

RESEARCH ARTICLE

Overall Dynamic Optimization of Metal Mine Technical Indicators Considering Spatial Distribution of Ore Grade Using AADE

XUNHONG WANG^{1,2,3,4}, YONGLIN TAN^{2,4}, AND LAN YANG⁵¹School of Information and Control Engineering, China University of Mining and Technology, Xuzhou 221000, China²School of Economic and Management, Guangxi University of Science and Technology, Liuzhou 545006, China³Keli Sensing Technology (Ningbo) Company Ltd., Ningbo 315033, China⁴Research Center for High-Quality Industrial Development of Guangxi, Liuzhou 545006, China⁵School of Foreign Studies, Guangxi University of Science and Technology, Liuzhou 545006, China

Corresponding authors: Yonglin Tan (tanyonglin2018@gmail.com) and Lan Yang (yanglan2018@gmail.com)

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ABSTRACT In optimizing the production of a metal mine, either the overall dynamic relations between technical indicators or the spatial distribution of the ore grade are usually considered, but few studies have considered both factors together. These two factors in combination have a greater effect on the optimization of mine production in terms of economic benefit and resource utilization than they do individually. We proposed an overall dynamic optimization model of technical indicators of metal mine production that considers the spatial distribution of the ore grade to better optimize the technical indicators and improve sustainable development of mineral resources. We incorporated an adaptive mutation strategy and adaptive control parameters into a differential evolution algorithm (AADE) in order to overcome the drawbacks of the differential evolution algorithm in solving this optimization model. The adaptive mutation strategy and adaptive control parameters were used to increase the rate of convergence and improve the search for a global maximum. To assess the performance of AADE, we used a real case and four test functions (the Sphere, Griewank, Rastrigin and Rosenbrock functions) in tests that compared AADE with a standard genetic algorithm, a standard differential evolution algorithm and the recently developed adaptive differential evolution algorithm. The results indicate that the optimization model we created is better aligned with mine production processes than current optimization models. In optimizing the technical indicators of metal mine production to maximize economic benefits, AADE performed significantly better than the other three algorithms tested in terms of convergence rate and global search ability.

INDEX TERMS Metal mine, technical indicator, overall dynamic relation, ore grade distribution, AADE.

I. INTRODUCTION

Metal minerals are an important non-renewable resource and are basic to social development and human survival. They are essential to national economic development, and maintaining the security of such resources has great strategic value. The rapid development of China's economy has resulted in tens of thousands of mines having been built, and the quantity of solid minerals mined in China is the highest in the world.

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However, in a time of product shortages in China, the pursuit of high quantities of mineral resources and increased development speed have resulted in a wide range of production methods, low levels of technology use, and insufficient investment in and attention to the sustainable development of mineral resources. Consequently, mineral resources are not fully utilized, and waste is a serious problem. It is therefore essential to develop efficient mining techniques for mineral resources.

The term "mineral resources" refers to geological bodies that can be mined and utilized under current technological

and economic conditions, which bring economic benefits to the state and business enterprises after extraction. Mineral resources are the product of geological action and are characterized by their scarcity and non-renewability. Whether a geological body can be considered to be a mineral resource is closely related to the current state of production technology and the mineral market. Ongoing changes in production technology and the volatility of mineral markets mean that minerals are a dynamic resource. Thus mining metal mineral resources to create economic and resource benefits is a significant research topic that many mining researchers have been investigating.

Optimization of the technology used for metal mine production will determine the best production indicators for optimal economic and resource use benefits. Changes in the mineral market and advances in production technology continually change the relevance of technological production indicators over time, so there is an ongoing need to adjust and optimize them. Optimization of the technical indicators of mine production is therefore a prerequisite for efficient mining of mineral resources.

Researchers have taken two approaches to optimization of the technical indicators of mine production in recent decades. The first approach [1], [2], [3], [4], [5] is the overall dynamic optimization of the technical indicators. This approach ignores the spatial distribution of the ore grade. However, assuming that the grade distribution is constant for the entire deposit, without considering the high-grade and low-grade regions in the deposit, leads to the waste of mineral resources. The second approach is to optimize the technical indicators of mine production, taking into account the spatial distribution of the ore grade. Wang *et al.* [6], [7] used dynamic programming to optimize the technical indicators of mine production. They included the mining method, production capacity and the mining sequence. They also considered the actual distribution of the ore grade in different zones of the orebody and created a dynamic programming model to optimize the technical indicators of mine production and applied the model to practical cases. However, in creating the model, they ignored the dynamic relations between the technical indicators of mine metal production. In other words, the model they developed did not result in the overall dynamic optimization of the technical indicators of mine production. Thus, the optimized, but not optimal, technical indicators led to inefficient mining of mineral resources.

The preceding studies included optimization of the technical indicators of mine production, and some of the research was used practically. However, these studies considered only one aspect, either the overall dynamic relations between the technical indicators or the spatial distribution of the ore grade. Few researchers have considered both factors at the same time, and this incompleteness has led to inefficient exploitation of mineral resources. It is therefore necessary to develop an optimization model and an optimization method to optimize the technical indicators of mine production in order to more efficiently exploit metal mineral resources.

Such an approach must consider two aspects, the overall dynamic relations between the technical indicators and the spatial distribution of the ore grade.

The production of metal mines is a multi-factor, multi-level, multi-constrained, complex dynamic process, so the optimization of technical indicators is a complex nonlinear optimization problem. It has been well documented that standard optimization methods cannot easily solve complex nonlinear optimization problems [8], [9], [10]. Many intelligent evolutionary methods have been proposed to solve complex nonlinear optimization problems, such as the genetic algorithm (GA) [11], the particle swarm algorithm (PS) [12], [13] and the differential evolution algorithm (DE) [14], [15]. DE is an easy-to-use algorithm that has few control parameters, is low in computational complexity, and shows good convergence. It is therefore used to solve many complex nonlinear optimization problems [16], [17], [18]. However, the standard DE algorithm has two drawbacks when used to optimize the overall dynamic behavior of technical indicators of metal mine production, considering the ore grade distribution.

First, the mutation strategy, determination of which is the most important step in this algorithm, has a great effect on the performance of DE. The mutation strategies used in standard DE algorithms are DE/rand/* and DE/best/* [19]. Many studies have shown that DE/rand/* has a global search capability but converges slowly. DE/best/*, in contrast, converges rapidly but has a tendency to fix on a local optimum [20], [21].

Second, DE has two important control parameters that affect its accuracy and its convergence rate: the scale factor F and the crossover rate CR [22], [23]. In the standard DE algorithm, the values of these two control parameters are preset and remain unchanged during evolution [24]. However, researchers have found that the optimal control parameter values are generally different for various problems or even for various evolutionary stages of the same problem [25]. It is therefore difficult to determine the optimal control parameter values to solve the overall dynamic optimization problem for metal mine technical indicators when considering the ore grade distribution.

To overcome the preceding drawbacks of the DE, we introduced an adaptive mutation strategy and adaptive control parameters into the standard DE algorithm and designed an adaptive mutation operator and adaptive control parameter for DE (AADE) to be incorporated into the algorithm in order to solve the overall dynamic optimization problem.

II. OVERALL DYNAMIC OPTIMIZATION MODEL OF METAL MINE TECHNICAL INDICATORS CONSIDERING THE SPATIAL DISTRIBUTION OF THE ORE GRADE

A. DYNAMIC RELATIONSHIP MODEL OF METAL MINE TECHNICAL INDICATORS

Mine production consists of a geological process, a mining process, and a beneficiation process, each of which has main technical indicators, as shown in Figure 1; the technical

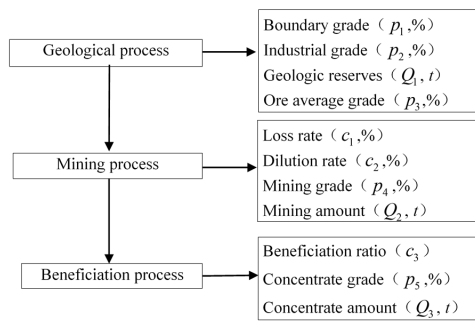


FIGURE 1. Production processes and main technical indicators of metal mines.

TABLE 1. Detailed definitions of main technical indicators.

Technical indicator	Definition
Boundary grade	Distinguish ore and rock.
Industrial grade	The lowest ore grade currently available for mining.
Geological reserves	The recoverable reserves of ore.
Ore average grade	The average grade of ore.
Loss rate	The ratio of the loss of geological reserves to the total geological reserves in the mining process.
Dilution rate	The rate at which ore grade decreases in the mining process.
Mining grade	Average grade of mining ore.
Mining amount	Amount of mining ore.
Concentration ratio	The ratio of the mining amount to the concentrate amount.
Concentrate grade	Average grade of concentrate ore.
Concentrate amount	Amount of concentrate ore.

indicators are defined or described in detail in Table 1. We model the three processes in the following sections.

1) GEOLOGICAL PROCESS

The model [2] of the relationship of geologic reserves and ore average grade with ore boundary grade and ore industrial grade is:

$$Q_1 = f_1(p_1, p_2) = Q_0 \times \frac{\int_{p_1}^{p_2} \varphi(x)g(x)c(x)dx + \int_{p_2}^{100} g(x)c(x)dx}{\int_{p_a}^{p_b} \varphi(x)g(x)c(x)dx + \int_{p_b}^{100} g(x)c(x)dx} \quad (1)$$

$$\varphi(x) = \left(\frac{x - p_1}{p_2 - p_1}\right)^z (p_1 \leq x \leq p_2) \quad (2)$$

$$p_3 = f_2(p_1, p_2) = \frac{\int_{p_1}^{p_2} x\varphi(x)c(x)dx + \int_{p_2}^{100} xc(x)dx}{\int_{p_1}^{p_2} \varphi(x)c(x)dx + \int_{p_2}^{100} c(x)dx} \quad (3)$$

where p_a and p_b are respectively the original boundary grade and original industrial grade; Q_0 is the geological reserve calculated using mining software with boundary grade and

industrial grade p_a and p_b ; $\varphi(x)$ is the probability function that the ore with a grade between the boundary grade and industrial grade is mined; z is a constant value, depending on the geological properties of the ore; $g(x)$ is a function of ore weight and grade; and $c(x)$ is the probability density function of the ore grade distribution.

2) MINING PROCESS

The ore characteristics and mining methods of each mining area are basically the same for an individual mine. In this case, there was some correlation between the dilution rate and the loss rate in the ore production process [1], and the relationship model is:

$$c_2 = f_3(c_1) \quad (4)$$

The dilution rate is the ratio of the difference between the ore average grade and the mining grade to the ore average grade:

$$c_2 = (p_3 - p_4)/p_3 \quad (5)$$

Rearranging equation (5), the mining grade can be calculated by equation (6):

$$p_4 = p_3(1 - c_2) \quad (6)$$

Depending on the amount of metal conserved during mining, it can be calculated that:

$$Q_2 \times p_4 = Q_1 \times (1 - c_1) \times p_3 \quad (7)$$

Combining equations (6) and (7), the equation to calculate the mining amount is:

$$Q_2 = Q_1 \frac{1 - c_1}{1 - c_2} \quad (8)$$

3) BENEFICIATION PROCESS

The concentration ratio is the ratio of the mining amount to the concentrate amount:

$$c_3 = Q_2/Q_3 \quad (9)$$

For an individual mine, the characteristics of the mining ore, the processing technology, the equipment, and the agent can be assumed to be constant. In this case, there are relationships between ore concentration ratio and mining grade, between concentrate grade and mining grade, between concentrate grade and ore concentration ratio, and between concentrate grade and concentrate selling price [26], [27], [28], [29], [30]. These relationships are modeled by equations (10–12):

$$c_3 = f_4(p_4) \quad (10)$$

$$p_5 = f_5(p_4, c_3) \quad (11)$$

$$q = f_6(p_5) \quad (12)$$

B. OVERALL DYNAMIC OPTIMIZATION MODEL OF TECHNICAL INDICATORS OF METAL MINE PRODUCTION CONSIDERING ORE GRADE DISTRIBUTION

1) MODELING STRATEGY

Metal mining is conducted as a series of units. To take account of the lack of ore homogeneity, the deposit to be optimized is divided into zones that are optimized according to the ore characteristics. Each optimized zone has its own ore grade distribution. The ore is mined in sequence according to the quality of the optimized zone. However, mining each optimized zone requires decisions to be made regarding the technical indicators for that zone; zones are not isolated, so the decision affects subsequent mining decisions for other zones. Therefore, the dynamic relationships between optimized zones must be considered in optimization.

2) OBJECTIVE FUNCTION

Profit calculations do not usually consider the time value of money, so using profits to calculate the return on investment of funds is not fruitful. Net present value not only considers the time value of a fund, but also facilitates the calculation of return on investment. We therefore used net present value as the measure of the economic benefit of metal mine production to be optimized. The objective function of the technical indicator optimization model of metal mine production based on the economic benefit is therefore:

$$\max \theta = \sum_{i=1}^N \theta_i \tag{13}$$

where θ is the total net present value; θ_i is the net present value of optimized zone i ; and N is the number of optimized zones.

Since the mining decision of the optimized zone mined first affects the starting time of the mining of subsequent optimized zones, the net present value is a function of time. Therefore, the net present value of each optimization zone is not independent but has a dynamic relationship with the net present values of other optimized zones. When the starting time of mining is 0, the calculation process for the net present value of optimized zone i is as follows.

(1) Calculate the mining time t_i of optimized zone i :

$$t_i = \frac{Q_{2,i}}{Q_z} \tag{14}$$

where $Q_{2,i}$ is the total mining quantity of optimized zone i , and Q_z is the annual production capacity.

(2) The mining start time $T_{1,i}$ of optimized zone i is the sum of the mining times of each previously optimized zone, and is calculated by equation (15):

$$T_{1,i} = \sum_{j=1}^{i-1} t_j \tag{15}$$

(3) The mining end time $T_{2,i}$ of optimized zone i is:

$$T_{2,i} = \sum_{j=1}^{i-1} t_j \tag{16}$$

(4) The total profit G_i of optimized zone i is:

$$G_i = Q_{3,i} * q_i - Q_{2,i} * h \tag{17}$$

where $Q_{3,i}$ is the concentrate amount in optimized zone i ; q_i is the selling price of the concentrate in optimized zone i ; and h is the total production cost per unit of ore.

(5) The average annual profit g_i of optimized zone i is:

$$g_i = \frac{G_i}{t_i} \tag{18}$$

(6) Total net present value of optimized zone i is:

$$\theta_i = \begin{cases} g_i^* (T_{2,i} - T_{1,i}) & T_{1,i}^- = T_{2,i}^- \\ (1+d)^{T_{1,i}^-} \left(\frac{(T_{1,i}^- + 1 - T_{1,i})}{(1+d)^{T_{1,i}^-}} + \frac{1}{(1+d)^{T_{1,i}^- + 1}} + \dots + \frac{1}{(1+d)^{T_{2,i}^- - 1}} + \frac{(T_{2,i}^- - T_{2,i})}{(1+d)^{T_{2,i}^-}} \right) & else \end{cases} \tag{19}$$

where $T_{1,i}^-$ is the integer part of $T_{1,i}$; d is the annual discount rate; and $T_{2,i}^-$ is the integer part of $T_{2,i}$.

3) CONSTRAINTS

(1) The boundary grade is not higher than the industrial grade:

$$p_{1,i} \leq p_{2,i} \tag{20}$$

where $p_{1,i}$ is the boundary grade of optimized zone i , and $p_{2,i}$ is the industrial grade of optimized zone i .

(2) The concentrate grade is not less than the minimum smelting grade:

$$p_{5,i} \geq p_y \tag{21}$$

where $p_{5,i}$ is the concentrate grade of optimized zone i , and p_y is the lowest smelting grade.

4) OPTIMIZATION MODEL

Combining the above objective function and constraints, the technical indicator optimization model for metal mine production to maximize economic benefit is:

$$\begin{cases} \max \theta = \sum_{i=1}^N \theta_i \\ s.t. \quad p_{1,i} \leq p_{2,i} \\ \quad \quad p_{5,i} \geq p_y \end{cases} \tag{22}$$

It is worth noting that the choice of decision variables is associated with the model of the relationships between indicators. A relational model must be identified before a decision variable can be identified. The relationship model is related to the geological conditions of the deposit and the ore characteristics, and the mining methods, beneficiation methods and beneficiation equipment of the mine [2]. The decision variable can therefore be determined only after determining the mine characteristics.

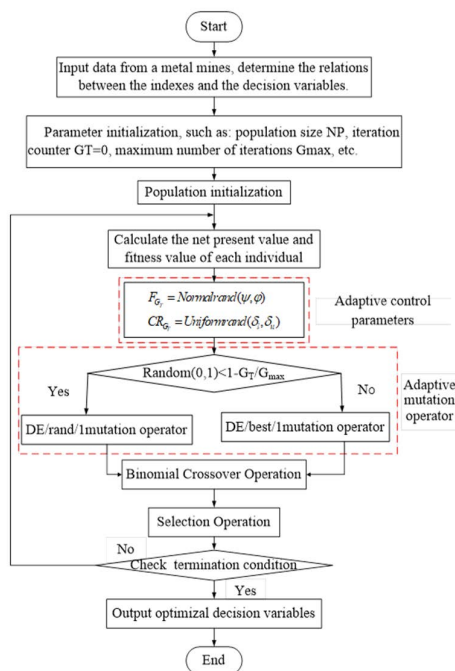


FIGURE 2. Flow chart of the AADE for optimizing the proposed model.

C. AADE

Adaptive differential mutation operators can better balance global exploration with local exploitation in DE and can improve optimization performance and increase algorithm robustness [31]. The use of adaptive control parameters improves optimization performance and algorithm robustness [32], [33]. The optimization performance of the DE algorithm can be improved in solving the overall dynamic optimization model without the necessity of estimating the appropriate proportion factor *F* or crossover rate *CR*.

We therefore introduced the adaptive mutation operator and adaptive parameters into the standard DE algorithm to create the AADE, and AADE was then used to solve the overall dynamic optimization model. The AADE flow chart is shown in Figure 2.

III. EXAMPLE OF MODEL APPLICATION

An orebody at -48 to -192 m in the large Yinshan copper mine in China is used as an example of the application of the AADE. The orebody was divided into five zones for optimization based on existing mine production data and the current production status of the min. The zones were optimized for technical indicators using the established model and AADE. All algorithms were implemented in Python. Calculations were performed on a PC having an Intel Core i5-9400 quad-core processor and 8 GB RAM running under the 64-bit Microsoft Windows 10 operating system.

Table 2 shows the ranges of the optimization zones and their original geological reserves, which are the geological reserves corresponding to the original boundary grade (0.15%) and the original industrial grade (0.25%).

TABLE 2. The range and original geological reserves of the optimized units of Yinshan copper mine.

Optimization zone	Horizontal range (m)	Original geological reserves (10 ⁴ t)
1	-48 to -72	384.6
2	-72 to -96	319.4
3	-96 to -120	258.1
4	-120 to -144	178.4
5	-144 to -192	118.1

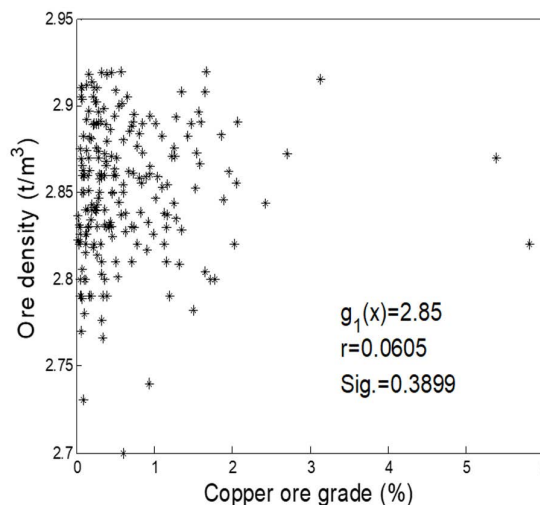


FIGURE 3. Scatter plot of orebody weight and copper grade of the Yinshan copper mine.

The production requirements of the Yinshan copper mine set the boundary grade and the industrial grade of each optimized unit in the range 0.05% to 0.45%. The parameter values for the Yinshan copper mine were as follows. The lower bound and upper bound of the boundary grade and industrial grade were respectively 0.05% and 0.45%; the lower bound of the smelting grade was 16%; the annual production capacity of the mine was 1.5 Mt; the *z* value in equation (2) was 0.5; the total production cost per unit of ore was 98 CNY/t; the sales price of #1 copper concentrate was 47,739 CNY/t; the discount rate was 6%.

A. MODEL OF TECHNICAL INDICATOR RELATIONSHIPS

1) RELATIONSHIP BETWEEN OREBODY WEIGHT AND GRADE

A scatter plot of the orebody weight and copper grade was plotted from the 204 items of orebody weight and grade data collected from the Yinshan copper mine, as shown in Figure 3. There was no correlation between orebody weight and copper grade. The results show that there was no relationship between orebody weight and copper grade and that orebody weight was not affected by copper grade. We therefore used the average value of the orebody weight for the ore weight function of the Yinshan copper mine. The

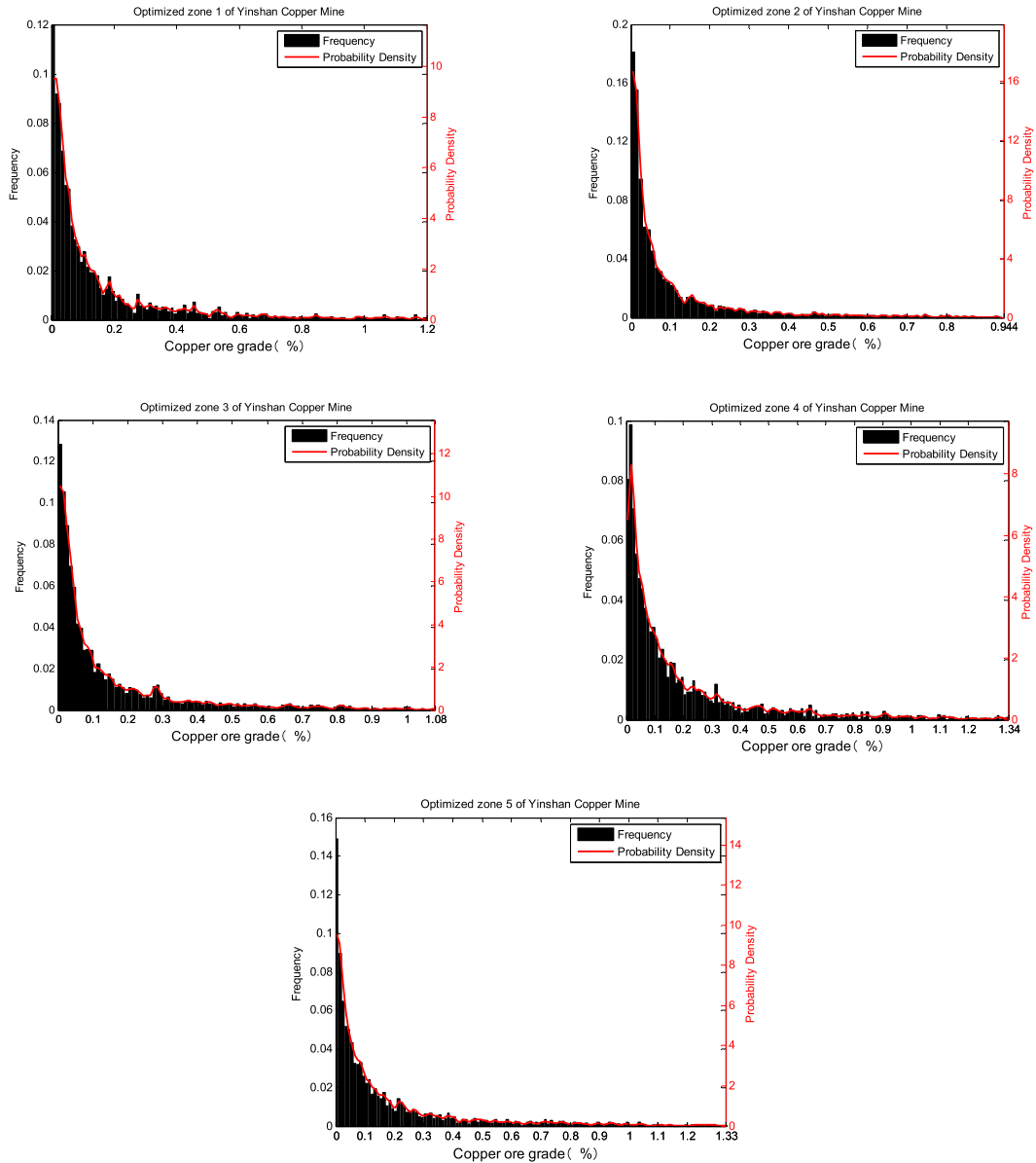


FIGURE 4. Fitting results of copper grade distribution in the Yinshan copper mine (optimized zones 1–5) for comparison.

mathematical function is:

$$g_1(x) = 2.85 \tag{23}$$

2) PROBABILITY DENSITY FUNCTION OF THE COPPER GRADE DISTRIBUTION

The copper grade distribution was fitted using kernel density estimation based on the characteristics and attributes of the data without any prior knowledge. This method provided better fitting of the probability density function than parameter estimation. Kernel density estimation was used to fit the probability density distribution of the Yinshan copper mine ore grade. Fitting did not result in a particular function or mathematical expression. Figure 4 shows that kernel density estimation well fitted the ore grade distribution.

3) RELATIONSHIP BETWEEN LOSS RATE AND DILUTION RATE

Aiming for an ore body of -48 to -192 m in the Yinshan copper mine, open-pit mining was used. The copper dilution and loss rates were collected for 64 items of open-pit mining data. Scatter plots of the copper dilution rate and loss rate were plotted, as shown in Figure 5. It can be seen from Figure 5 that there was no correlation between copper dilution rate and loss rate. The correlation coefficient between copper dilution rate and loss rate was -0.0771 , and the F-test was significant at a level of 0.5449 , which was >0.05 . There was therefore no relationship between copper dilution rate and loss rate. In the subsequent optimization, the values used for both dilution rate (2%) and loss rate (9%) were the planned values.

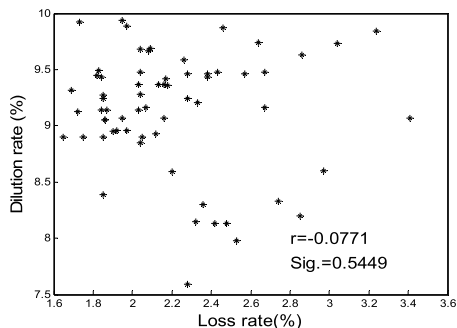


FIGURE 5. Scatter plot of the copper loss rate and dilution rate of the Yinshan copper mine.

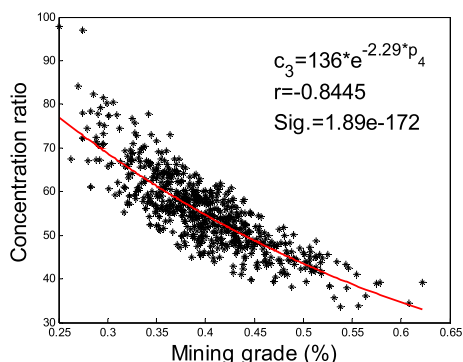


FIGURE 6. Exponential function fitting the relationship between mining grade and concentration ratio for the Yinshan copper mine.

4) RELATIONSHIP BETWEEN MINING GRADE AND CONCENTRATE RATIO

The scatter plot for 630 items of ore dressing data, mining grade and concentrate ratio, that were collected from the Yinshan copper mine is shown in Figure 6. It can be seen from the figure that mining grade is exponentially related to concentrate ratio. The exponential function was used for regression fitting, and the correlation coefficient was -0.8445 . The F test was significant at the level 1.89×10^{-172} . Since the significance level was much less than 0.05, the regression was significant and the regression model can be applied. The exponential function used to fit the relationship between mining grade and concentrate ratio is equation (24):

$$c_3 = 136 * e^{-2.29 * p_4} \tag{24}$$

5) CONCENTRATE GRADE

A BP neural network [34], [35], [36], [37] was used to determine the relationships between copper mining grade and concentrate grade and between concentrate ratio and concentrate grade in the Yinshan copper mine. A total of 630 data items were collected; the training sample consisted of the first 530 data items, and the test sample was the remaining 100 items; mining grade and concentrate ratio were used as inputs, and the copper ore concentrate grade was the output. There were two nodes in both the input and hidden layers and one node in the output layer. The transfer

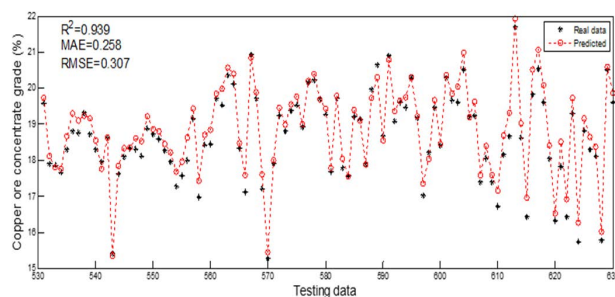


FIGURE 7. Fitting results of the copper ore concentrate grade of the Yinshan copper mine using BP neural network.

TABLE 3. Compensation prices and price adjustment coefficients of different copper concentrate grades.

Grade (%)	Price adjustment coefficient	Compensation price (CNY • t ⁻¹)
[23,1]	0.86	330
[22.00,22.99]	0.85	220
[21.00,21.99]	0.84	110
[20.00,20.99]	0.83	0
[19.00,19.99]	0.81	-110
[18.00,18.99]	0.80	-220
[17.00,17.99]	0.78	-330
[16.00,16.99]	0.77	-440

functions used in the training function, input layer and output layer were respectively *traingdm*, *tansig* and *purelin*. The learning rate was 0.1, training error accuracy was 0.001, and the maximum number of iterations was 2500. The fitting diagram of copper concentrate grade produced by the BP neural network is shown in Figure 7.

Figure 7 shows that for the fitting, the coefficient of determination R^2 was 0.939, mean absolute error MAE was 0.258, and root mean square error RMSE was 0.307. R^2 was >0.9 , and both MAE and RMSE were <0.5 . These results indicate that the BP neural network well fitted the model of the relationships of copper mining grade with concentrate grade and concentrate ratio with concentrate grade in the Yinshan copper mine.

6) COPPER ORE CONCENTRATE PRICE

The market transaction price of copper ore concentrate is based mainly on a 20% concentrate grade (#1 grade), and the price of any other copper ore concentrate grade is a function of this price. The price adjustment factors and the compensation prices are shown in Table 3. The copper ore concentrate price q is calculated by equation (25):

$$q = f_6(p_5) = k_1 \times p_5 \times \lambda + k_2 \tag{25}$$

where k_1 is the sales price of #1 copper concentrate; λ is the price adjustment coefficient; k_2 is the compensation price.

B. DECISION VARIABLES AND PARAMETER SETTINGS

1) DECISION VARIABLES

In the model of relationships between the technical indicators of the Yinshan copper mine described in Subsection A,

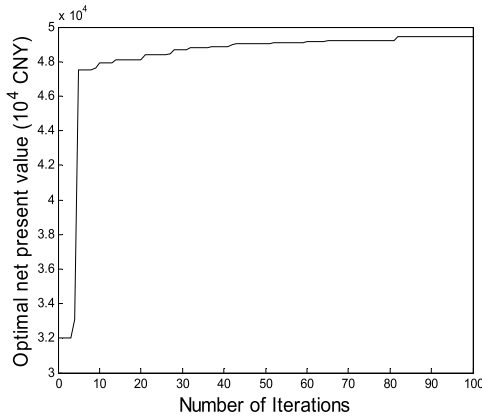


FIGURE 8. Iterative process to calculate the optimal net present value.

Section III, boundary grade, industrial grade, loss rate, and dilution rate are independent variables and are not affected by other indicators; geological ore reserves, ore average grade, mining grade, mining amount, concentration ratio, concentrate grade, concentrate amount, and ore mining grade are dependent variables. When the value of an independent variable has been determined, the value of any variable dependent on it has also been influenced. Therefore, the independent variable is the decisive variable in optimization.

The dilution rate and loss rate depend on ore body characteristics and mining technology, which are basically unchanged over a short period of time. These two variables were therefore taken to be constant for each optimization zone, and the values are the planned values. Dilution rate was 2% and loss rate was 9%. Boundary grade and industrial grade of each optimization unit are thus the decision variables of the optimization model; there are 10 decision variables for the five optimization zones.

2) SETTING PARAMETERS

The parameters of the AADE algorithm were set as follows. The dimension D_T of the decision variable was set to 10; the initialization population size NP was set to 50; the maximum number of iterations G_{max} was set to 100; and the adaptive control parameters ψ , φ , δ_l and δ_u were respectively set to 0.7, 0.1, 0, and 1. Encoding of the related evolutionary algorithms was real number encoding. The parameters of the Yinshan copper mine and the AADE algorithm are given in Table 4.

C. OPTIMIZATION RESULTS AND ANALYSIS

The production specifications of the Yinshan copper mine were optimized using the optimization model and the AADE algorithm with the parameter settings shown in Table 4. The iterative process of the optimal net present value calculation is shown in Figure 8, and the optimization results are given in Table 5.

Figure 8 shows that the optimal net present value converged after about 80 iterations, which indicates that AADE converged rapidly to optimize the model of technical indicators for maximum economic benefit.

TABLE 4. Parameters of Yinshan copper mine and AADE algorithm.

Parameter	Value
Yinshan copper mine	
Original boundary grade of each optimization unit p_a (%)	0.15
Original industrial grade of each optimization unit p_b (%)	0.25
Original geological reserves of optimization unit 1 $Q_{0,1}$ (10^4 t)	384.6
Original geological reserves of optimization unit 2 $Q_{0,2}$ (10^4 t)	319.4
Original geological reserve of optimization unit 3 $Q_{0,3}$ (10^4 t)	258.1
Original geological reserves of optimization unit 4 $Q_{0,4}$ (10^4 t)	178.4
Original geological reserves of optimization unit 5 $Q_{0,5}$ (10^4 t)	118.1
Constant z	0.5
Total production cost per unit ore h (CNY/t)	98
Sales price of 1# copper concentrate k_1 (CNY/t)	47 739
Lower bound of boundary grade of each optimization unit p_{1min} (%)	0.05
Upper bound of boundary grade of each optimization unit p_{1max} (%)	0.45
Lower bound of industrial grade of each optimization unit p_{2min} (%)	0.05
Upper bound of industrial grade of each optimization unit p_{2max} (%)	0.45
Loss rates c_1 (%)	9
Dilution rate c_2 (%)	2
Lower bound of the smelting grade c_3 (%)	16
Annual production capacity of the mine Q_z (10^6 t)	1.5
Discount rate d (%)	6
AADE Algorithm	
Dimension of the decision variable D_T	10
Initialization population size NP	50
Maximum number of iterations G_{max}	100
Adaptive control parameters of scale factor ψ	0.7
Adaptive control parameters of scale factor φ	0.1
Adaptive control parameters of crossover rate δ_l	0
Adaptive control parameters of crossover rate δ_u	1
Encoding type	Real

Table 5 shows that the boundary grades of optimized zones 1–5 were respectively 0.425 3%, 0.328 8%, 0.235 1%, 0.425 1% and 0.379%; the industrial grades of optimized zones 1–5 were respectively 0.434%, 0.373 4%, 0.440 7%, 0.438 1% and 0.393 4%. The corresponding values differ from each other, indicating that the boundary grades and industrial grades differ between optimized zones. If the spatial distribution of ore grades is not considered and one overall grade distribution is adopted, the boundary grade and the industrial grade are both the same. Obviously, if the same boundary grade and industrial grade are used in high-grade and low-grade zones, mineral resources will be wasted. Considering differences in the spatial distribution of grades produces a model that is more in line with actual production and is therefore very important.

The optimized scheme was compared with the current scheme; the technical index values and net present value of the current scheme are shown in Table 6.

TABLE 5. Technical indexes and net present values of the optimization scheme.

Metrics	Optimized unit 1	Optimized unit 2	Optimized unit 3	Optimized unit 4	Optimized unit 5
Boundary grade (%)	0.425 3	0.328 8	0.235 1	0.425 1	0.379
Industrial grade (%)	0.434	0.373 4	0.440 7	0.438 1	0.393 4
Geological reserves (t)	1 628 326	1 458 961	1 580 292	734 353	560 164
Ore average grade (%)	0.683 4	0.528 7	0.529 1	0.713 9	0.695 7
Mining grade (%)	0.621 9	0.481 1	0.481 5	0.649 7	0.633 1
Mining amount (t)	1 753 582	1 571 189	1 701 853	790 842	603 254
Concentrate ratio	32.94	45.45	45.40	30.91	32.11
Concentrate recovery rate (%)	88.52	86.92	86.92	89.71	88.95
Concentrate grade (%)	18.13	19.00	19.00	18.02	18.08
Concentrate amount (t)	53 236	34 571	37 484	25 582	18 786
Concentrate prices (CNY/t)	6 663	7 238	7 238	6 618	6 642
Average annual profit (10^4 CNY)	15 639.94	9 189.66	9 212.14	17 413.41	16 327.62
Duration of mining (y)	1.169 1	1.047 5	1.134 6	0.527 2	0.402 2
Net present value (10^4 CNY)	18 134.29	8 974.69	9 139.13	7 708.41	5 295.68

TABLE 6. Technical indexes and net present values of the current scheme.

Metrics	Optimized unit 1	Optimized unit 2	Optimized unit 3	Optimized unit 4	Optimized unit 5
Boundary grade (%)	0.15	0.15	0.15	0.15	0.15
Industrial grade (%)	0.25	0.25	0.25	0.25	0.25
Geological reserves (t)	3 838 012	3 188 784	2 595 674	1 777 375	1 179 807
Ore average grade (%)	0.447 2	0.372 5	0.412 5	0.454 5	0.466 5
Mining grade (%)	0.407	0.338 9	0.375 4	0.413 6	0.424 5
Mining amount (t)	4 133 244	3 434 075	2 795 341	1 914 096	1 270 561
Concentrate ratio	53.833 6	62.892 9	57.866 2	53.028 5	51.717 7
Concentrate recovery rate (%)	86.163 6	85.496	85.777 4	86.246 7	86.381 5
Concentrate grade (%)	18.8783	18.225	18.632 7	18.915 4	18.965 9
Concentrate amount (t)	76 778	54 602	48 307	36 096	24 567
Concentrate prices (CNY/t)	6 945	6 697	6 852	6 959	6 978
Average annual profit (10^4 CNY)	4 650.65	1 272.02	3 060.54	4 984.34	5 538.85
Duration of mining (y)	2.755 5	2.289 4	1.863 6	1.276 1	0.847
Net present value (10^4 CNY)	12 165.13	2 395.03	4 144.39	4 213.56	2 937.38

By comparing Tables 5 and 6, it is clear that by adjusting the technical indicators for optimized production, the net present values of optimized zones 1 to 5 respectively increased by 10^4 CNY 5 969.16, 6 579.66, 4 994.74, 3 494.85 and 2 358.3 over the current scheme. The total net present value reached CNY $49 252.2 \times 10^4$, with an increase of CNY $23 396.71 \times 10^4$, i.e., 90.5%. The adjusted technical indicators are aligned with the actual situation of the mine and significantly increase mine profits.

D. ALGORITHM COMPARISON

We compared the AADE algorithm with the standard genetic algorithm (GA) [38], [39], [40], the standard DE algorithm (DE) [41], [42], [43] and the adaptive DE algorithm (ADE) [44], [45], [46] in optimizing the technical indicators. All four algorithms were used to solve the optimization model.

To ensure we were comparing like with like, the parameters of the four algorithms were set to be as consistent as far as possible. The adaptive control parameters ψ , φ , δ_l and δ_u

of AADE were respectively set to 0.7, 0.1, 0, and 1. The mutation rate and crossover rate of GA were respectively set to 0.7 and 0.5. The proportion factor F and crossover rate CR of DE were respectively set to 0.7 and 0.5. The distribution function and the adaptive control parameters of ADE were set to be the same as those of AADE. The population size of all four algorithms was set to 50, and the maximum number of iterations was set to 100.

To avoid any random effects in algorithm operation, the four algorithms were independently run 31 times each, and the total net present value of each run was recorded. The results are shown in Table 7.

The maximum total net present value, the average total net present value, and the minimum total net present value was calculated for each of each algorithm. The results are shown in Table 8.

Table 8 shows that the maximum total net present value (CNY $49 429.32 \times 10^4$), the average total net present value (CNY $49 316.79 \times 10^4$), and the minimum total net present

TABLE 7. Total net present values of the four algorithms.

Times	Total net present values (10 ⁴ CNY)			
	GA	DE	ADE	AADE
1	49 184.36	49 220.23	49 176.92	49 252.20
2	49 273.87	49 177.93	49 241.91	49 235.23
3	49 086.83	49 235.05	49 166.49	49 359.06
4	49 204.24	49 158.87	49 221.70	49 289.85
5	49 320.12	49 186.01	49 206.18	49 257.78
6	49 272.84	49 162.13	49 215.25	49 316.98
7	49184.61	49 232.68	49 208.83	49 347.00
8	49 194.39	49 195.08	49 183.03	49 259.09
9	49 302.25	49 195.71	49 180.15	49 378.56
10	49 252.60	49 195.13	49 167.72	49 380.02
11	49 354.63	49 249.13	49 198.80	49 373.83
12	49 354.59	49 147.81	49 207.46	49 328.96
13	49 207.02	49 180.28	49 215.44	49 289.79
14	49 234.70	49 192.14	49 225.94	49 246.40
15	49 300.47	49 222.71	49 224.24	49 313.97
16	49 260.89	49 165.61	49 225.78	49 364.56
17	49 064.62	49 176.73	49 166.78	49 392.34
18	49 215.07	49 333.47	49 209.94	49 375.92
19	49 243.46	49 191.69	49 224.23	49 329.26
20	49 243.59	49 158.98	49 162.90	49 339.04
21	49 185.42	49 180.32	49 203.50	49 264.78
22	49 218.17	49 189.78	49 219.60	49 237.72
23	49 139.31	49 159.63	49 240.94	49 251.08
24	49 339.83	49 212.90	49 258.89	49 284.75
25	47 791.30	49 208.93	49 236.72	49 322.56
26	49 173.63	49 194.91	49 183.47	49 376.70
27	49 030.36	49 230.96	49 116.00	49 257.51
28	49 247.37	49 238.63	49 184.85	49 372.49
29	48 819.65	49 229.45	49 177.84	49 332.19
30	49 182.05	49 193.89	49 259.66	49 429.32
31	49 331.46	49 211.69	49 204.81	49 261.57

value (CNY 49 235.23 × 10⁴) given by AADE were all greater than the corresponding values given by GA, DE and ADE. Since economic benefit pursues the maximization of net present value, AADE performs better than GA, DE, and ADE in terms of optimizing the technical indicators for maximum economic benefit.

A one-tailed *t*-test was used for statistical analysis to determine the significance of the advantage of using AADE to optimize the technical indicators. AADE was compared individually with each of the other three algorithms. For the two algorithms being compared, the *t*-statistic is calculated by equation (26):

$$t = \frac{|\tau_1 - \tau_2|}{\eta/\sqrt{n}} \tag{26}$$

where τ_1 is the index mean value of AADE; τ_2 is the index mean value of the comparison algorithm (GA, DE or ADE);

η is the index standard deviation of AADE; n is the total number of runs. The significance level was set at 0.05, and degrees of freedom was the total number of runs (31) minus 1, which was 30. The *t* value was obtained from a standard *t*-distribution table: $t_{0.025,30} = 2.042$. If $|t| > t_{0.025,30}$, the two algorithms were significantly different; if $t \leq t_{0.025,30}$, then the two algorithms were not significantly different.

Table 7 shows that the standard deviation of the AADE solution was 47.31. Using this value and the average total net present value shown in Table 8, the *t*-statistics for the individual comparisons of AADE with the other three algorithms were calculated using equation (26); the results are shown in Table 9.

Table 9 shows that the *t*-statistic for AADE when compared with each of the other three algorithms was in all cases greater than $t_{0.025,30} = 2.042$. This shows that AADE performed significantly better than GA, DE and ADE in optimizing the technical production in terms of maximizing economic benefit. In the light of these results, we conclude that AADE is more effective and therefore preferable in optimizing the dynamic technical indicators when considering the spatial distribution of the ore grade. This advantage of AADE is mainly due to the adaptive mutation strategy and the use of control parameters, which improves both the convergence rate and the global search capability at the same time.

E. ALGORITHM PERFORMANCE TEST

We used four commonly used single-objective continuous test functions to test the performance of AADE: the Sphere, Griewank, Rastrigin and Rosenbrock functions. The four test functions can be divided into three categories: the Sphere function is a unimodal convex function; the Griewank and Rastrigin functions are multimodal functions with many local optimum points, and how to step out from a local optimum point to find the global optimum point is a major challenge for any optimization algorithm; and the Rosenbrock function is a non-convex function for which the global minimum is in a flat valley, which makes it very difficult to find the global optimum points. The overall dynamic optimization of the technical indicators basically falls into one of the three categories. We therefore chose the four test functions to assess the performance of AADE.

Each of the four functions was used as the objective function to be minimized; the equations are shown in Table 10. In calculating the minimum value, the variable dimension was 10 dimensions. The three-dimensional graphs of the four functions are shown in Figure 9.

AADE was tested using each the four single-objective continuous test functions, as were GA, DE and ADE, and the results were compared. The parameters of the four algorithms were set as follows. The maximum number of iterations was set to 100 (Sphere), 1000 (Griewank), 500 (Rastrigin), and 1000 (Rosenbrock). All other parameter values were the same as those described in the preceding section. Each algorithm was independently run 31 times for each test function, and the worst value, mean value and optimum value of each algorithm

TABLE 8. Optimal net present values given by the four algorithms for comparison.

Statistical Indicators	GA	DE	ADE	AADE
Maximum total net present value (10 ⁴ CNY)	49 354.63	49 333.47	49 259.66	49 429.32
Average total net present value (10 ⁴ CNY)	49 168.18	49 200.92	49 203.74	49 316.79
Minimum total net present value (10 ⁴ CNY)	47 791.30	49 147.81	49 116.00	49 235.23

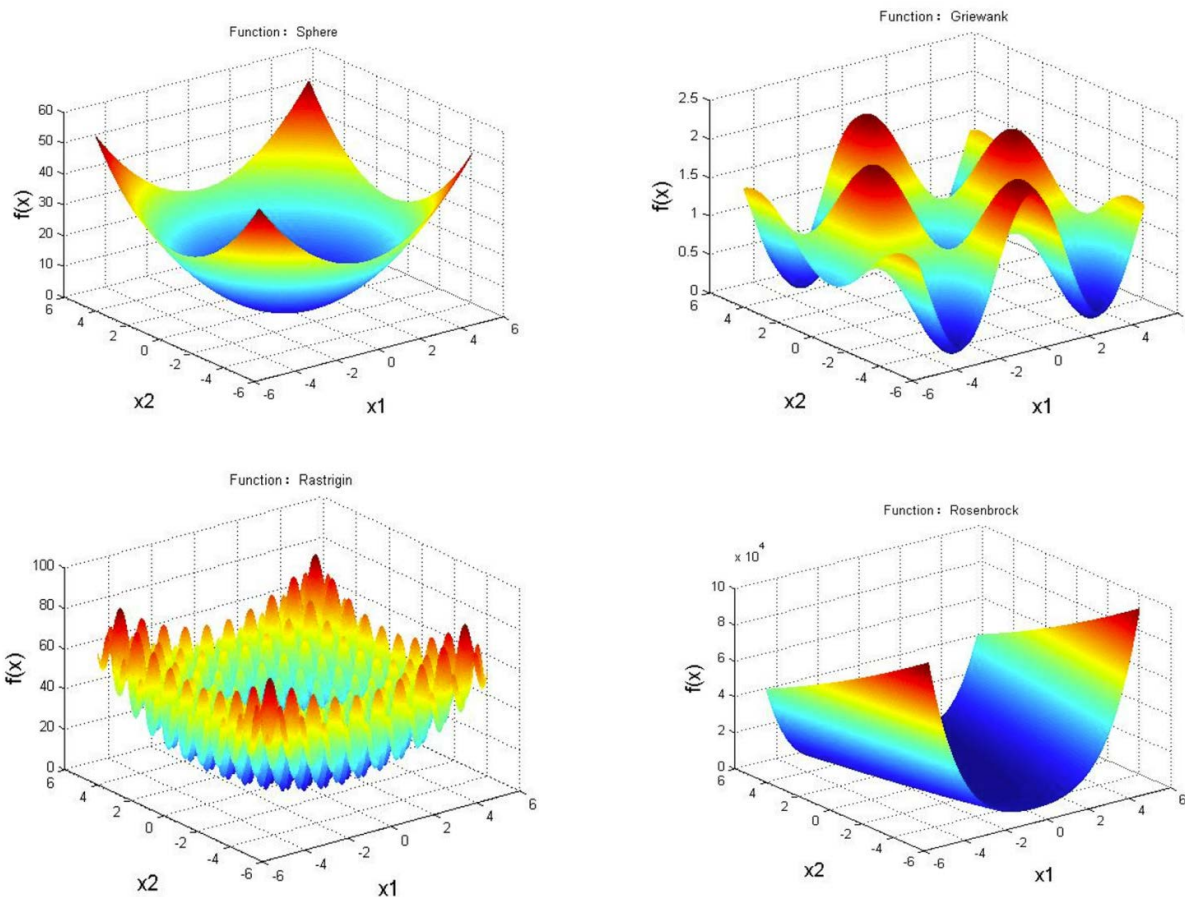


FIGURE 9. Three-dimensional graphs of single-objective continuous test functions (Sphere, Griewank, Rastrigin, and Rosenbrock).

TABLE 9. T-statistics of total net present values.

Comparison algorithm	GA	DE	ADE
t-statistic value	17.49	13.64	13.30

for each test function were calculated. The results are shown in Table 11.

Table 11 shows that for the four test functions, the worst value, average value and optimum value of AADE were all lower than the corresponding values of GA, DE and ADE. Since the test function was used to minimize, AADE performed better than GA, DE and ADE in solving complex single-objective continuous optimization problems.

One-tailed *t*-tests were performed for the four test functions to see if the advantage of AADE in solving complex single-objective continuous optimization problems was significant. The standard deviations of AADE results were 0.000 578 (Sphere), 0.053 592 (Griewank), 0.175 768 (Rastrigin) and $6.400\ 64 \times 10^{-10}$ (Rosenbrock). Using these standard deviation values and the average values of the algorithms, shown in Table 11, the *t*-statistics for AADE compared with the other three algorithms were calculated using equation (26); the results are shown in Table 12.

Table 12 shows that for the four test functions, the *t*-statistic for AADE compared with GA, DE and ADE, was always $> t_{0.025,30} = 2.042$, which indicates that AADE performed significantly better than GA, DE and ADE in solving complex single-objective continuous optimization problems. Comparison of the test results showed that AADE not only

TABLE 10. Single-objective continuous test functions.

Test function	Mathematical expression	Dimension	Variable value
Sphere	$f(x) = \sum_{i=1}^{10} x_i^2$	10	$x_i \in [-5.12, 5.12]$
Griewank	$f(x) = \sum_{i=1}^n \frac{x_i^2}{4000} - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}}) + 1$	10	$x_i \in [-5.12, 5.12]$
Rastrigin	$f(x) = 10n + \sum_{i=1}^n [x_i^2 - 10 \cos(2\pi x_i)]$	10	$x_i \in [-5.12, 5.12]$
Rosenbrock	$f(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	10	$x_i \in [-5.12, 5.12]$

TABLE 11. Test results of the four single-objective continuous test functions.

Test function	Global minimum	Algorithm	Worst value	Average value	Optimum value
Sphere	0	GA	0.025 503 2	0.010 297 9	0.001 282 4
		DE	0.045 009 4	0.025 044 3	0.011 273 1
		ADE	0.056 245 8	0.022 029 8	0.007 160 2
		AADE	0.002 244	0.000 687 5	0.000 126 8
Griewank	0	GA	0.260 763	0.091 229 7	3.366 39E-06
		DE	0.364 12	0.249 011 8	0.161 735
		ADE	0.207 001	0.124 289 6	0.039 400 6
		AADE	0.203 264	0.050 718 9	1.562 46E-06
Rastrigin	0	GA	3.981 4	1.612 988 7	4.767 88E-06
		DE	17.969 9	13.594 378	8.594 01
		ADE	5.073 24	2.708 707 1	0.214 63
		AADE	0.994 96	0.032 243 6	4.172 89E-10
Rosenbrock	0	GA	7.184 18	4.866 276 7	0.059 404 9
		DE	1.600 16	1.272 785 6	0.988 255
		ADE	0.056 301 4	0.009 891 4	0.000 307 1
		AADE	2.584E-09	3.062E-10	4.20991E-14

TABLE 12. T-test results for comparisons of AADE with the four single-objective continuous test functions.

Test functions	vs.GA	vs.DE	vs.ADE
Sphere	92.579 05	234.634 1	205.594 99
Griewank	4.208 733	20.600 95	7.643 37
Rastrigin	50.072 78	429.603 6	84.781 50
Rosenbrock	4.23E+10	1.11E+10	86 043 359

had advantages in optimizing metal mine technical indicators in terms of economic benefit, but also had advantages in optimizing other complex single-objective continuous functions. Therefore, the AADE algorithm has wide applicability.

IV. CONCLUSION

The results presented above support the following conclusions:

- 1) The proposed model, which considers the overall dynamic relationships between technical indicators and the spatial distribution of the ore grade, is better aligned

with the metal mine production process than the currently used optimization model.

- 2) Optimizing the technical indicators for metal mine production in terms of economic benefit is a complex nonlinear single-objective optimization problem that the AADE algorithm is proposed to solve. AADE uses adaptive control parameters and a mutation strategy based on the DE algorithm to improve the optimal performance of DE.
- 3) The total net present value of the optimization scheme is greater than that of the currently used scheme, and the optimized technical production indicators are better aligned with the actual operation of the mine, which should guide mine production and planning.
- 4) AADE performs significantly better than GA, DE and ADE in optimizing the technical indicators of metal mine production in terms of economic benefits.

We created an effective optimization model and a method for optimizing metal mine technical indicators that considers the overall dynamic relationships between technical indicators and the spatial distribution of the ore grade. There are

two aspects of the model that can be improved in future research. (1) The proposed model only optimizes the technical indicators and does not optimize the mining sequence. The indicators and the mining sequence are interrelated, and we intend to devote future research to their simultaneous optimization. (2) It is well known that different algorithms have different advantages. The method we proposed optimized the technical indicators of metal mine production with rapid convergence and a global search capability, but the model can be improved. We intend to make the AADE model more widely applicable by increasing the initial population and by applying our method to optimize production in more real world metal mines.

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XUNHONG WANG received the B.S. degree in mathematics and applied mathematics and the M.S. degree in mining engineering from the Jiangxi University of Science and Technology, Ganzhou, China, in 2013 and 2016, respectively, and the Ph.D. degree in mining engineering from the College of Resources and Civil Engineering, North Eastern University, China, in 2021. He was granted the "3331 Outstanding Young Scholars" of Guangxi University of Science and Technology, as an Associate Professor, in 2021. His research experiences in more than five research projects during the last ten years allow him authoring more than 10 refereed journal articles. His research interests include intelligence optimization and prediction, resource management, and risk assessment of engineering.



YONGLIN TAN was born in Chongqing, China. He received the B.S. degree from the Chongqing University of Arts and Sciences, Chongqing, in 2005, the M.S. degree from Chongqing Technology and Business University, Chongqing, in 2013, and the Ph.D. degree from the University of the Cordilleras, Baguio, Philippines, in 2021. He is currently an Associate Professor with the Guangxi University of Science and Technology, Liuzhou, China. His research interest includes process optimization.



LAN YANG was born in Yibin, China. She received the B.S. degree from Yibin University, Yibin, in 2007, the M.S. degree from Chongqing Normal University, Chongqing, China, in 2012, and the Ph.D. degree from the University of the Cordilleras, Baguio, Philippines, in 2020. She is currently an Associate Professor with the Guangxi University of Science and Technology, Liuzhou, China. Her research interest includes optimization.

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