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RESEARCH ARTICLE

Simultaneous Dynamic Optimization of Technical Indicators and Mining Sequence in Metal Mines Using Hybrid Coding AADE

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ABSTRACT Technical indicators and mining sequence are often optimized separately when optimizing metal mine production. This approach ignores the mutual influence between indicators and mining sequence, and the optimization results may not reach the global optimum. This study focuses on the entire production process of a metal mine and establishes a model and creates an algorithm for the simultaneous dynamic optimization of the technical indicators and mining sequence of a metal mine. A model of the dynamic relationships between technical indicators is initially created in order to derive an optimization model that dynamically optimizes both the technical indicators and the mining sequence of a metal mine. A hybrid coding AADE algorithm is developed to solve the optimization equation. A test case of the Huogeqi copper mine is presented to demonstrate the use of the model and the algorithm. The simultaneous dynamic optimization of technical indicators and mining sequence produced greater NPV in the test case than the optimization of technical indicators alone; NPV increased by 1161.01 10^4 CNY. In addition, the hybrid coding AADE algorithm was compared with hybrid coding GA, DE and ADE algorithms. The hybrid coding AADE algorithm performed searches significantly better than the other three hybrid coding algorithms in solving the simultaneous dynamic optimization for technical indicators and mining sequence.

INDEX TERMS Metal mine, technical indicators, mining sequence, simultaneous optimization, overall dynamic, hybrid coding AADE.

NOMENCLATURE

Model Parameters

p_1	Boundary grade.
p_2	Industrial grade.
p_3	Average ore grade.
p_4	Extracted grade.
p_5	Concentrate grade.
p_a	Initial boundary grade.
p_b	Initial industrial grade.
c_1	Loss rate.
c_2	Depletion rate.
c_3	Beneficiation ratio.
Q_0	Initial geological reserves.
Q_1	Geological reserves.
Q_2	Extracted ore volume.
Q_3	Concentrate volume.
q	Concentrate selling price.
z	Constant that depends on the geological conditions of the ore body.
θ	Total NPV.
$\theta_{v,j}$	NPV of mining area v.
$p_{1,v}$	Boundary grade of mining area v.
$p_{2,v}$	Industrial grade of mining area v.
$p_{3,v}$	Average ore grade of mining area v.

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$p_{4,v}$	Extracted grade of mining area v.
$p_{5,v}$	Concentrate grade of mining area v.
t_v	Mining time of mining area v.
Qz	Annual mining capacity.
h	Total cost of production of unit ore.
G_v	Total profit of mining area v.
g_v	Average annual profit of mining area v.
$T_{v,j,1}$	Start mining time of mining area v.
$T^{-}_{v,j,1}$	Integer component of $T_{v,j,1}$.
$T_{v,j,2}$	End mining time of mining area v.
$T^{-}_{v,j,2}$	Integer component of $T_{v,j,2}$.
p_y	Minimum smelting grade.
$c_{4,v}$	Beneficiation recovery rate of mining area v.
R^2	Coefficient of determination.
k_1	Price adjustment factor.
k_2	Compensation price.
λ	Trading price of copper concentrate that is mainly based on 20% grade of concentrate.

Functions

$\varphi(x)$	Mining probability of ore grade with grade between boundary grade and industrial grade.
$g(x)$	Ore weight function.
$c(x)$	Probability density function of ore grade distribution. Algorithm parameters.
D_T	Total number of decision variables.
NP	Population size.
G_T	Iteration counter.
$G_{\max}$	Maximum number of iterations.
F	Scale factor.
CR	Crossover rate.
ψ	Probability parameters of F.
φ	Probability parameters of F.
δ_l	Probability parameters of CR.
δ_u	Probability parameters of CR.
τ_1	Mean of the metrics of the proposed algorithm.
τ_2	Mean of the metrics of the comparison algorithm.
η	Standard deviation of the metrics of the proposed algorithm,.
n	Total number of runs.

Abbreviations

AADE	Adaptive mutation operator and adaptive control parameter for differential evolution algorithm.
GA	Genetic algorithm.
DE	Differential evolution algorithm.
ADE	Self-adapting control parameters in differential evolution.
NPV	Net present value.
MAE	Mean absolute error.
RMSE	Root mean square error.

I. INTRODUCTION

Metal mine production includes related geological, mining, and mineral treatment processes. The three processes influence and constrain each other, and each process continues the previous process and melds into the subsequent process [1], [2]. Principal technical indicators of metal mine characteristics include the boundary grade, industrial grade, geological reserves, average ore grade, loss rate, depletion rate, extracted grade, extracted ore volume, beneficiation ratio, concentrate grade and concentrate volume [3]. Mine production is a complex activity, and the relationships between technical indicators are complex [4]. For example, boundary grade and industrial grade affect geological reserves; average ore grade and geological reserves affect extracted volume and concentrate volume; and average grade of ore body affects extracted grade and concentrate grade.

Creating an optimization model that accurately represents mine production processes is an extremely difficult task because of the multiplicity of factors that affect metal mine production processes at various levels and the complexity, dynamics, and multiplicity of constraints. Optimization requires the creation of a model of the relationships between mine production indicators that is accurate with respect to both the observed data of mine production and the parameters identified for optimization. The optimal solution of the model must be computed by an effective algorithm so that it can be used to guide the efficient mining of mineral resources.

If the time value of money is considered, the economic benefits of a given profit will vary depending on the time taken to realize it. Even if the technical indicators are unchanged, the mining sequence can produce different economic benefits from the same mine [5]. The mining sequence therefore affects the optimization of the technical indicators.

Recent research has focused on three aspects of metal mine technical indicator optimization. (1) Optimizing the technical indicators but excluding the dynamics of extraction and the mining sequence [6], [7], [8], [9], [10], [11], [12], [13]. (2) Dynamic optimization of the technical indicators but with no consideration of the mining sequence [2], [4], [14], [15], [16], [17], [18]. (3) Dynamic optimization of the technical indicators with consideration of the mining sequence but without simultaneous optimization of the two influences [5].

In summary, there has been no consideration of the overall dynamics of technical indicators in conjunction with the interactions between technical indicators and the mining sequence. Therefore, current attempts at optimization fail to reach a global optimum. The simultaneous dynamic optimization of metal mine technical indicators and mining sequence is required in order to better promote the sustainable development of metal mineral resources.

The comprehensive simultaneous optimization of dynamic technical indicators and mining sequence is a mixed integer single-objective optimization problem with both continuous (technical indicators) and integer (mining sequence) decision variables [19]. There are two methods for solving mixed-integer optimization problems: the exhaustive method, which consists mainly of branch-and-bound techniques [20], and the Lagrangian relaxation method [21]. Branch-and-bound techniques are effective in solving simple mixed-integer single-objective optimization problems but cannot rapidly solve complex mixed-integer single-objective optimization problems [22], [23], [24]. Lagrangian relaxation methods are intelligent evolutionary methods that are mainly mixed coding genetic algorithms and mixed coding differential evolutionary algorithms. These methods have the advantages of global searching and robustness, and they have been used to solve mixed-integer optimization problems with good results [20], [25], [26].

When an adaptive mutation operator and adaptive control parameter for differential evolution (AADE) algorithm were used for the dynamic optimization of metal mine technical indicators considering the spatial distribution of ore grade, good results were obtained [5]. However, AADE can only be used to solve continuous variable single-objective optimization problems.

To overcome this weakness of the AADE algorithm in solving the simultaneous dynamic optimization of technical indicators and mining sequence, we propose the hybrid coding AADE algorithm that incorporates chromosome coding and an evolutionary operator to improve the AADE algorithm. Initially, the concept of hybrid coding is integrated into the initial population. Technical indicators are treated as continuous variables and encoded using floating-point representation. Conversely, the mining sequence is identified as an integer variable and is subjected to arrangement coding. Subsequently, specialized hybrid evolutionary operators are incorporated into the AADE algorithm. Adaptive differential evolution mutation and binomial crossover are employed to execute mutation and crossover operations on the technical indicators, respectively. Meanwhile, reverse mutation and partial matching crossover operators are utilized to facilitate the mutation and crossover processes for the mining sequence.

The remainder of the paper is structured as follows. Section II describes the derivation of a simultaneous dynamic optimization model and solution algorithm for the technical indicators and mining sequence. Section III presents an illustrative case study to show an application of the algorithm. Section IV gives our conclusions.

II. SIMULTANEOUS DYNAMIC OPTIMIZATION MODEL OF TECHNICAL INDICATORS AND MINING SEQUENCE

A. MODEL OF THE DYNAMIC RELATIONSHIPS BETWEEN TECHNICAL INDICATORS

Metal mine production consists of three main processes: geological process, mining process, mineral process. Each process can be characterized by a set of technical indicators [27]. The principal technical indicators used in this study are shown in Table 1.

A comprehensive model of the dynamic behavior of metal mine technical indicators has been presented in previous work. For completeness, this model is now briefly described [5].

TABLE 1. Principal technical indicators of metal mine production.

Process	Technical indicators	Definition
Geological	Boundary grade	Distinguishes between ore and rock.
	Industrial grade	Minimum industrial minable grade.
	Geological reserves	The recoverable reserves of ore.
	Average ore grade	The average grade of ore.
Mining	Loss rate	The ratio of the loss of geological reserves to the geological reserves.
	Depletion rate	The rate at which ore grade decreases during the mining process.
	Extracted grade	Mean grade of mining ore.
	Extracted ore volume	Quantity of mined ore.
Mineral	Beneficiation ratio	The ratio of the mining quantity to the concentrate quantity.
	Concentrate grade	Mean grade of concentrate ore.
	Concentrate volume	Volumetric quantity of concentrate ore.

The determination of geological reserves and average ore grade is typically guided by boundary and industrial grades. Optimizing such processes often necessitates calculating multiple solutions, making it a substantial task to estimate the average ore grade and geological reserves through the enveloping of the ore body using mining software like Geovia Surpac and 3DMine. A method rooted in mathematics and statistics was developed, following a comprehensive review of existing research. This method creates a relevant mathematical model for the accurate computation of geological reserves and average ore grade. The relationships between geological reserves and average ore grade, boundary grade, and industrial grade are modeled as follows [17]:

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

$$\varphi(x) = (\frac{x - p_1}{p_2 - p_1})^z (p_1 \le x \le p_2) \tag{2}$$

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

Extracted grade is determined by average ore grade and depletion rate [18]:

$$p_4 = p_3(1 - c_2) \tag{4}$$

Extracted ore volume is determined by geological reserves, depletion rate and loss rate [17]:

$$Q_2 = Q_1 \frac{1 - c_1}{1 - c_2} \tag{5}$$

Concentrate volume is determined by the ratio of extracted ore volume to beneficiation ratio:

$$Q_3 = Q_2 / c_3 \tag{6}$$

For an individual mine, ore properties, beneficiation, equipment and chemicals all remain essentially the same. In the case of an individual mine, there are certain relationships between loss rate and depletion rate, beneficiation ratio and extracted grade, concentrate grade and extracted grade and beneficiation ratio, and concentrate grade and concentrate selling price. The mathematical models of these relationships are as follows [5].

$$c_2 = f_3(c_1) \tag{7}$$
$$c_3 = f_4(p_4) \tag{8}$$
$$p_5 = f_5(p_4, c_3) \tag{9}$$
$$q = f_6(p_5) \tag{10}$$

Eqs. (1)-(10) each embody a model that elucidates the internal dynamics of various technical indicators. Collectively, these formulas illustrate the dynamic processes inherent to the entire production cycle.

B. MODEL OF SIMULTANEOUS DYNAMIC RELATIONSHIP OF TECHNICAL INDICATORS AND MINING SEQUENCE

Mining activity moves from one mining area to another [5], [28]. Since each mining area has a distinct spatial distribution of ore body grades, mining an area requires decisions to be made about its technical characteristics that affect subsequent mining decisions for that mining area. However, mining areas are not isolated from one another. Therefore, the dynamic relationships between mining areas need to be considered when optimizing the entire mining process. The time value of money and differences in ore body grades between mining areas are influential factors, and the mining sequence and technical indicators also interact with each other and need to be considered in the dynamic optimization of the entire mining process.

1) DECISION-MAKING VARIABLES

There are two types of decision variable in the simultaneous dynamic optimization model of metal mine technical indicators and mining sequence: the technical indicators and the mining sequence. The technical indicators are real variables and the mining sequence is an integer variable. The total number of decision variables in the two sets of variables is D_T.

The selection of technical indicator variables for optimization depends on the model that relates them, and is in turn related to the geological characteristics of the deposit, the mining equipment, mining processes, and the beneficiation of the mine [17]. It is therefore necessary to first characterize the mine and then determine which decision variables are used to represent the technical indicators. The technical indicator variables are real number variables.

The mining areas are numbered consecutively with the integers $1, \ldots, N$. The mining sequence is a variable arrangement of these integers, so the mining sequence $Y = \{y_1, y_2, \cdots, y_e, \cdots, y_N\}$ is an arrangement of the integers in the set $\{1, 2, \cdots, N\}$ where N is the total number of mining areas; y_e is the position in the mining sequence of mining area e. To illustrate, if $Y = \{2, 5, 4, 3, 6, 1\}$, then the corresponding mining sequence for the 6 mining areas is mining area 2 → mining area 5 → mining area 4 → mining area 3 → mining area 6 → mining area 1.

2) OBJECTIVE FUNCTION

NPV takes account of the time value of money and facilitates the calculation of return on investment [29], [30]. Maximization of NPV is therefore the objective function.

$$\max \theta = \sum_{j=1}^{N} \theta_{v,j} \tag{11}$$

The end time of any but the last mining area is the start time of the succeeding mining area. NPV is a function of time. The NPV of an individual mining area is therefore not independent, but is dynamically related to the NPVs of other areas. If the start time of mining the entire deposit is 0, then the NPV of mining area v is calculated in the following steps.

(1) Calculate the mining time of mining area v using

$$t_v = \frac{Q_{2,v}}{Qz} \tag{12}$$

(2) The total profit of mining area v is

$$G_v = Q_{3,v} * q_v - Q_{2,v} * h \tag{13}$$

(3) The average annual profit of mining area v is

$$g_v = \frac{G_v}{t_v} \tag{14}$$

(4) Let the vectors $g = [g_1, g_2, \cdots, g_e, \cdots, g_N]$ and $t = [t_1, t_2, \cdots, t_e, \cdots, t_N]$ represent the average annual profit and mining time of each mining area, respectively. However, the mining sequence affects the start and end mining time of the mining area, and the start and end mining time affects the NPV. Therefore, the elements of the vectors g and t need to be arranged according to the mining sequence $Y = \{y_1, y_2, \cdots, y_e, \cdots, y_N\}$. When the mining sequence is $Y = \{y_1, y_2, \cdots, y_e, \cdots, y_N\}$, the adjusted vectors are respectively

$$g' = \left[g_{y_1}, g_{y_2}, \cdots, g_{y_e}, \cdots, g_{y_N}\right] \tag{15}$$
$$t' = \left[t_{y_1}, t_{y_2}, \cdots, t_{y_e}, \cdots, t_{y_N}\right] \tag{16}$$

For example, if $Y = \{2, 5, 4, 7{,}3, 6, 1\}$, then $g' = [g_2, g_5, g_4, g_7, g_3, g_6, g_1]$ and $t' = [t_2, t_5, t_4, t_7, t_3, t_6, t_1]$.

(5) The mining start time of the first area is 0. The mining start time of the mining sequence of mining area j is $T_{v,j,1}$ and it is the sum of the previous mining sequence, calculated by

$$T_{v,j,1} = \sum_{m=1}^{m=j-1} t'(m) \tag{17}$$

(6) The mining sequence is the end mining time of mining area j is $T_{v,j,2}$, which is the sum of its start time and its own

mining time, calculated by

$$T_{v,j,2} = \sum_{m=1}^{m=j} t'(m) \tag{18}$$

(7) The NPV of the mining sequence for mining area j is

$$\theta_{v,j} = \begin{cases} g_v * \dfrac{(T_{v,j,2} - T_{v,j,1})}{(1+d)^{T_{v,j,1}+1}} \; T^-_{v,j,1} = T^-_{v,j,2} \\ g_v * \left(\dfrac{(T^-_{v,j,1} + 1 - T_{v,j,1})}{(1+d)^{T^-_{v,j,1}+1}} + \cdots + \dfrac{1}{(1+d)^{T^-_{v,j,2}}} \right. \\ \left. + \dfrac{(T_{v,j,2} - T^-_{v,j,2})}{(1+d)^{T^-_{v,j,2}+1}} \right) else \end{cases} \tag{19}$$

(8) The total NPV of all mining areas is

$$\theta = \sum_{j=1}^{N} \theta_{v,j} \tag{20}$$

The collection of Eqs. (11)-(20) structures a procedure for the simultaneous optimization of technical indicators and mining sequence. When these equations are integrated with Eqs. (1)-(10), a model emerges for the simultaneous dynamic optimization of technical indicators and mining sequence.

3) CONSTRAINTS

(1) Based on the definition of boundary and industrial grades, the boundary grade is not greater than the industrial grade, i.e.,

$$p_{1,v} \le p_{2,v} \tag{21}$$

(2) Considering smelting requirements, the concentrate grade is not less than the minimum smelting grade, i.e.,

$$p_{5,v} \ge p_y \tag{22}$$

(3) Considering the mass conservation of metal elements, beneficiation recovery rate is <1, i.e.,

$$c_{4,v} < 1 \tag{23}$$

(4) Mining area e needs to be mined completely before mining area h is mined, i.e.,

$$y_e < y_h \tag{24}$$

4) OPTIMIZATION MODEL

Combining the preceding decision variables, objective functions and constraints, and using the technical indicators and mining sequence as described, the complete optimization model is

$$\begin{cases} \max \theta = \sum_{j=1}^{N} \theta_{v,j} \\ s.t. p_{1,v} \le p_{2,v} v = 1, 2, \cdots, N \\ \quad p_{5,v} \ge p_y v = 1, 2, \cdots, N \\ \quad c_{4,v} < 1 v = 1, 2, \cdots, N \\ \quad y_e < y_h e, h \in \{1, 2, \cdots, N\} \end{cases} \tag{25}$$

5) HYBRID CODING OF AADE TO SOLVE THE MODEL

Hybrid coding techniques [31], [32] were introduced into the AADE algorithm to create the hybrid coding AADE algorithm, which was then used to solve the simultaneous dynamic optimization model of technical indicators and mining sequence. The basic steps of the optimization algorithm are as follows [33], [34], [35], [36], [37].

(1) Collect mine production data and determine the model that relates decision variables to technical indicators, which together with the mining sequence are the decision variables for the optimization model.

(2) Parameter initialization. Initialize the population size NP, the iteration counter $G_T = 0$, the maximum number of iterations $G_{\max}$, the upper (X^u) and lower (X^l) limits of the decision variables, the total number of optimization areas N, the probability parameters ψ and φ for the scaling factor F_{G_T}, and the probability parameters δ_l and δ_u for the crossover rate CR_{G_T}.

(3) Hybrid chromosome coding. The technical indicators of metal mines are coded using floating point coding, and the mining sequence is coded using arrangement coding.

(4) Population initialization. Initialize the initial population at X_0 using the following procedure.

(4.1) Set the initial populations $X_0 = [\Phi]$ and $j = 1$.

(4.2) Generate the genetic segment $X_{j,0}$ of the technical indicator using

$$X_{j,0} = X^l + random(0, 1) * (X^u - X^l) j = 1, 2, \cdots, NP \tag{26}$$

(4.3) Generate the genetic segment $Y_{j,0}$ of the mining sequence using

$$Y_{j,0} = randPerm(N) \tag{27}$$

where $randPerm(N)$ is a nonrepeating random permutation of consecutive integers $1, \ldots, N$.

(4.4) Set $X_0 = [X_0; X_{j,0}, Y_{j,0}]$ and $j = j + 1$.

(4.5) Determine whether or not to terminate. If $j > NP$, then stop iterating (i.e., X_0 is the initial population); otherwise go back to step 4.2.

(5) Calculate the total NPV of the population individuals θ and the adaptation value $f_T(X_{G_T})$.

(6) Using the scale factor F_{G_T} and crossover rate CR_{G_T} for creating each generation of technical indicator chromosomes, and the variation rate p_{m,G_T} and crossover rate p_{c,G_T} for mining sequential chromosomes, the following equations are calculated:

$$F_{G_T} = Normalrand(\psi, \varphi) \tag{28}$$
$$CR_{G_T} = Uniformrand(\delta_l, \delta_u) \tag{29}$$
$$p_{m,G_T} = F_{G_T} \tag{30}$$
$$p_{c,G_T} = CR_{G_T} \tag{31}$$

(7) Mutation operation. Adaptive differential evolution mutation is used as the operation for the mutation of technical indicators, and reverse mutation is used as the operation for the mutation of mining sequence.

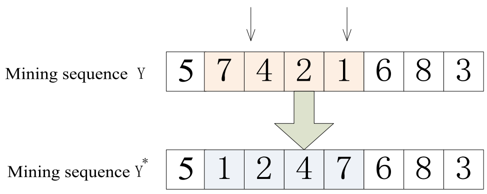

FIGURE 1. Reverse mutation process of mining sequence.

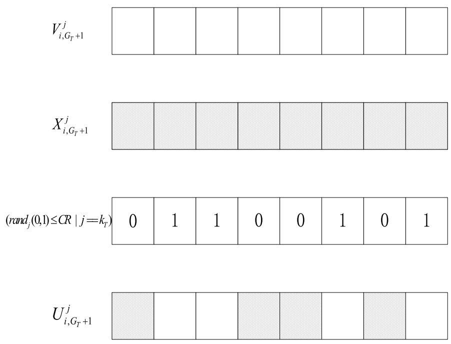

FIGURE 2. Binomial crossover process.

(7.1) Mutation operation of technical indicators. If $random(0, 1) < 1 - G_T / G_{\max}$, the DE/rand/1 mutation strategy is invoked; otherwise, the DE/best/1 mutation strategy is implemented. The corresponding mathematical expression is as follows:

$$V_{i,G_T+1} = \begin{cases} X_{r1,G_T} + F * (X_{r2,G_T} - X_{r3,G_T}) \\ \quad random(0, 1) < 1 - G_T / G_{\max} \\ X_{best,G_T} + F * (X_{r1,G_T} - X_{r2,G_T})\ else \end{cases} \tag{32}$$

(7.2) Mutation operation of mining sequence. Two disparate positions within the chromosome are randomly selected. The gene sequence between these positions is subsequently inverted and reintegrated into the original chromosome. For instance, Figure 1 schematically illustrates the reverse mutation process for an 8-dimensional mining sequence.

(8) Crossover operation. Binomial crossover is used as the crossover operation for technical indicators and partial matching crossover is used as the crossover operation for the mining sequence.

(8.1) Crossover operation of technical indicators. The binomial crossover method is chosen for each component. The associated mathematical expression is articulated below:

$$U^j_{i,G_T+1} = \begin{cases} V^j_{i,G_T+1} rand_j(0, 1) \le CR or\ j = k_T \\ X^j_{i,G_T+1} else \end{cases} ,j=1, 2, \cdots , D_T \tag{33}$$

To elucidate, Figure 2 schematically depicts the binomial crossover process in the context of an 8-dimensional optimization problem.

(8.2) Crossover operation of mining sequence. The partially matched crossover procedure is delineated in the subsequent steps and is also illustrated in Figure 3:

Step 1: Initially, two chromosomes from the mining sequence are randomly chosen, along with two specific positions, as depicted in Figure 3(a).

Step 2: Subsequently, the genes situated between these two positions are swapped, as illustrated in Figure 3(b).

Step 3: A mapping relationship is established based on the swapped genes, as indicated in Figure 3(c).

Step 4: In accordance with this mapping relationship, any conflicting genes outside the designated positions are substituted, thereby generating two conflict-free offspring genes, as represented in Figure 3(d).

(9) Select the operator. Create the next generation of individuals using:

$$X_{i,G_T+1} = \begin{cases} U_{i,G_T+1} f_T(U_{i,G_T+1}) \le f_T(X_{i,G_T}) \\ X_{i,G_T} else \end{cases} \tag{34}$$

(10) Determine whether or to terminate iteration. If $G_T < G_{\max}$, then return to step 4; otherwise, stop iterating.

(11) Output the best technical indicators, mining sequence and maximum total NPV.

The flowchart of the hybrid coding AADE algorithm for solving the simultaneous dynamic optimization model of technical indicators and mining sequence is shown in Figure 4. The simultaneous optimization of dynamic technical indicators and mining sequence is a mixed integer optimization issue involving both continuous (technical indicators) and integer (mining sequence) decision variables. To address this, hybrid chromosome coding and mixed evolutionary operators are capable of optimizing such mixed integer optimization problems, while single chromosome coding and single evolutionary operators are limited to solving continuous optimization problems. Thus, the hybrid coding AADE algorithm is appropriate for optimizing both the technical indicators and the mining sequence in metal mines concurrently.

III. CASE STUDY

The ore body from 1450 to 1750 m of the Huogeqi copper mine was used as an illustrative case with actual production data and the current production status. The ore body from 1450 to 1750 m was divided into five mining zones, and the model we created and the algorithm derived were applied to simultaneously dynamically optimize the entire set of technical indicators and mining sequence. The scope and original geological reserves of each defined copper mining area of Huogeqi mine are shown in Table 2. The initial geological reserves are the geological reserves corresponding to the original cut-off grade (0.3%) and the original industrial grade (0.5%).

Based on the present mine production level, the lower limits of the boundary and industrial grades were 0.1% and the upper limits were 0.8%; the lower limit of the smelting

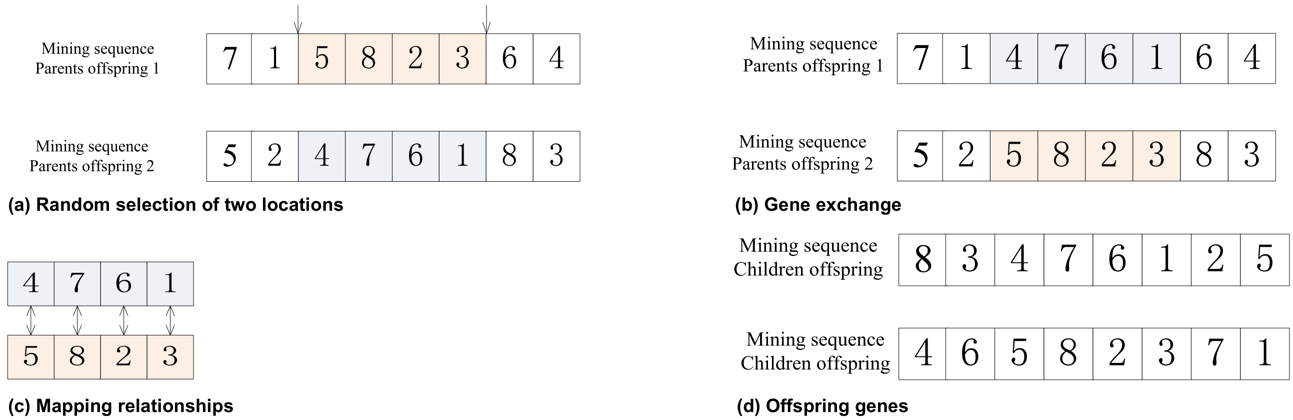

FIGURE 3. Partially matched crossover process of mining sequence.

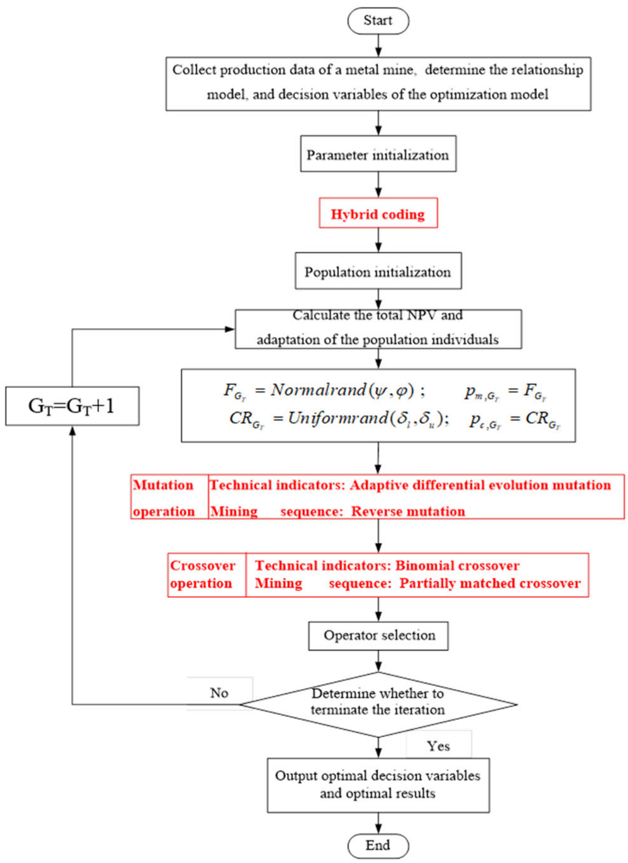

FIGURE 4. Flowchart of the hybrid coding AADE algorithm.

grade was 16%; the annual production capacity of the mine was 3 kt; the value of the constant z in Equation (2) was 0.66; the total production cost of ore was 226 CNY/t; the sales price of #1 copper concentrate was 47,739 CNY/t; and the annual discount rate was 6%.

Areas for optimization were based on the middle section of the ore body, and infill mining was used to mine the copper ore at Huogeqi. It is therefore theoretically possible to mine

TABLE 2. Scope and initial geological reserves of each copper mining area of Huogeqi mine.

Mining area	Horizontal range (m)	Initial geological reserves (Mt)
1	1690 – 1750	480.4585
2	1630–1690	440.5495
3	1570–1630	475.0247
4	1510–1570	407.9881
5	1450–1510	503.2427

in any optimized area sequence, so the contiguity constraint of Equation (24) does not apply in this case.

A. MODEL OF DYNAMIC RELATIONSHIPS BETWEEN TECHNICAL INDICATORS

1) PROBABILITY DENSITY FUNCTION OF THE GRADE DISTRIBUTION

Kernel density estimation methods fit distributions based on the characteristics and properties of the data without any prior knowledge and can fit probability density functions better than parameter estimation methods [38]. Kernel density estimation was used to fit the probability density distribution function of the ore grade, and the fitting is shown in Figure 5. Figure 5 shows that kernel density estimation fitted the ore grade distribution well.

2) MODEL OF THE ORE BODY WEIGHT AND ORE GRADE RELATIONSHIP

The scatter plot of ore weight vs copper grade was plotted for 157 sets of ore body weight and grade data collected from the Huogeqi copper mine, as shown in Figure 6. The figure shows that there was no correlation between ore weight and copper grade. The coefficient of correlation between ore weight and copper grade was $r = -0.004$. An F-test was performed to test the relationship between them, which produced a significance level of 0.9608. The significance level was

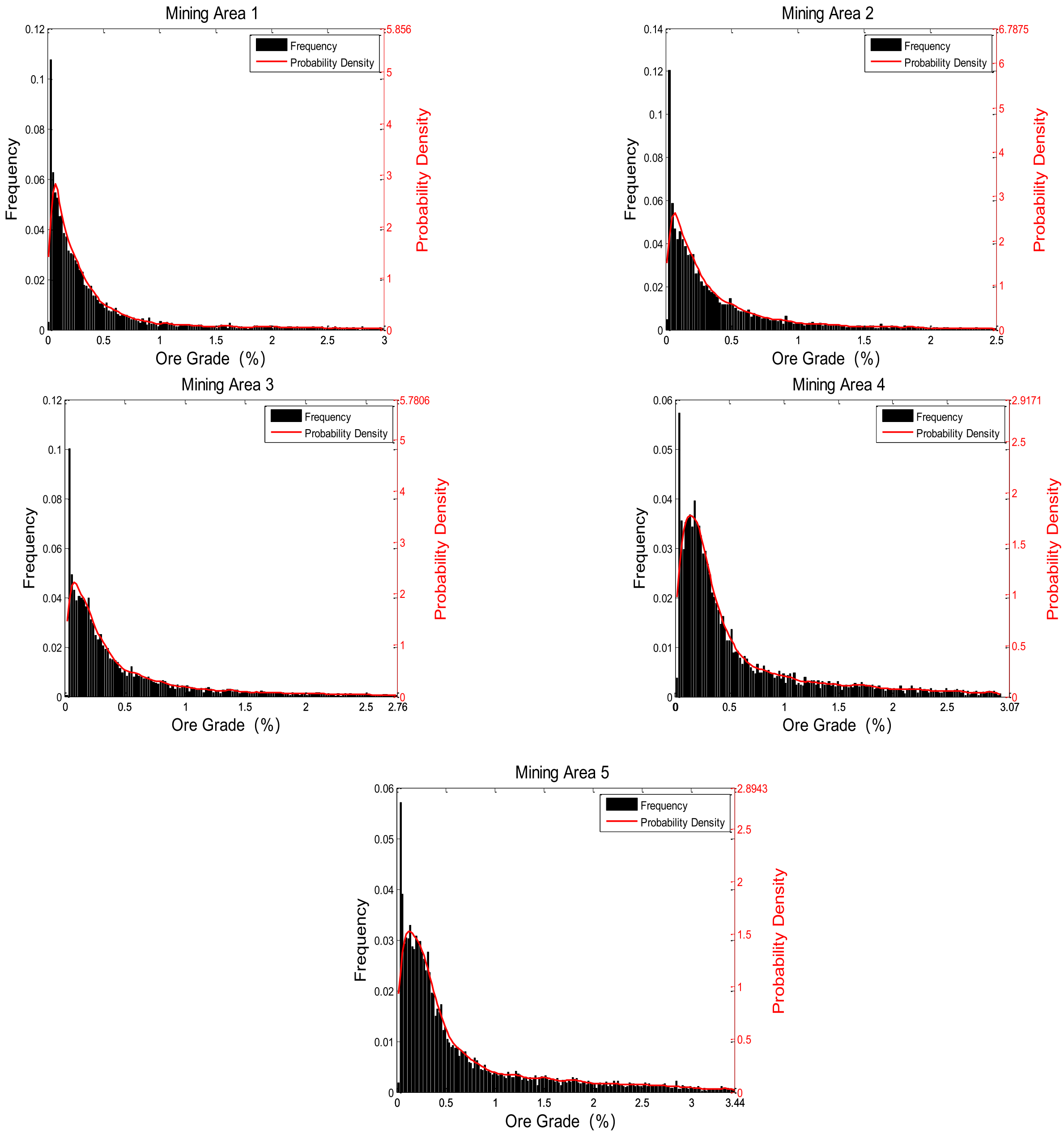

FIGURE 5. **Ore grade distribution fitting for each mining area.**

>0.05, which indicates that there was no relationship between ore weight and copper grade [39]. Thus, ore weight was not influenced by copper grade, and the ore weight function for Huogeqi copper ore was obtained using the average value of ore weight given by

$$g(x) = 3.16t/m^3 \tag{35}$$

3) MODEL OF THE DEPLETION RATE AND LOSS RATE RELATIONSHIP

The 1450–1750 more body of the Huogeqi copper mine is mined using various mining methods (deep hole subsequent filling, upward horizontal layered filling). The model of the relationship between depletion rate and loss rate requires that a single mining method be used, and so the relationship between loss rate and depletion rate could not be modeled. In the subsequent optimization, the planned values of both loss rate and depletion rate were used; both were 9%.

4) MODEL OF THE EXTRACTED GRADE AND BENEFICIATION RATIO RELATIONSHIP

The scatter plot of copper extracted grade vs beneficiation ratio was drawn using 711 sets of beneficiation data, as shown in Figure 7. The figure shows that there was a linear

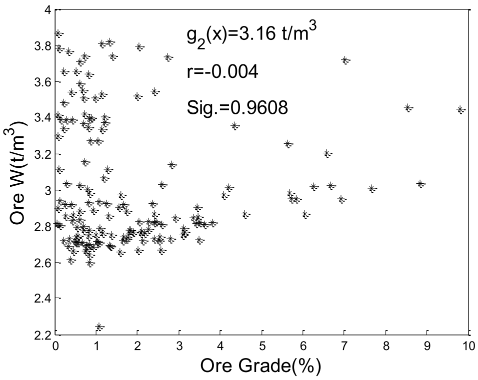

FIGURE 6. Scatter plot of ore body weight vs grade.

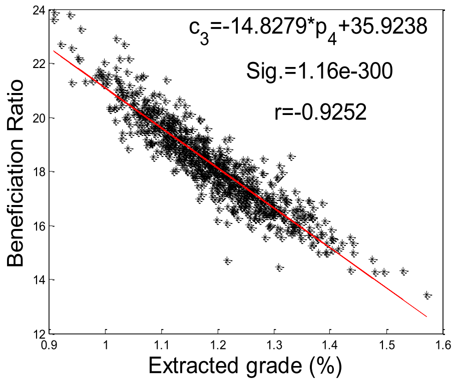

FIGURE 7. Relationship between extracted grade and beneficiation ratio.

relationship between copper extracted grade and the beneficiation ratio. A linear regression function with the correlation coefficient $r = -0.9252$ was used to fit the data. An F-test was performed to test the relationship between them, which produced a significance level of 1.16×10^{-300}. The significance level was <0.05, so the regression was significant and the proposed model could be used. The following linear function was therefore used to describe the relationship between copper extracted grade and beneficiation ratio:

$$c_3 = -14.8279 * p_4 + 35.9238 \tag{36}$$

5) CONCENTRATE GRADE MODEL

A back-propagation (BP) neural network [40], [41] was used to model the relationship between the extracted grade and beneficiation ratio and the concentrate grade using 711 sets of data; the first 611 sets were used as training samples, and the last 100 sets were used as test samples. The extracted grade and beneficiation ratio were the input, and the concentrate grade was the output. There were 2 nodes in the input layers, 2 nodes in the implicit layers, and 1 node in the output layer. The training functions and the transfer functions for the input and output layers were respectively 'traingdm', 'tansig' and 'purelin'. The learning rate was 0.1, training error precision was 0.001, and the maximum number of iterations was 2500.

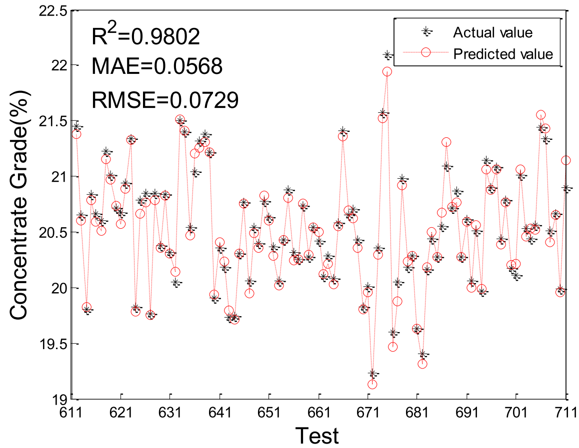

FIGURE 8. Fitting of copper concentrate grade using the BP neural network.

TABLE 3. Copper concentrate price adjustment factors and compensation prices.

Grade (%)	Price adjustment factor	Compensation price (CNY/t)
≥23	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	0.795	-220
17.00–17.99	0.78	-330
16.00–16.99	0.77	-440

The BP neural network fitting to the copper concentrate grade is shown in Figure 8.

The coefficient of determination of the BP neural network was 0.9802, MAE was 0.0568, and RMSE was 0.0729. The coefficient of determination was close to 1, and MAE and RMSE were both <0.1, which indicates that the BP neural network well fitted the model relating extracted grade and beneficiation ratio with concentrate grade.

6) CONCENTRATE PRICES

The study mine is a copper mine. The market trading price of copper concentrate is based on a 20% concentrate grade, and the prices of other grades of copper concentrate are adjusted from this price. The price adjustment factors and compensation prices are shown in Table 3. Copper concentrate prices are calculated by [18]:

$$q = f_6(p_5) = k_1 \times p_5 \times \lambda + k_2 \tag{37}$$

B. DECISION VARIABLES AND PARAMETER SETTINGS

1) DECISION-MAKING VARIABLES

Decision-making variables are the technical indicators and the mining sequence. The model of relationships between technical indicators developed in section III-A shows that

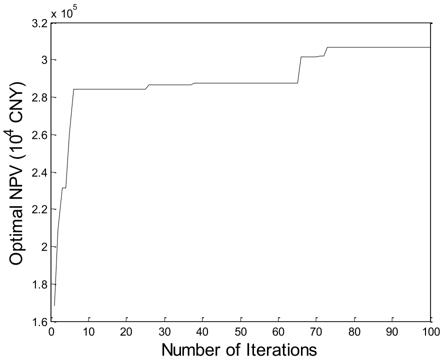

FIGURE 9. **Iterative process for the optimal NPV.**

boundary grade, industrial grade, depletion rate and loss rate are independent variables and are therefore not influenced by other indicators. The indicators geological reserves, average ore grade, extracted grade, extracted volume, beneficiation ratio, concentrate grade and concentrate volume are dependent variables. The loss rate and depletion rate are influenced by ore body characteristics as well as the mining technology employed. Consequently, these rates can generally be regarded as constant over short time frames. We used the planned values for each mining area as constant values for these two variables, both of which were 9%. Since the independent variables are decision variables in optimization, boundary grade and industrial grade for each mining area are decision variables for the technical indicators. In summary, boundary grade, industrial grade and mining sequence for each mining area are the decision variables of the optimization model, so there are 15 decision variables for each of the five mining areas.

2) SETTING ALGORITHM PARAMETERS

The parameters of the hybrid coding AADE algorithm were set as follows. The dimensionality of the decision variables D_T was set to 15, the initial population size NP was set to 100, the maximum number of iterations $G_{\max}$ was set to 100, and the adaptive control parameters ψ, φ, δ_l and δ_u were set respectively to 0.7, 0.1, 0 and 1.

C. OPTIMIZATION RESULTS AND ANALYSIS

The optimization model and the algorithm we created were used to optimize the technical indicators and mining sequence of the Huogeqi copper mine using the parameter settings described. The iterative process for optimal NPV is shown in Figure 9, and the optimization results are given in Table 4.

Figure 9 shows that optimal NPV converges in approximately 70 iterations. This indicates that the hybrid AADE algorithm solves the metal mine technical indicators and mining sequence and that the dynamic optimization model converges quickly. These results were compared with the results of optimization without considering the mining sequence, using the AADE algorithm to solve the optimization model without considering the mining sequence; the results are shown in Table 5.

Comparison of Tables 4 and 5 shows that the simultaneous dynamic optimization of metal mine technical indicators and mining sequence increases maximum NPV by 1161.01 10^4 CNY compared to optimization without considering the mining sequence. This result indicates that optimization considering the mining sequence is more valuable than optimization of technical indicators only. Therefore, in planning the production process, the technical indicators and mining sequence should be simultaneously and dynamically optimized together.

1) ALGORITHM COMPARISON

We demonstrated the superiority of the hybrid coding AADE algorithm for solving the simultaneous dynamic optimization model of technical indicators and mining sequence by comparing it with the hybrid coding GA algorithm [42], the hybrid coding DE algorithm [43], and the hybrid coding ADE algorithm [44]. All three algorithms incorporated hybrid coding and corresponding evolutionary operators. The incorporations were similar to that described for our modification of the AADE algorithm into the hybrid coding AADE algorithm, so they are not detailed here.

All four algorithms were used to solve the simultaneous dynamic optimization model of technical indicators and mining sequence. The parameter settings of the four algorithms were as follows. The adaptive control parameters ψ, φ, δ_l and δ_u were set respectively to 0.7, 0.1, 0 and 1 for the hybrid coding AADE algorithm. The mutation rate and crossover rate were set respectively to 0.7 and 0.5 for the hybrid coding GA algorithm. The scale factor F and crossover rate CR were set respectively to 0.7 and 0.5 for the hybrid coding DE algorithm. The distribution functions and parameters of the ADE algorithm were set to be equal to those of the hybrid coding AADE algorithm. The population size for all four algorithms was set to 100, and the maximum number of iterations was set to 100.

To avoid the randomness of error inherent in a single operation of an algorithm, each of the four algorithms was independently executed 31 times. For each run, the total NPV was recorded. The aggregated results are tabulated in Table 6.

The maximum, minimum, and average values for the total NPV of each algorithm were computed based on the data presented in Table 6. These calculated metrics are subsequently presented in Table 7.

Table 7 shows that maximum total NPV, minimum total NPV and average total NPV produced by the hybrid coding AADE algorithm were respectively 3306503.29 10^4 CNY, 304847.41 10^4 CNY, and 301127.78 10^4 CNY. These values were all greater than the corresponding values for any of the other three hybrid coding algorithms. Since the objective function maximizes NPV, the hybrid coding AADE algorithm solves the technical indicators and mining sequence, and the dynamic optimization model searches better than the other three hybrid coding algorithms. In the event of the worst-case

TABLE 4. Technical indicators, mining sequence and NPV of the optimized scheme.

Indicator	Mining area 1	Mining area 2	Mining area 3	Mining area 4	Mining area 5
Boundary grade (%)	0.7449	0.6933	0.6372	0.5700	0.6298
Industrial grade (%)	0.7512	0.8000	0.7156	0.8000	0.6527
Geological reserves (t)	2218359	2053616	2747175	2518894	3272148
Average ore grade (%)	1.5016	1.2664	1.2954	1.4411	1.5277
Extracted grade (%)	1.3665	1.1524	1.1788	1.3114	1.3902
Extracted ore volume (t)	2218359	2053616	2747175	2518894	3272148
Beneficiation ratio	15.66	18.84	18.44	16.48	15.31
Beneficiation recovery rate (%)	95.09	94.54	94.62	94.97	95.15
Concentrate grade (%)	20.35	20.52	20.57	20.52	20.25
Concentrate volume (t)	141643	109026	148941	152858	213720
Concentrate price (CNY/t)	8064	8131	8152	8132	8024
Average annual profit (10^4 CNY)	86658.65	61701.21	64783.11	80243.63	89433.94
Mining years (y)	0.7395	0.6845	0.9157	0.8396	1.0907
Mining sequence	2	5	4	3	1
NPV (10^4 CNY)	60452.83	34670.96	50886.80	60691.30	97087.79

TABLE 5. Optimization results without considering the mining sequence.

Indicator	Mining area 1	Mining area 2	Mining area 3	Mining area 4	Mining area 5
Boundary grade (%)	0.0080	0.8000	0.7913	0.7512	0.7013
Industrial grade (%)	0.008	0.8000	0.7959	0.7513	0.7917
Geological reserves (t)	2042822	1844468	2393227	2276145	3079463
Average ore grade (%)	1.5631	1.3250	1.3847	1.5233	1.5823
Extracted grade (%)	1.4224	1.2058	1.2601	1.3862	1.4399
Extracted ore volume (t)	2042822	1844468	2393227	2276145	3079463
Beneficiation ratio	14.83	18.04	17.24	15.37	14.57
Beneficiation recovery rate (%)	95.25	92.37	94.85	96.71	96.59
Concentrate grade (%)	20.10	20.10	20.60	20.60	20.27
Concentrate volume (t)	137728	102218	138820	148098	211304
Concentrate price (CNY/t)	7963	8164	8164	8031	7926
Average annual profit (10^4 CNY)	93259.82	67934.58	74267.20	88968.07	95367.60
Mining years (y)	0.6809	0.6148	0.7977	0.7587	1.0265
NPV (10^4 CNY)	63500.61	40629.11	55519.16	60074.82	82904.96

scenario, the total NPV optimized by our suggested algorithm is 301127.78 10^4 CNY, which falls short of the best-case optimized value by a relatively insignificant 1.75%. Therefore, the hybrid coding AADE algorithm is effective in solving the simultaneous dynamic optimization model of technical indicators and mining sequence.

A one-sided t-test was used for statistical analysis to demonstrate that the AADE algorithm solves the technical indicators and mining sequence and that the dynamic optimization model has significant advantages [45]. For each pair of compared algorithms, the t statistic was calculated as follows.

The significance level is set to be 0.05, and the degrees of freedom is the total number of runs minus 1, which is 30. The critical value for the t-test is found at $t_{0.025,30} = 2.042$. If $|t| > t_{0.025,30}$, then the two algorithms are significantly different. If $|t| \leq t_{0.025,30}$, then the two algorithms are not significantly different.

Table 6 shows that the standard deviation of the solution given by the AADE algorithm was 1470.93. Using this standard deviation and average total NPV from Table 7 in Equation (36), t values for comparisons of the hybrid coding AADE with each of the other three hybrid coding algorithms, are tabulated in Table 8.

TABLE 6. Total NPV provided by the four algorithms.

Number of times	Total NPV			
	Hybrid coding GA	Hybrid coding DE	Hybrid Coding ADE	Hybrid coding AADE
1	299024.86	304829.90	304440.77	303789.67
2	299322.18	299848.64	304965.46	305367.68
3	304782.49	296738.93	302332.98	306010.22
4	303351.83	301719.23	300493.03	305843.82
5	304820.00	299938.81	302563.51	306054.31
6	304216.80	297505.91	302416.83	302454.78
7	299040.53	304112.93	305676.98	305799.14
8	303981.27	302588.08	292850.47	301997.08
9	299091.59	304497.58	294939.44	303771.42
10	303708.43	304569.39	304036.91	305099.02
11	304227.20	298174.27	302206.76	305370.10
12	304832.37	304194.05	303084.97	305552.91
13	304047.48	302871.01	297855.71	306142.83
14	299322.21	305363.23	303319.39	306218.33
15	300342.27	305884.39	299942.01	305485.99
16	303959.76	296039.36	300662.33	304382.55
17	302342.99	305159.36	305734.38	303918.89
18	297238.88	292368.34	299027.59	306134.48
19	298219.98	305291.85	301488.72	304846.97
20	297263.02	306095.33	303385.12	305971.75
21	301075.09	304838.41	292277.55	305884.26
22	305803.03	302374.90	298490.60	305900.45
23	305010.82	305070.02	301203.68	305706.91
24	301894.29	297770.54	306246.40	305742.49
25	304610.52	304284.48	302862.07	305527.67
26	296030.51	302235.70	305714.36	301883.48
27	305497.19	297893.09	294132.36	306503.29
28	304436.61	299216.69	294829.50	302507.17
29	301352.16	292101.28	296762.33	301127.78
30	304709.43	283761.83	304357.48	305650.96
31	302094.99	305575.71	305623.91	303623.16

TABLE 7. Statistics of the four algorithms for comparison.

Statistical indicators	Hybrid coding GA	Hybrid coding DE	Hybrid coding ADE	Hybrid coding AADE
Maximum total NPV (10^4 CNY)	305803.03	306095.33	306246.40	306503.29
Average total NPV (10^4 CNY)	302117.77	301061.72	301094.31	304847.41
Minimum total NPV (10^4 CNY)	296030.51	283761.83	292277.55	301127.78

TABLE 8. Results of *t* tests for total NPV.

Comparison algorithm	Hybrid coding GA	Hybrid coding DE	Hybrid coding ADE
Value of t statistics	10.33	14.33	14.21

Table 8 shows that the t statistics for the comparisons of the AADE algorithm with each of the other three algorithms were greater than $t_{0.025,30} = 2.042$. These values indicate that the hybrid coding AADE algorithm searched significantly better in solving the simultaneous dynamic optimization model of technical indicators and mining sequence.

The numerical stability of our proposed algorithm was further examined by introducing perturbations to the parameters within the algorithm. The algorithm was then employed to optimize the case with the perturbed parameters, the results of which are presented in Table 9. We used the minimum and maximum values optimized by the hybrid AADE algorithm,

TABLE 9. Total NPV of the perturbation parameters.

ψ	φ	δ_l	δ_u	Total NPV
0.9	0.1	0.1	0.9	304335.76
0.8	0.1	0.2	0.8	303718.17
0.8	0.2	0.3	0.7	304587.11
0.7	0.2	0.2	0.8	302210.10
0.6	0.2	0.3	0.6	304973.87
0.5	0.1	0.4	0.6	301958.77
0.4	0.1	0.2	0.4	300965.44
0.4	0.05	0.5	0.7	304550.14
0.3	0.1	0.8	0.9	301868.62
0.2	0.1	0.2	0.1	291409.81

as listed in Table 6, to set the lower and upper boundaries, respectively. This established an interval of [301127.78 306503.29]. Out of the results presented in Table 9, 80% of the optimized results are within this interval, and the maximum relative distance outside this interval is a mere 3%. Thus, this demonstrates the robust numerical stability of our proposed algorithm in simultaneously optimizing technical indicators and mining sequence.

IV. CONCLUSION

We investigated the problem of simultaneous dynamic optimization of technical indicators and mining sequence for a metal mine and created an optimization model and algorithm. The use of the proposed optimization model and algorithm was demonstrated as a test case using the Huogeqi copper mine. Our work is summarized as follows.

(1) A model for the simultaneous dynamic optimization of technical indicators and mining sequence of a metal mine was derived. The model was shown to simultaneously optimize the technical indicators and mining sequence.

(2) The simultaneous dynamic optimization of technical indicators and mining sequence of a metal mine is a complex mixed integer single-objective optimization problem. The mixed coding AADE algorithm was proposed and developed to solve it. The hybrid coding AADE algorithm was a modification of the AADE algorithm that incorporated hybrid coding and a corresponding evolutionary operator.

(3) The simultaneous dynamic optimization of technical indicators and mining sequence increased NPV over the optimization of technical indicators only.

(4) The hybrid coding AADE algorithm performed searches significantly better than the hybrid coding GA algorithm, the hybrid coding DE algorithm, and the hybrid coding ADE algorithm when solving the simultaneous dynamic optimization of technical indicators and mining sequence. The efficacy of the hybrid coding AADE algorithm can be ascribed to the integration of hybrid chromosome encoding and hybrid evolutionary operators.

This study provides a model and an accompanying methodology for the simultaneous optimization of metal mine technical indicators and mining sequence that takes into account the dynamic relationships between technical indicators. There are three aspects of the model and method that can be improved in future work. (1) The objective function considers economic efficiency (NPV). However, resource use efficiency is also an important objective for mineral resource extraction. We intend to incorporate both economic and resource benefits into the objective function in future research. (2) The model must be further refined to include other mining activities such as release, transportation, hoisting, crushing, grinding and flotation, which will be the focus of future studies. (3) The high-performing algorithm introduced within the recent 2-3 years will be taken into account for future work aimed at optimizing both technical indicators and mining sequence in metal mines simultaneously.

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