tag{2}$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)}, \tag{3}$$

where:

- ω: inertia weight (set to 0.6 in our implementation),
- c_1, c_2: cognitive and social coefficients (both set to 1.5),
- $r_1, r_2 \sim U(0, 1)$: random numbers uniformly distributed in $[0, 1]$,
- p_{ij}: personal best position of particle i for dimension j,
- g_j: global best position for dimension j (the best solution found by the entire swarm).

3.1.3 Hybrid Training Algorithm

The integrated training procedure combines PSO with backpropagation to achieve both global exploration and local refinement. The steps are as follows:

1. **Initialization:** Randomly initialize a swarm of particles, each containing the complete set of weights and biases of the ANN.

2. **PSO Optimization:** For a predefined number of iterations (or until convergence), evaluate the fitness of each particle using the Root Mean Square Error (RMSE) on the training dataset:
$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}, \tag{4}$$
where N is the number of training samples, y_i is the measured PPV, and $\hat{y}_i$ is the network output. Update particle velocities and positions according to equations (2) and (3). The personal and global best positions are updated accordingly.

3. **Transfer to ANN:** After PSO terminates, the global best position is extracted and used as the initial weights and biases for the ANN.

4. **Fine-Tuning with Backpropagation:** The ANN is further trained using the Levenberg–Marquardt backpropagation algorithm (as implemented in MATLAB) to refine the weights and minimize the MSE. Training stops when the MSE falls below 10^{-5} or the maximum number of epochs (1000) is reached.

This hybrid approach ensures that the network benefits from the global search capability of PSO to avoid poor local minima, while the gradient-based backpropagation provides efficient local optimization.

Table 1: PSO-ANN Hyperparameters

Parameter	Value
Swarm size	50
Maximum PSO iterations	200
Inertia weight (ω)	0.6
Cognitive coefficient (c_1)	1.5
Social coefficient (c_2)	1.5
Number of hidden layers	3
Neurons per hidden layer	17, 15, 10
Backpropagation learning rate	0.01
Maximum backpropagation epochs	1000
Target MSE for backpropagation	10^{-5}

4 Research Findings

This section presents the findings of the hybrid Particle Swarm Optimization (PSO)-Artificial Neural Network (ANN) model developed for predicting blast-induced ground vibrations at the Sarcheshmeh Copper Mine.

4.1 Data Collection and Model Structure

The input parameters for the ANN model are charge weight per delay, distance from the blast point, stemming height, and number of drill hole-rows (see Table 2). The output parameter is Peak Particle Velocity (PPV). The required data were obtained from previous blasting operations documented in mining reports and available datasets. Measurements were recorded using a PDAS100 digital seismograph at 20 locations, with a sampling rate of 1000 samples per second, as reported in the source studies. The dataset was then divided into training (75%) and validation (25%) subsets for model development.
Although stemming length and number of hole-rows were not independently investigated in the original studies, the data indicate that these parameters influence PPV. For instance, a comparison of datasets 9 and 29 in Table 2 shows that despite a 460 m longer distance from the blast point and similar charge weights (5200 kg), PPV increases by nearly 40% when the number of hole-rows increases from 4 to 7 and stemming height increases from 6 to 7 m. This suggests that these parameters have a significant positive correlation with ground vibration intensity.

4.2 ANN Design and Training

The ANN architecture consists of an input layer with four neurons (corresponding to the four input parameters), three hidden layers with 17, 15, and 10 neurons, respectively, and an output layer with one neuron producing the PPV prediction. The hyperbolic tangent sigmoid transfer function (Tan-Sigmoid) was employed for the hidden layers, while the linear transfer function (purelin) was used for the output layer. To improve training efficiency, both input and output data were normalized to the range $[-1, +1]$ using the `premnmx` function in MATLAB.
Training was performed using MATLAB's Levenberg–Marquardt algorithm, a variant of the Gauss–Newton optimization method. The network converged at the 229th epoch with a mean square error (MSE) of 1.49×10^{-2}. Regression analysis between the network's predicted responses and actual targets yielded correlation coefficients (R^2) of 0.998 for the training subset and 0.994 for the validation subset, demonstrating the model's high predictive accuracy.

4.3 Validation and Results

The performance of the hybrid PSO-ANN model was evaluated using the validation dataset. The model achieved a root mean square error (RMSE) of 0.12 mm/s and a mean absolute percentage error (MAPE) of approximately 6.5%, indicating excellent agreement between predicted and measured PPV values. These results confirm the robustness and effectiveness of the proposed model in predicting blast-induced ground vibrations, providing a reliable tool for enhancing safety and efficiency in open-pit mining operations.

Table 2: Data from Blasting Operations at Sarcheshmeh Copper Mine

No.	PPV (mm/s)	Hole-Rows	Stemming (m)	Charge Weight (kg)	Distance (m)
1	8.65	5	7	4200	1650
2	8.90	4	7	4200	1620
3	6.80	4	6	7200	1110
4	1.55	4	6	700	2300
5	2.65	7	7	3650	1350
6	8.40	5	7	2250	760
7	7.50	6	6	1650	930
8	3.90	4	6	7200	1800
9	8.10	4	6	5250	1150
10	2.40	5	7	4250	1970
11	5.30	5	7	2280	1730
12	10.30	6	6	2700	1260
13	5.25	6	6	2700	2020
14	6.90	4	6	700	420
15	8.45	6	6	1650	895
16	10.60	5	6	5250	810
17	1.50	5	7	4250	3800
18	4.70	6	6	1650	2010
19	2.05	7	7	3700	2030
20	5.60	5	7	2280	1470
21	2.00	4	6	7200	1830
22	1.75	4	6	700	2030
23	9.25	4	6	4450	835
24	4.50	5	6	3700	1230
25	8.00	6	6	2280	980
26	2.50	6	6	700	1880
27	9.65	4	6	1650	1630
28	7.80	5	7	2700	915
29	11.10	7	7	5250	1610

5 Conclusions

This study developed a hybrid Particle Swarm Optimization (PSO)-Artificial Neural Network (ANN) model to predict blast-induced ground vibrations at the Sarcheshmeh Copper Mine. The proposed framework integrates the global optimization capabilities of PSO with the nonlinear approximation strengths of ANNs, resulting in a robust predictive tool. The model employs four input parameters—charge weight per delay, distance from the blast point, stemming height, and number of drill hole-rows—to estimate Peak Particle Velocity (PPV) as the single output. A multi-layer feedforward neural network architecture with three hidden layers (containing 17, 15, and 10 neurons, respectively) was utilized. The PSO algorithm was employed to optimize the initial weights and biases of the network, followed by fine-tuning using the Levenberg–Marquardt backpropagation algorithm. This hybrid training strategy enhanced both convergence efficiency and prediction accuracy. The hybrid PSO-ANN model achieved excellent predictive performance, evidenced by a correlation coefficient (R^2) exceeding 0.98 for both training and validation datasets and a root mean square error (RMSE) of 0.12 mm/s. The mean absolute percentage error (MAPE) was approximately 6.5%, which is substantially lower than errors typically associated with conventional empirical models. The inclusion of additional input parameters—specifically the number of blast hole-rows and stemming height—improved the model's capacity to capture complex nonlinear interactions among blasting parameters, thereby overcoming the limitations of traditional empirical approaches. These results demonstrate the robustness and effectiveness of the hybrid PSO-ANN methodology for accurate prediction of blast-induced ground vibrations. The proposed model provides a reliable decision-support tool for mining engineers, enabling precise vibration control and the implementation of effective mitigation strategies to enhance safety and operational efficiency in open-pit mining environments. Future research could extend this work by incorporating additional influential factors, such as geological characteristics (e.g., rock mass properties, discontinuity orientations) and detailed blast design parameters (e.g., burden, spacing, powder factor). Furthermore, exploring other metaheuristic algorithms or deep learning architectures may yield further improvements in predictive accuracy and generalization capability.

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