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Optimization of Open-pit Mining Planning Based on Particle Swarm Optimization and BP Neural Network

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Abstract: In the process of open-pit mining planning, there are problems such as low mineral resource recovery rate, inaccurate slope stability control, and insufficient production cost optimization. To this end, this paper combines the particle swarm algorithm (PSO) with the BP neural network to improve the level of detail control in open-pit mining planning and optimize the mining plan. First, the particle swarm algorithm is used for preliminary global optimization, and dynamic optimization is performed for key parameters in open-pit mining (such as mining path, stripping ratio, slope angle, etc.) to ensure the rationality of the overall planning. Then, a BP neural network is constructed to train historical data and predict resource recovery rate, slope stability trend and economic cost under different mining schemes. Finally, the global optimization results of the particle swarm algorithm are used as input parameters of the BP neural network to achieve refined control and improve the safety and economy of open-pit mining by iteratively adjusting the optimization scheme. The experiment shows that the PSO optimized BP method performs best in mining efficiency, reaching 145 tons/hour, significantly higher than the other two methods. In contrast, the BP neural network has a mining efficiency of 120 tons/hour, achieving more accurate optimization of open-pit mining planning.

1. Introduction

Open-pit coal mining is a complex giant system with multiple process links and intersecting processes. Its spatiotemporal evolution is to scientifically plan its three-dimensional dynamic spatiotemporal development process. However, due to the lack of open-pit coal mining time sequence planning methods for a long time, open-pit coal mining plans still rely on manual compilation, resulting in rough mining planning and frequent production decision adjustments, and unable to form the optimal material mining sequence plan in the closed time and space field of the open-pit coal mine to efficiently guide the mine production operations. This paper suggests a hybrid optimization approach that combines the BP neural network and the PSO method in order to get over these restrictions. With its ability to search globally, the PSO algorithm is capable of effectively adjusting the BP neural network's weights and bias parameters, increasing the model's training effectiveness and prediction accuracy. The PSO optimal of the neural network created by BP serves as the foundation for this study's mining planning optimization model, which is then empirically shown to be superior in terms of important metrics including conserving resources rate, mining cost, and mining efficiency. In addition, the Kruskal-Wallis H test and one-way analysis of variance (ANOVA) are used to perform significance tests on the experimental data to ensure the statistical reliability of the optimization method.

This paper first introduces the main problems in open-pit mining planning, and proposes a method that combines PSO with BP neural network for optimization. Then, the basic principles of PSO and BP neural network are elaborated in detail, and their applicability in optimization calculation is analyzed. Subsequently, an optimization model based on PSO-BP is designed, including key steps such as data preprocessing, network training, and parameter adjustment. Then, the effectiveness of the optimization method is verified through experiments, and the changes in the detailed control indicators before and after optimization are compared and analyzed. Finally, the study's findings are compiled, and the path for future development is examined.

2. Related Work

In open-pit mining investigations into optimization, many scholars are committed to improving mining efficiency, optimizing production scheduling and reducing operating costs to achieve efficient resource utilization and sustainable development. Shi et al. built an ontology based on technical requirements and literature and examined the reasons behind construction accident reports utilizing an adjacency entropy and mutually beneficial information-based domain name discovery method. They used the TransH model to convert the report into a concept vector and combined it with the TextCNN (Convolutional Neural Networks) model for prediction. Experimental results show that the TextCNN model combined with the ontology effectively improves the performance of construction safety accident prediction [1]. Nancel-Penard and Jelvez proposed an integer linear programming model that takes into account the minimum mining width requirement. The model uses a time-space decomposition heuristic method to simplify sub-problems by gradually aggregating/deaggregating time and space. The results show that this method can generate more operational production plans and narrow the gap between actual net present value and expected value [2]. In order to determine the transition excavation method within the planned production area of open-pit mining, Turan and Onur studied the improved cone mining sequence to determine the final pit limit, and used parameter analysis methods and improved floating cone algorithms to develop long-term production plans [3]. Mirzaei-Nasirabad et al. studied the real-time dispatch of trucks in open-pit mining operations through two stages: allocation planning and dynamic allocation. Among them, in terms of dynamic allocation problems, they used heuristic methods to construct a multi-objective mathematical model to minimize the waiting time of the fleet and the expected deviation of allocation planning [4]. Shi et al. built an ontology based on technical requirements and literature and examined the reasons behind construction accident reports utilizing an adjacency volatility and collaborative information-based domains word discovery method. Experimental results show that the research scheme improves the net present value and increases revenue [5]. In order to update the short-term plan based on the optimal location and relocation time of the crusher, Habib et al. set up a mixed integer programming model. The model minimizes material handling costs and maximizes revenue based on multiple objectives such as the maximum allowable tonnage change required by the factory and the location constraints of crushing and conveying in the open-pit mine. The practical case verifies the rationality of the proposed model [6]. To address the open-pit operations operations' future planning issue, Nabavi et al. constructed a mathematical model based on the idea that the grade uncertainty risk has been incorporated into the simulated grade. The model sets the constraints of the model with profit and loss functions. Compared with the traditional model, the present value of the net present is decreased by 2.23% using the loss functionality method[7]. Noriega and Pourrahimian constructed a shovel allocation planning model for short-term planning of open-pit mines based on the deep Q learning algorithm. In the actual research case, the allocation plan of the model successfully achieved the required production target[8]. In order to effectively manage the micro-scheduling criteria (in hours, minutes, and seconds) related to the iron mineral open-pit mining sector, Liu et al. presented a novel short-term Mine Excavator Scheduling (MET) issue. The results showed that the hybrid algorithm significantly outperformed the exact solution method in solving small and medium-scale problems and could significantly reduce the cost of excavator relocation [9]. Dehghani et al. suggested a technique based on a financial block paradigm to calculate the depth at which open pit and underground processing transitions while accounting for the ultimate boundary's uncertainty and mineral price. According to the study, 375 meters is the suggested transition depth for the mining approach when dealing with the uncertainty of swings in mineral prices [10]. The effectiveness of the Genetic Algorithm (GA) in designing the ultimate pit limit (UPL) in open pit mines was assessed by Azadi et al. The UPL value of GA was modified to 20940 following sensitivity analysis of GA crossover and mutation probabilities, which is only 8% less than the LP value[11]. Although existing research has made some progress in improving open-pit mining efficiency, optimizing production scheduling and reducing operating costs, it still faces challenges such as optimization algorithms being prone to falling into local optimality, high computational complexity, insufficient ability to adapt to complex geological conditions, and limited adaptability to ore grade and market price uncertainties. Further improvement and optimization are urgently needed.

3. Method

3.1 Objective Function Design in Open-Pit Mining Planning

3.1.1 Objective functions such as mining efficiency, cost, and resource protection

In open-pit mining, mining efficiency, cost, and resource protection are the most critical objectives. Usually, the objective function can be expressed as a weighted sum of multiple sub-objectives, as follows:

Mining efficiency target:

Mining efficiency refers to the amount of minerals extracted per unit time, which is usually affected by factors such as the productivity of the mining operation, the efficiency of the use of machinery and equipment, and the mineability of the ore body. Efficiency targets can be defined in the following ways:

$$f_{efficiency} = \frac{Q_{mine}}{T_{operation}} \tag{1}$$

Among them, Q_{mine} is the amount of ore mined per unit time; $T_{operation}$ is the time of mining operation.

Mining cost target:

Mining costs include equipment use, labor, fuel consumption, transportation and other aspects. Usually, the objective function needs to minimize the total cost, which is defined as:

$$f_{cost} = C_{equipment} + C_{labor} + C_{fuel} + C_{transport} \tag{2}$$

Among them, $C_{equipment}$ is the equipment cost; C_{labor} is the labor cost; C_{fuel} is the fuel cost; $C_{transport}$ is the transportation cost.

Resource protection goal:

The resource protection goal mainly refers to minimizing the waste of non-recyclable resources during the mining process and protecting unmined mineral resources. This goal can be achieved by optimizing the mining sequence and depth control to reduce ore body losses. The resource protection objective function can be expressed as:

$$f_{resource} = 1 - \frac{V_w}{V_T} \tag{3}$$

Among them, V_w is the volume of ore lost during mining, and V_T is the total ore volume.

Combining the above objectives, the comprehensive objective function can be expressed as:

$$f_{total} = w_1 . f_{effciency} - w_2 . f_{cost} + w_3 . f_{resource} \tag{4}$$

Among them, w_1, w_2, and w_3 are the weight coefficients of each objective, indicating their relative importance in the overall optimization.

3.1.2 Environmental and safety constraints

In the mining process, environmental impact and safety are constraints that cannot be ignored. Common environmental and safety constraints include:

Environmental constraints:

The mining process may cause pollution, noise, dust and other impacts on the environment, so it is necessary to consider limiting these adverse effects. Environmental constraints can be expressed by the following formula:

$$\mathrm{I}_{\mathrm{environment}} \leq \mathrm{Threshold} \tag{5}$$

Among them, $\mathrm{I}_{\mathrm{environment}}$ includes factors such as pollution emissions, noise, and dust, and Threshold is the maximum value allowed, which is usually set by government regulations or environmental standards.

Safety constraints:

Safety is the primary condition for open-pit mining, especially in the process of mining operations, the safety of miners needs to be ensured. Safety constraints may include slope stability, equipment operation safety, etc. The specific constraints are:

$$S_{slope} \geq F_{safety} \tag{6}$$

$$T_o \leq T_{o,max} \tag{7}$$

Among them, S_{slope} is the mining slope's security feature, and $T_{o,max}$ is the maximum safe time of a single operation.

3.2 The Role of Particle Swarm Optimization and BP Neural Network in the Objective Function

Open-pit coal mining management optimization challenges with multiple objectives can be resolved by combining PSO and BP neural networks (BPNN). In this combined optimization, a neural network constructed by BP is utilized to model and forecast the intricate mining process, while the particle swarm method is utilized for optimum performance the objective function's parameters (such as the excavation path, mined sequence, equipment arrangement, as well as etc.).

The role of particle swarm optimization:

PSO simulates group collaboration by using particles in the search area to identify the best solution. Particle swarm can effectively optimize mining efficiency, cost, resource protection and other goals, and can also adjust the weight coefficients between various goals to achieve the comprehensive optimization goal more accurately.

The particle swarm optimization update formula is as follows:

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i - x_i^t) + c_2r_2(g^t - x_i^t) \tag{8}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{9}$$

Among them, v_i is the rate of travel of the fragments; x_i is the location of the molecule; p_i is the particle's ideal arrangement for itself; w is the residual component; g is the universal ideal positioning; c_1 and c_2 are the learning factors; r_1 and r_2 are random numbers.

The role of BP neural network:

BP neural network is used to predict certain key variables in the mining process (such as ore grade, mining cost, etc.) through historical data or simulation results. BP neural network can be used as part of the objective function, input various characteristic data of the mining area, and output the predicted value of the objective function as the evaluation standard of particle swarm optimization.

The forward propagation formula of BP neural network is:

$$\mathrm{y} = \mathrm{f}(\mathrm{Wx} + \mathrm{b}) \tag{10}$$

The vector that is input is denoted by x; the weighted the matrix by W; the bias by b, the action equation by f; and the obtained result by y.

3.3 Construction and Application of Particle Swarm Optimization BP Neural Network Model

When constructing a particle swarm optimization BP neural network model, the selection of training data and input and output design are crucial. The data usually comes from historical mining data or simulation models, and needs to include various features that may affect the objective function during the mining process.

Selection of training data:

The training data set should contain variables that affect mining efficiency, cost, resource protection and other objectives. Typical input data include:

Mining depth, ore body shape, ore grade, equipment type, working time, fuel consumption, environmental and safety factors, such as mining area slope, environmental protection measures.

Output data usually includes: mining efficiency (amount of ore mined per unit time); mining cost (including equipment, labor, fuel, transportation, etc.); resource protection rate (degree of resource loss)

The training data set can be expressed as:

$$\mathrm{D} = \{(\mathrm{X}_1, \mathrm{Y}_1), (\mathrm{X}_2, \mathrm{Y}_2), \cdots, (\mathrm{X}_n, \mathrm{Y}_n)\} \tag{11}$$

Among them, X_i is the input vector, which contains the characteristic data of the mining process. Y_i is the corresponding output target, such as mining efficiency, cost, etc.

Input and output design:

The input layer of the BP neural network contains multiple nodes, representing various factors that affect the mining process. The output layer contains the value of the objective function, such as mining efficiency, cost, etc. The design of the hidden layer depends on the complexity of the data and the model requirements.

Input layer: It contains features that affect the mining process, assuming $\mathrm{X} = [\mathrm{x}_1, \mathrm{x}_2, \cdots, \mathrm{x}_m]$, where m is the number of features.

Hidden layer: The number of layers and nodes is selected by experience or cross-validation.

Usually, deeper networks can capture more complex nonlinear relationships.

Output layer: It outputs the optimized objective function value, usually $Y = [y_1, y_2, \cdots, y_k]$, where k is the number of targets (such as the value of multiple target synthesis).

4. Results and Discussion

4.1 Data Preparation

The experimental data comes from the mining process of the simulated mining area, covering multiple aspects such as ore body geometric parameters, mining equipment parameters, environmental constraints, etc. The data set is divided into a training set (accounting for 70%), a validation set (accounting for 15%), and a test set (accounting for 15%). The input variables include parameters of the open-pit ore body, such as the depth of the deposit (DD), the thickness of the ore layer (TT) and the ore grade (GG); parameters of the mining equipment, including equipment type, energy consumption per unit operating time (EE) and the number of equipment (NN); transportation conditions, including transportation distance (LL) and transportation cost; and resource protection factors, such as waste rock disposal rate and ore loss rate. The output variables include optimization objectives: mining efficiency (the amount of ore mined per hour), total mining cost (covering equipment, fuel, manpower, transportation, etc.) and resource protection rate (ore recovery rate).

4.2 Evaluation Indicators

To ensure the rationality of the experimental results, we evaluate the model optimization effect from three dimensions: mining efficiency, cost, and resource protection:

The mining efficiency improvement rate is the increase in the ore mining volume per hour. The cost reduction rate represents the reduction in the total mining cost, including equipment, fuel, manpower, and transportation expenses. The resource protection improvement rate measures the improvement in ore recovery rate. The convergence speed describes the speed at which the optimization algorithm reaches the optimal solution.

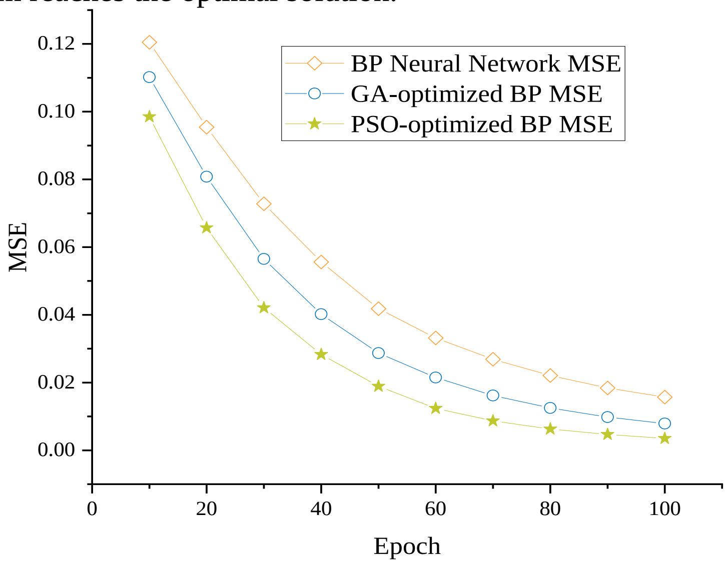

Figure 1. MSE decline trend of loss function of different methods (recorded every 10 rounds)

As can be seen from Figure 1, the BP neural network optimized by PSO performs best among all methods, with its MSE decreasing from the initial 0.0985 to 0.0035, and has the fastest convergence speed. PSO-BP has significantly reduced the error in the first 50 rounds, and maintained a steady decline in the later period. The final MSE value is much lower than BP and GA-BP, indicating that the PSO optimization algorithm can more effectively adjust weights and biases, thereby accelerating the model to converge to the optimal solution.

In order to evaluate the generalization ability of the three methods of BP, GA-BP, and PSO-BP, we calculate their MSE errors on three different test data sets and calculated their variances. The smaller the variance, the more stable the performance of the model on different data sets and the stronger the generalization ability.

Table 1. MSE and variance of different optimization methods on different data sets

Method	Dataset 1	Dataset 2	Dataset 3	Variance
BP Neural Network	0.0161	0.0183	0.0174	1.10×10^{-6}
GA Optimized BP	0.0085	0.0098	0.0092	3.73×10^{-7}
PSO Optimized BP	0.0039	0.0042	0.0041	2.00×10^{-7}

According to the experimental data analysis in Table 1, the mean square error (MSE) of the BP neural network on the three data sets is 0.0161, 0.0183 and 0.0174, respectively, with a variance of 1.10×10^{-6}, showing a certain error and fluctuation. The MSE of the BP neural network optimized by GA is reduced to 0.0085, 0.0098 and 0.0092, respectively, with a variance of 3.73×10^{-7}, showing that the optimized model has good accuracy and stability. The MSE of the BP neural network optimized by PSO on the three data sets is further reduced to 0.0039, 0.0042 and 0.0041, with a variance of 2.00×10^{-7}, showing the best prediction performance and the smallest fluctuation. Therefore, the BP neural network optimized by PSO outperforms other methods in all indicators, indicating that it has higher accuracy and stability when processing data sets.

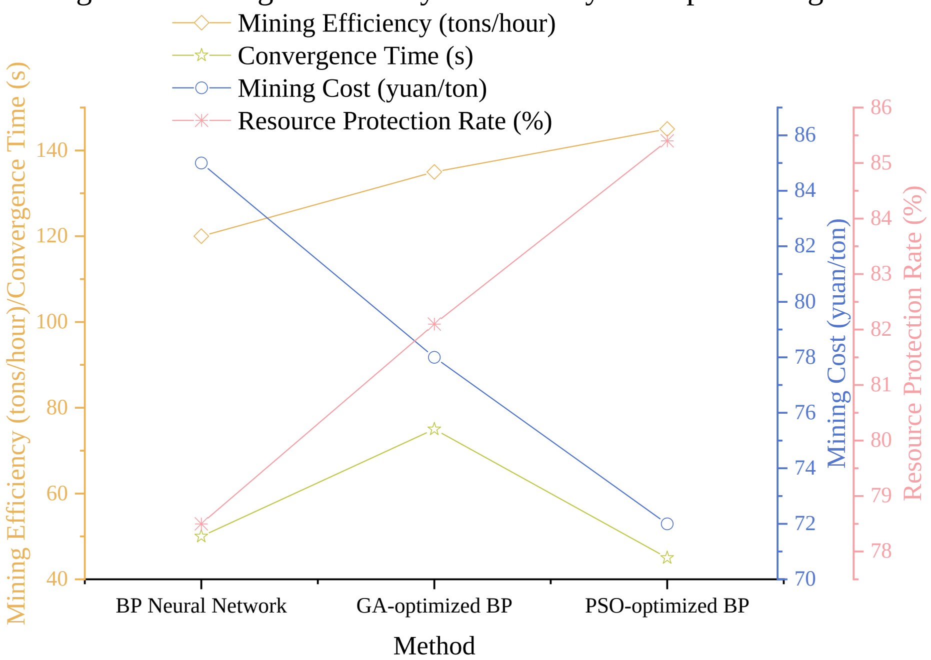

Figure 2. Experimental data of mining efficiency, cost and resource protection rate

The mining efficiency of the GA optimized BP is 135 tons/hour, between the two. This shows that the PSO optimized BP has obvious advantages in improving mining efficiency. In terms of mining cost, PSO optimized BP also performs well, with a unit mining cost of 72 yuan/ton, which is much lower than 85 yuan/ton of BP neural network and 78 yuan/ton of GA optimized BP. This result shows that the PSO optimization method can more effectively control mining costs and reduce the economic burden of ore mining. PSO optimized BP also performs well in resource protection rate, reaching 85.4%, which is higher than 82.1% of GA optimized BP and 78.5% of BP neural network (as shown in Figure 2).

In order to verify whether the differences among the three optimization methods of BP, GA-BP and PSO-BP in mining efficiency, mining cost, resource protection rate and MSE error are statistically significant, we use Kruskal-Wallis H test and one-way analysis of variance (ANOVA) for statistical tests.

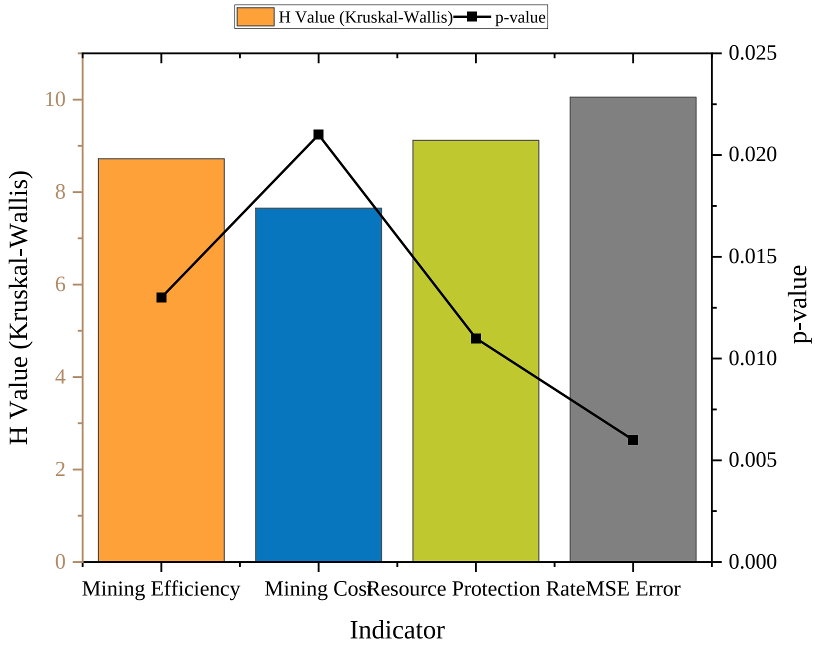

Figure 3. Kruskal-Wallis H test results (measure the significant differences between methods)

According to Figure 3, Kruskal-Wallis H test results, we can see that the differences between different optimization methods in mining efficiency, mining cost, resource protection rate and MSE error are significant. The specific analysis is as follows:

The H value is 8.72, and the p value is 0.013, which is less than the significance level α=0.05, indicating that the difference in mining efficiency between different optimization methods is statistically significant. It can be inferred that the PSO optimization BP method has a significant advantage in improving mining efficiency compared with the BP neural network and GA optimization BP methods. The difference in mining frequency between multiple methods of optimization is also substantial, as indicated by an H-value of 7.65 and the Pearson's correlation coefficient of 0.021, both of which are under the threshold of 0.05. The PSO optimized BP method performs well in reducing mining costs and can effectively reduce unit mining costs. Compared with the traditional BP neural network and GA optimized BP, it shows obvious advantages. The H value is 9.12 and the p value is 0.011, which is also less than 0.05, indicating that the differences in resource protection rates among the optimization methods are statistically significant. This further verifies the significant advantages of the PSO optimization BP method in resource protection, and its optimization effect is more prominent than that of BP and GA optimization BP. The H value is 10.05 and the p value is 0.006, which is also less than 0.05, indicating that the difference between the optimization methods is significant in terms of error, as shown in Figure 3. The PSO optimization BP method performs best in error control, can significantly reduce the MSE error, and has the most obvious optimization effect.

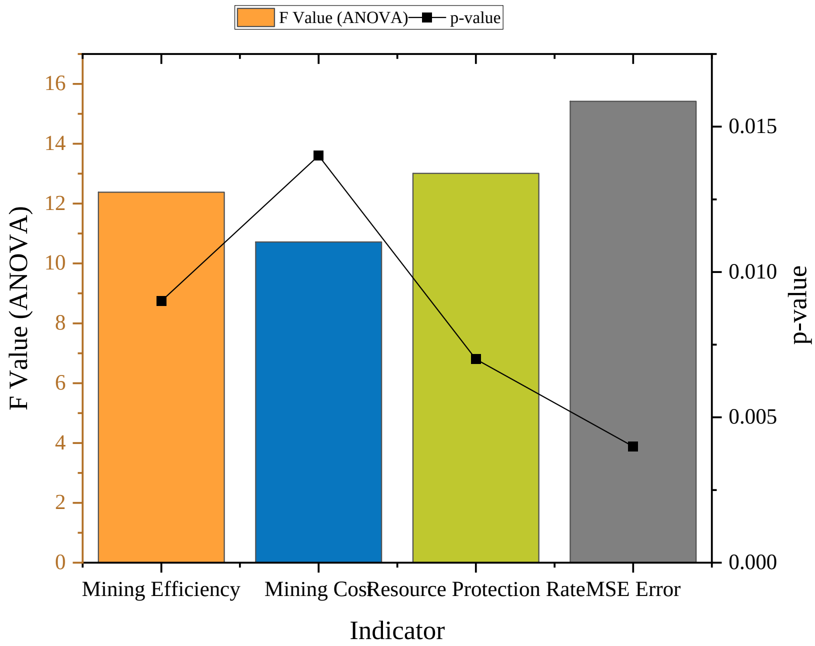

Figure 4. One-way ANOVA results

The difference in mining efficiency across various optimization techniques is substantial, as indicated by the F value of 12.38 and the p value of 0.009, both of which are below the significance level of 0.05. Compared to the GA optimized BP method and the conventional BP neural network, the PSO optimized BP approach greatly increases mining efficiency. The variations in mining costs across the various optimization techniques are statistically significant, as indicated by the F value of 10.72 and the p value of 0.014, both of which are less than 0.05, as shown in Figure 4. The PSO optimized BP method performs best in reducing MSE errors, which can effectively reduce errors and ensure more accurate mining planning.

5. Conclusion

In recent years, several large open-pit mines in China have needed to undergo technical transformation to varying degrees due to changes in mining technology conditions and changes in market requirements for production scale and product quality. Therefore, this open-pit mining planning decision model was applied to complete the reasonable planning of mining plans, minimize mining production costs and maximize comprehensive benefits, which has important guiding significance for the development of mining areas. In order to optimize open-pit mining planning, this paper suggests a hybrid optimization model that combines the BP neural network and the particle swarm optimization (PSO) method. In order to improve the model's forecasting precision and completion speed, the study builds an optimization objective function and applies the PSO method to modify the biases as well as weights of the BP neural network. The experiments conducted demonstrate that the PSO optimized BP model performs better in key metrics such mining effectiveness while mining cost, safeguarding resources rate, and MSE error control when compared to the classic BP neural network design and GA optimized BP neural network. Specifically, the PSO optimized BP model can find the optimal solution in a shorter convergence time, improve the ore mining efficiency, and effectively reduce the unit mining cost. At the same time, the model can better optimize resource utilization, improve resource protection rate, and reduce mineral resource waste. In addition, the differences between different optimization methods are verified by Kruskal-Wallis H test and one-way analysis of variance (ANOVA), which further proves the effectiveness and reliability of the proposed method.

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