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A Multi-Objective Optimization Model Using Improved NSGA-II for Optimizing Metal Mines Production Process

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ABSTRACT Production process optimization is an indispensable step in industrial production. The optimization of the metal mines production process (MMPP) can increase production efficiency and thus promote the utilization rate of the metal mineral resources in the frame work of sustainable development. This study establishes a multi-objective optimization model for optimizing the MMPP by maximizing economic and resource benefits. To get better non-dominated Pareto optimal solutions, an improved non-dominated sorting genetic algorithm-II (NSGA-II) is proposed. The symmetric Latin hypercube design is adopted to generate the initial population with high diversity. The mutation and crossover of the differential evolution algorithms are introduced into the NSGA-II to replace the genetic algorithm for improving convergence. The control parameters of the mutation scale factor and crossover rate of the differential evolution algorithm are adaptively adjusted to improve the diversity of candidate solutions. To verify the performance of the improved NSGA-II, four test functions from the ZDT series functions are chosen for experimentation. The experimental results indicate that the improved NSGA-II outperforms the comparative algorithms in diversity and convergence. Moreover, the application of the proposed method to the Yinshan copper mines shows that the improved NSGA-II is effective in optimizing the MMPP and a reliable method in promoting utilization rate of metal mineral resources in the framework of sustainable development.

INDEX TERMS Metal mines production process, multi-objective optimization, symmetric Latin hypercube design, differential evolution, parameter adaptation, improved NSGA-II.

I. INTRODUCTION

Metal mineral resources are non-renewable resources and raw materials for industrial development. The gap between society demand and industrial supply has become increasingly challenging with continuous exploitations of the non-renewable resources [1]. Therefore, it is an urgent problem to optimize the metal mine production process (MMPP) for obtaining metal mineral resources with high utilization rate under the frame work of sustainable development.

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The optimization of the metal mines production process is to calculate the most reasonable technical production indexes, such as the mineable reserve, geological cutoff grade, loss rate, raw ore quantity, concentrate quantity, concentration rate. These indexes directly affect the economic benefits of metal mines enterprise and the utilization rate of metal mineral resources. As a result, optimizing the MMPP is an efficient way to mine metal mineral resources. It has been recognized that the traditional method of calculating production technical indexes depends on experiences of workers. However, worker experience-depended methods have limitations in carrying out a multi-objective optimization problem with many input indexes. For example, the experience-dependent methods can increase the production costs and the waste of resources [2]. Therefore, an effective optimization method is necessary to optimize the MMPP.

In the last decades, many methods and models have been proposed to optimize the MMPP. These methods can be mainly classified into four categories. The first applied to optimize the MMPP is the Lane's theory [3]–[7]. The second is the dynamic programming method [8]–[11] which considers the different ore areas of metal mines. The third is the single-objective evolutionary algorithm, such as the genetic algorithm [12]–[14], the particle swarm optimization algorithm [2] and the differential evolution algorithm [15]. The fourth is the multi-objective optimization algorithm, such as the non-dominated sorting genetic algorithm-II (NSGA-II) [16] that can consider multiple objectives in optimization.

The Lane's theory, the dynamic programming method, and the single-objective evolutionary algorithms belong to the class of single-objective optimization method. Those single-objective optimization methods have made many achievements in metal mines optimization, in which only a single objective is considered. Hence, these single-objective optimization methods are not appropriate for multi-objective optimizations. With the increase in scarcity and contradiction between resource demand and supply of the metal mineral resources, experts and managers have recognized that the economic and resource benefits must be considered both as the objectives for the MMPP. Therefore, the single-objective optimization methods are insufficient to optimize the MMPP.

In recently years, the NSGA-II method was applied to optimize the multi-objective optimization model of the MMPP, which considers both the economic and resource benefits [16]. However, the MMPP is a complex and nonlinear [2], [15] multi-objective optimization problem with different constraints. Numerous studies [17]–[19] have shown that the NSGA-II method has some difficulties in solving complex multi-objective optimization problems. First, the initial population is generated by the uniform distribution, which has been reported to be not a good strategy [20], [21] due to its insufficiency of diversity. Second, the NSGA-II uses the mutation and crossover of the genetic algorithm, which is with slow speed and unstable convergence [22], [23]. The mutation and crossover of the genetic algorithm reduce the convergence rate and efficiency of the NSGA-II [20].

To overcome the above disadvantages of the NSGA-II, an improved NSGA-II for optimizing the MMPP is proposed. Firstly, the symmetric Latin hypercube design (SLHD) is adopted to generate the initial population. Secondly, the mutation and crossover of the differential evolution algorithm are introduced into the NSGA-II. Thirdly, the control parameters of mutation scale factor and crossover rate of the differential evolution algorithm are adaptively adjusted.

The rest of the present paper is organized as follows. Section II establishes the multi-objective optimization model of the MMPP. Section III proposes an improved NSGA-II for optimizing the MMPP. Section IV verifies the performance of the improved NSGA-II on four test functions. Section V validates the performance of the improved NSGA-II with an actual case of the Yinshan Copper Mine. Section VI comes the conclusion.

II. MULTI-OBJECTIVE OPTIMIZATION MODEL OF METAL MINES PRODUCTION PROCESS

An multi-objective optimization model was introduced for the MMPP in a former work [16] as a first trial. For completeness, this paper briefly introduces the multi-objective optimization model of the MMPP. It should be noted that the metal mines in China use the ''double-grade'' (geological cutoff grade and minimum industrial grade) instead of the international ''single-grade'' (cutoff grade).

A. RELATIONS AMONG PRODUCTION TECHNICAL INDEXES

The MMPP includes three stages, respectively the exploration stage, the mining stage, and the ore-dressing stage. Each stage has main production technical indexes. For example, the exploration stage has mainly four production technical indexes, i.e., the mineable reserve (a_1, t), geological cutoff grade (g_1, %), minimum industrial grade (g_2, %), and mean grade of ore (g_3, %). The mining stage has mainly four production technical indexes, i.e., the dilution rate (r_1, %), loss rate (r_2, %), grade (g_4, %), and quantity (a_2, t) of raw ore. The ore-dressing stage has mainly three production technical indexes, i.e., the concentration rate (r_3), ore concentrate grade (g_5, %), and concentrate quantity (a_3, t). Since these indexes affect each other, relations among them should be considered in the MMPP.

The mineable reserve and mean grade of ore are determined by the geological cutoff grade and minimum industrial grade. In the MMPP, the mathematical-statistical methods are generally used to calculate the mineable reserve and mean grade of ore [8], [16]. They are expressed as:

$$\varphi(x) = (\frac{x - g_1}{g_2 - g_1})^h, \ g_1 \le x \le g_2 \tag{1}$$

$$\begin{aligned} a_1 &= f_1(g_1, g_2) \\ &= a_0 \times \frac{\int_{g_1}^{g_2} \varphi(x)\delta(x)f(x)dx + \int_{g_2}^{100} \delta(x)f(x)dx}{\int_{g_a}^{g_b} \varphi(x)\delta(x)f(x)dx + \int_{g_b}^{100} \delta(x)f(x)dx} \end{aligned} \tag{2}$$

$$\begin{aligned} g_3 &= f_2(g_1, g_2) \\ &= \frac{\int_{g_1}^{g_2} x\varphi(x)f(x)dx + \int_{g_2}^{100} xf(x)dx}{\int_{g_1}^{g_2} \varphi(x)f(x)dx + \int_{g_2}^{100} f(x)dx} \end{aligned} \tag{3}$$

where g_a and g_b are respectively the initial value of the geological cutoff grade and minimum industrial grade, which can be randomly selected; a_0 is the mineable reserves corresponding to g_a and g_b, which is calculated by the mine software; $\varphi(x)$ is a mining possibility function of ore with grade belongs to $[g_1, g_2]$; $\delta(x)$ is the ore density function; $f(x)$ is the ore grade probability density function; h is a constant relying on the ore body characteristic.

The dilution rate is the rate of the reducing ore grade during the mining to the mean grade of ore, i.e.,

$$r_1 = (g_3 - g_4)/g_3 \tag{4}$$

According to formula (4), the grade of raw ore is given by

$$g_4 = g_3 \times (1 - r_1) \tag{5}$$

According to the mass conservation, the metal content included in the ore is balanced during the mining, i.e.,

$$a_2 \times g_4 = a_1 \times (1 - r_2) \times g_3 \tag{6}$$

According to formula (5) and (6), the raw ore quantity is

$$a_2 = a_1 \frac{1 - r_2}{1 - r_1} \tag{7}$$

The concentration rate is the rate of the raw ore quantity to the ore concentrate quantity [24], [25], i.e.,

$$a_3 = a_2/r_3 \tag{8}$$

In general, the loss rate and dilution rate are related to the mining approach and ore body characteristic. The concentration rate and ore concentrate grade rely on the ore-dressing method, raw ore characteristic, ore-dressing plant design. For the same mine, the method of mining and ore-dressing, the characteristic of ore body and raw ore, and the ore-dressing plant design are similar. Therefore, the loss rate and dilution rate, concentration rate and raw ore grade, ore concentrate grade with concentration rate and grade of raw ore may have a correlation in the same mine [16]. Those relations are established by production data and are given as follows:

$$r_2 = f_3(r_1) \tag{9}$$

$$r_3 = f_4(g_4) \tag{10}$$

$$g_5 = f_5(g_4, r_3) \tag{11}$$

The price of unit ore concentrates (q, $\$/t$) is determined by its grade. It is given as follows:

$$q = f_6(g_5) \tag{12}$$

B. MATHEMATICAL FORMULATION OF MULTI-OBJECTIVE OPTIMIZATION MODEL

In the frame work of sustainable development, the economic and resource benefits must be considered both as the optimization objectives. The profit (β, \$) and resource utilization ratio (R) can represent the economic and resource benefits, respectively. Therefore, we assign the profit and resource utilization ratio as the optimization objective functions with maximizing them. The multi-objective optimization model of MMPP is mathematically formulated as follows:

$$\begin{cases} \max \beta = a_3 q - a_2(c_1 + c_2) \\ \max R = \dfrac{a_3 \times g_5}{f_1(g_{1\min}, g_{2\min}) \times f_2(g_{1\min}, g_{2\min})} \\ \text{s.t. } g_1 \le g_2 \\ \quad g_5 \ge g_{\text{smelter}} \end{cases} \tag{13}$$

where c_1 is the unit direct cost (\$/t); c_2 is the unit indirect cost (\$/t); g_{smelter} is the grade of minimum smelter (%); $g_1 \le g_2$ means that the geological cutoff grade should be smaller than the grade of minimum industrial; $g_5 \ge g_{\text{smelter}}$ represents that the final ore concentrate grade should be greater than the grade of minimum smelter.

It should be noted that the functions f_3, f_4, and f_5 might change when the objective mines are different. Since the decision variables are related to these functions, which cannot be determined now.

III. AN IMPROVED NSGA-II FOR OPTIMIZING THE METAL MINES PRODUCTION PROCESS

NSGA-II is a very famous multi-objective optimization method, and firstly put forward by Deb *et al.* [26]. The NSGA-II is improved from the NSGA [27]. It has numerous advantages than the NSGA [28], such as low computational complexity, high global search performance, and fewer parameters.

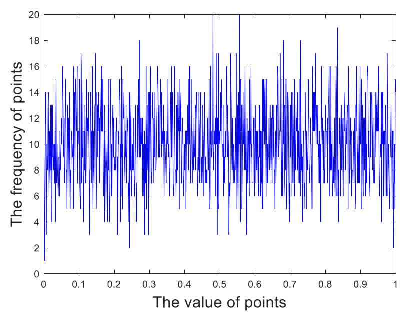
In this work, we put forward an improved NSGA-II for optimizing the MMPP. Firstly, the SLHD is adopted to generate the initial population to enhance the diversity of the initial population. Secondly, the mutation and crossover of the differential evolution algorithm are introduced into the NSGA-II to replace the genetic algorithm to improve convergence. Moreover, the control parameters of mutation scale factor and crossover rate of the differential evolution algorithm are adaptively adjusted to improve the diversity of candidate solutions. In the next work, we introduce the main operators and the procedure of the improved NSGA-II for optimizing the MMPP.

A. SYMMETRICAL LATIN HYPERCUBE DESIGN GENERATES INITIAL POPULATION

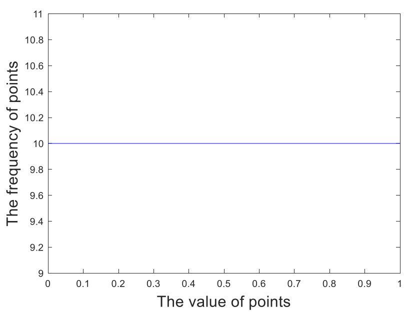
In the NSGA-II, the initial population is generated by the uniform distribution, which has been reported to be not a good strategy due to its insufficiency of diversity [20], [21]. The diversity of the initial population seriously affects the performance of the NSGA-II [29]. In order to overcome this shortcoming, the SLHD is adopted to generate the initial population of the NSGA-II to enhance the diversity of the initial population. The SLHD is improved from the Latin hypercube design. The former is more uniform than the Latin hypercube design and advantageous to the Latin hypercube design [30], [31]. The pseudocode of the SLHD is given in Table 1. A performance comparison is carried out in order to show the advantages of the SLHD. Figure 1 shows the distribution of 10,000 points generated by the uniform distribution and the SLHD in the interval [0, 1]. From Figure 1, one can see that the uniformity of points generated by the SLHD is superior to that by the uniform distribution. Thus, the diversity of the initial population is enhanced by adopting the SLHD into NSGA-II.

TABLE 1. **Pseudocode of SLHD.**

Line	Pseudocode of SLHD
1	Initialize a matrix T of size $NP \times D$.
2	If N is even, define $i = NP/2$.
3	Else, define $i = (NP-1)/2$ and set $T((NP+1)/2, k) = (NP+1)/2$. End if.
4	For $k = 1$ to D , a random permutation of the integers from 1 to i and denote it by ε_k . End for.
5	For $j = 1$ to i and $k = 1$ to D .
6	Generate a random number (w) of uniform distribution in the interval [0, 1].
7	If $w < 0.5$, set $T(j,k) = \varepsilon_k(j)$, $T(NP+1-j,k) = NP+1-\varepsilon_k(j)$
8	Otherwise, set $T(j,k) = NP+1-\varepsilon_k(j)$, $T(NP+1-j,k) = \varepsilon_k(j)$. End if. End for.
9	For $k = 1$ to D , set $\pi_k = T(:,k)$
10	For $j = 1$ to NP , set $s_k^{(j)} = a_k - (b_k - a_k)/(n-1)*(j-1)$. End for. End for.
11	For $j = 1$ to NP , set $T(j,:) = (s_1^{\pi 1(j)}, s_2^{\pi 2(j)}, \ldots, s_D^{\pi D(j)})$, End for.



(a) Distribution of points generated by the uniform distribution



(b) Distribution of points generated by the SLHD

FIGURE 1. **Distribution of 10000 points generated by the uniform distribution and the SLHD.**

B. DIFFERENTIAL EVOLUTION ALGORITHM

The NSGA-II takes the mutation and crossover of the genetic algorithm. The mutation and crossover of the genetic algorithm reduce the convergence rate and efficiency of the NSGA-II [20]. In order to improve the convergence of NSGA-II, the mutation and crossover of the differential evolution algorithm are introduced into the NSGA-II to replace the genetic algorithm.

The differential evolution algorithm is a powerful and effective evolutionary algorithm firstly proposed by Storn and Price [32]. It is an algorithm that can be implemented easily with very few parameters [33]. It has been proven to be superior to the algorithms such as the genetic algorithm, evolution strategy, adaptive simulated annealing [32], and particle swarm optimization [34], [35].

The differential evolution algorithm utilizes a group of candidate solutions noted by a NP-dimensional vector as a population $X_G = [x_{1,G}, x_{2,G}, \ldots, x_{NP,G}]$, where NP and G are respectively the population size and current generation. The mutation and crossover of the differential evolution algorithm are carried out in the following steps.

(i) Mutation: for each goal population, $X_{i,G}, i = 1, 2, 3, \ldots, NP$, the mutant population is generated by:

$$V_{i,G} = X_{r1,G} + F \times (X_{r2,G} - X_{r3,G}) \tag{14}$$

where F is the mutation scale factor, which controls the scale of $(X_{r2,G} - X_{r3,G})$; $r1, r2, r3 \in \{1, 2, 3, \ldots, NP\}$, and the values of them are different.

(ii) Crossover: following the mutation operation, the binomial crossover operation is adopted to generate the trial vector $(U_{i,t} = [u_{i,t}^1, u_{i,t}^2, \ldots, u_{i,t}^D,])$, i.e.,

$$u_{i,G}^j = \begin{cases} v_{i,G}^j, & \text{if } rand_j(0,1) \leq CR \text{ or } j = j_{rand} \\ x_{i,G}^j, & \text{otherwise} \end{cases} \tag{15}$$

where D is the number of decision variables;rand$_j(0, 1)$ is a random number of uniform distribution in the interval [0, 1], and $j = 1, 2, \ldots, n$; $j_{rand} \in \{1, 2, \ldots D\}$; CR is a crossover rate and belongs to the interval [0, 1].

C. ADAPTIVE CONTROL PARAMETERS

The mutation scale factor and crossover rate are two important control parameters that affect the performance of the differential evolution algorithm. The two control parameters are presented as constants and fixed in the evolutionary process. Adjusting the mutation scale factor and crossover rate can improve the diversity of candidate solutions [36], [37]. We propose an adaptive method to adjust the mutation scale factor and crossover rate to improve the diversity of candidate solutions.

For each generation, the mutation scale factor of each goal population is generated by the normal distribution of average (m_f) and standard deviation (θ_f). It can be expressed as

$$F_i = Normalrand(m_f, \theta_f) \tag{16}$$

For each generation, the crossover rate of each goal population is generated by the uniform distribution in the interval $[m_{cr}, \theta_{cr}]$. It can be expressed as

$$CR_i = Uniformrand(m_{cr}, \theta_{cr}) \tag{17}$$

D. PROCEDURE OF IMPROVED NSGA-II FOR METAL MINES PRODUCTION PROCESS

We use the improved NSGA-II to optimize the MMPP. Firstly, we determine the relations among production technical indexes by production data. Secondly, we define the decision variables by analyzing the relations among production technical indexes, and then get the relations among the decision variables and the objective functions. Finally, we use the improved NSGA-II to search the optimal decision variables for maximizing economic and resource benefits. The flow chart and pseudocode of the improved NSGA-II for optimizing the MMPP are respectively shown in Table 2 and Figure 2.

IV. EXPERIMENTAL ANALYSIS

A. PERFORMANCE MEASURE OF MULTI-OBJECTIVE OPTIMIZATION ALGORITHM

Performance evaluation of the multi-objective optimization algorithm has to consider two main problems. The first is the convergence of the Pareto optimal solutions, and the second is its diversity. In this paper, we select the hypervolume *(HV)* to evaluate the performance of the multi-objective optimization algorithm.

The hypervolume reflects the approximation degree of the Pareto optimal solutions to the true Pareto optimal front. The hypervolume can evaluate the performance of convergence and diversity simultaneously [38], [39]. The greater the hypervolume is, the better the convergence and diversity performance will be. The hypervolume can be defined as [40]:

$$HV(S) = VOL(\bigcup_{s \in S}[\lambda_1(s), z_1^r] \times \cdots \times [\lambda_m(s), z_m^r]) \quad (18)$$

where VOL is the Lebesgue measure; m is the number of objectives; $Z^r = (z_1^r, \cdots, z_m^r)$ is a reference point in the target space.

B. RESULTS ANALYSIS OF TEST FUNCTIONS

To verify the superiority of the improved NSGA-II, four test functions (ZDT1, ZDT2, ZDT3, and ZDT6) are chosen from the ZDT series functions [41]. The improved NSGA-II is compared with the NSGA-II and the non-dominated sorting differential evolution (NSDE) [23] on four test functions. The related parameters of the three algorithms are set as follows.

The population size is 100, the maximum number of evaluation is 20000, the distribution indices of mutation operator and crossover operator are both 20, the crossover operator probability is 0.5, the mutation operator probability is $1/D$, the crossover rate is 0.75, the mutation scale factor is 0.5, and the adaptive control parameters m_f, θ_f, m_{cr}, and θ_{cr} are respectively 0.75, 0.1, 0, and 1.

In order to decrease the random error of the simulation, each algorithm independently runs 31 times on four test functions. The mean and standard deviation of the hypervolume are listed in Table 3. From Table 3, the mean of the hypervolume obtained by the improved NSGA-II is higher than that by the NSGA-II and that by the NSDE on four test functions. It means that the improved NSGA-II outperforms the NSGA-II and the NSDE in diversity and convergence. Besides, the standard deviation of hypervolume obtained by the improved NSGA-II is smaller than that by the NSGA-II and that by the NSDE on four test functions. It means that the improved NSGA-II has higher reliability.

Moreover, we analyze the hypervolume using the one-tailed t-test to show further the advantage of the improved NSGA-II over the NSGA-II and the NSDE. The one-tailed t-test can be expressed:

$$t = \frac{|\tau_1 - \tau_2|}{\eta/\sqrt{n}} \quad (19)$$

TABLE 2. Pseudocode of improved NSGA-II for optimizing the MMPP.

Pseudocode of improved NSGA-II
Procedure
Input related data of a metal mine, i.e., the value of every index and the cost. Determine the relations among the indexes and the decision variables.
Input the parameters of improved NSGA-II: the maximum number of generations Gmax, G=1, NP, D, m_f, θ_f, m_{cr}, and θ_{cr}.
//SLHD
Generate an initial population by the symmetrical Latin hypercube design.
Calculate the profit and resource utilization ratio of individuals in population P.
While $G \leq G_{max}$
Fast non-dominated sorting and calculate the virtual fitness values of population P.
For i=1 to NP
//Adaptive control parameters
F_i=Normalrand(m_f, θ_f), CR_i=Uniformrand(m_{cr}, θ_{cr}).
//Selection operator
Binary tournament selection.
// Mutation operation of DE
For goal population $X_{i,g}$, a mutation population is generated by: $v_{i,G}=X_{r1,G}+F*(Xr2-Xr3)$
// Crossover operation of DE
For j=1 to N
If random(1)$<CR_i$ or j=randbetween（1,N）
The trial vector $u_{i,j,o}=v_{i,j,o}$,
Else $u_{i,j,o}=x_{i,j,o}$
End if.
End for.
End for.
Generate an offspring population $P1$.
Combine offspring $P1$ and parent population P to form new population $P2$.
Calculate profit and resource utilization ratio of individuals in population $P2$.
Calculate the virtual fitness values of population $P2$.
Fast non-dominated sorting of population $P2$.
Calculate the crowded distance of population $P2$.
Select the front NP best individual of population R based on ranks and crowing distance.
G=G+1.
End while.
Output the optimal results.

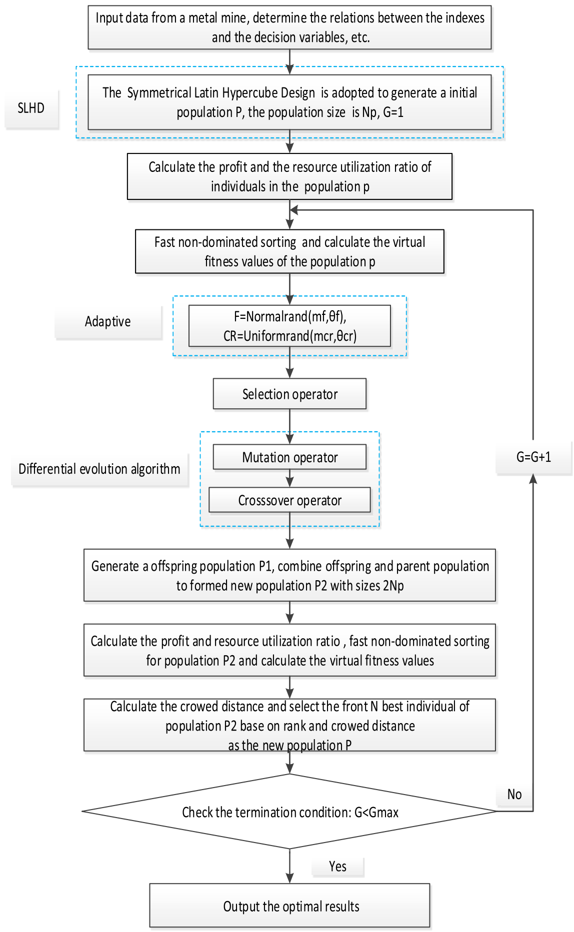


FIGURE 2. Flow chart of the improved NSGA-II for optimizing the MMPP.

TABLE 3. Mean and standard deviation of *HV* on four test functions.

Test function	Algorithm	Mean of HV	Standard deviation of HV
ZDT1	NSGA-II	0.82981	0.03340
	NSDE	0.86134	0.01672
	Improved NSGA-II	0.86539	0.00794
ZDT2	NSGA-II	0.37628	0.09685
	NSDE	0.49228	0.05995
	Improved NSGA-II	0.50998	0.04179
ZDT3	NSGA-II	0.91035	0.10577
	NSDE	0.89095	0.12273
	Improved NSGA-II	0.93785	0.07915
ZDT6	NSGA-II	0.42096	0.00713
	NSDE	0.42895	0.00178
	Improved NSGA-II	0.42999	0.00163

where τ_1 is the mean of the hypervolume of the improved NSGA-II; τ_2 is the mean of the hypervolume of the NSGA-II or the NSDE; η is the standard deviation of the hypervolume of the improved NSGA-II; n is the number of running times.

The significance is set as 0.05, and n is 31. According to the critical table of the t- test, $t_{0.05,31}$ equals to 1.696. If $t > t_{0.05,31}$, it means that the two algorithms have a significant difference. Otherwise, the two algorithms are insignificantly different. According to the mean and standard deviation of hypervolume on four test functions from Table 3, the results of t-test statistics are listed in Table 4.

TABLE 4. *T*- test results of hypervolume on four test functions.

Test functions	NSGA-II	NSDE
ZDT1	+	+
ZDT2	+	+
ZDT3	+	+
ZDT6	+	+

In Table 4, "+" represents that the proposed algorithm is significantly superior to another algorithm; "=" represents that the performances of the two compared algorithms are similar; "−" represents that the proposed algorithm is significantly inferior to the compared algorithm. As indicated, the improved NSGA-II has significant superiority to the NSGA-II and the NSDE on the four test functions.

V. APPLICATION OF THE MULTI-OBJECTIVE MODEL FOR YINSHAN COPPER MINES

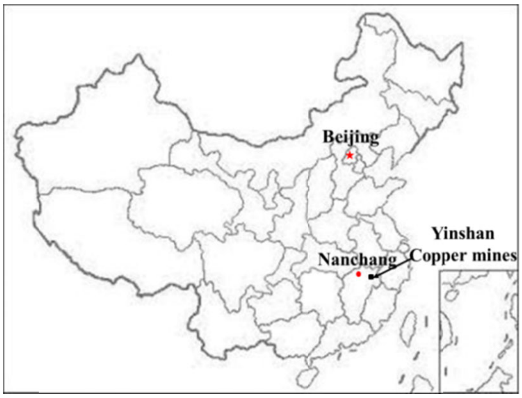
In this section, the multi-objective optimization of the Yinshan Copper Mines is introduced. The improved NSGA-II, the NSGA-II, and the NSDE are tested on this actual case.

A. BRIEF INTRODUCTION OF YINSHAN COPPER MINES

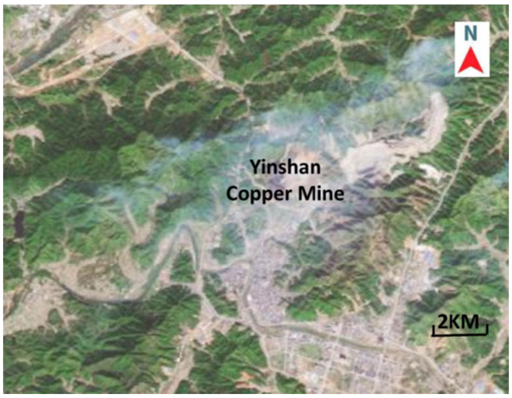
The Yinshan Copper Mine (a subsidiary of the Jiangxi Copper Corporation Limited) is located in the north of Dexing city, Jiangxi province, China. It is about 100km far from Shangrao city and 200km from Nanchang city. Figure 3 shows the location of the Yinshan Copper Mines. It composes of four ore bodies and has exploited for approximately 40 years. Daily mining and ore-dressing capacity have changed from 700 tons to 5000 tons. The main target mineral has been converted from lead and zinc to copper.

At present, the determination of the production technical indexes only considers the economic benefits without considering resource benefits. The mineable reserve of the Yinshan Copper Mines has gradually reduced. The managers have realized that the resource efficiency has to be considered for achieving sustainable development in the mines. Therefore, it is necessary to optimize the production process of this metal mine by considering both economic and resource benefits.

In the next six years, the Yinshan copper mines will produce the ore from −84m to −192m by open pit mining method. The elevation of −192m is the bottom of the first phase ultimate pit. In this work, the MMPP of ore from −84m to −192m is used as an example to establish a multi-objective optimization model of the MMPP. Then, the improved NSGA-II, the NSGA-II, and the NSDE are applied to solve the multi-objective optimization model. Finally, we verify the performance of the improved NSGA-II



(a) Location of Yinshan Copper Mines.



(b)Satellite of Yinshan Copper Mines.

FIGURE 3. **Location and satellite of yinshan copper mines.**

by comparing optimization results. Nowadays, the geological cutoff grade and minimum industrial grade are 0.15% and 0.25% of copper, respectively. The mineable reserve and mean ore grade of ore from −84m to −192m are respectively 10.46 million tons and 0.42% of copper. h is 0.5 relying on the ore body characteristic. $g_{smelter}$ is 16%. The unit cost of copper ore production is about 14 \$/t, including direct cost (10.78 \$/t) and indirect cost (3.22 \$/t). Since the price of copper ore concentrate is related to the concentrate grade, and the rest is very small. The resource tax, sale tax, and other fees are equally distributed to direct cost and indirect cost. In China, #1 copper (q_1, %) is 6915.73 \$/t. The price of copper ore concentrate can be calculated by [16]:

$$q = f_6(g_5) = q_1 \times g_5 \times \lambda + q_2 \tag{20}$$

where λ is the adjustment coefficient; q_2 is the price of compensation. The adjustment coefficient and price compensation of different grade are summarized in Table 5.

TABLE 5. **Adjustment coefficient and compensation price of different grade.**

Grade of Copper	Adjustment coefficient	Compensation price (\$•t^{-1})
16.00%~16.99%	0.77	-63.2
17.00%~17.99%	0.78	-47.4
18.00%~18.99%	0.795	-31.6
19.00%~19.99%	0.81	-15.8
20.00%~20.99%	0.83	0
21.00%~21.99%	0.84	15.8
22.00%~22.99%	0.85	31.6
≥23%	0.86	47.4

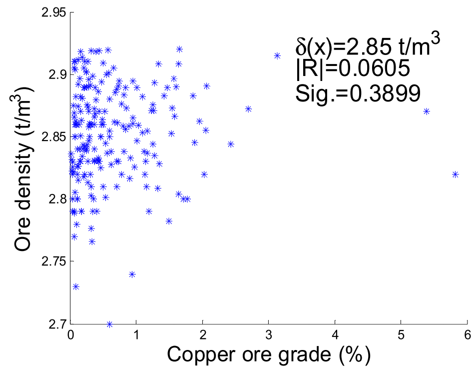


FIGURE 4. **Scatter plot of the copper ore density and grade.**

B. RELATIONS AMONG PRODUCTION TECHNICAL INDEXES IN THE YINSHAN COPPER MINES

As presented in Section 2, there are some relations among production technical indexes in the MMPP. We must first determine the relations among the technical production indexes, and then optimize the MMPP. We collect the sample data of exploration, mining, and ore-dressing from the Yinshan copper mines. These data include 204 sets of ore density and grade, 15216 sets of copper ore grade and ore length of the sample, 64 sets of monthly data of loss rate and dilution rate, and 630 sets of daily data of raw ore grade, concentration rate, and ore concentrate grade.

1) RELATION MODEL BETWEEN ORE DENSITY AND GRADE

Figure 4 shows the scatter plot of the copper ore density and grade. The correlation coefficient between the ore density and grade is 0.0605, and the significance level is 0.3899. Since the significance level 0.3899 is bigger than 0.05, it indicates that there is no relation between the ore density and grade. The ore density is not influenced by its grade. Therefore, the ore density function uses the average of the ore density, i.e.,

$$\delta(x) = 2.85\text{t/m}^3 \tag{21}$$

2) ORE GRADE DISTRIBUTION PROBABILITY DENSITY FUNCTION

The advantage of the kernel smoothing density is that it can fit the ore grade distribution depending on the characteristics and properties of the mine data without any prior knowledge. It can fit a probability density function, which is different from the parameter estimation method [42], [43]. Thus, the kernel smoothing density is taken to fit the ore grade probability density distribution function. The result of the fitting is not an explicit function. Figure 5 presents the histogram of ore grade frequency distribution. Figure 6 presents the ore grade probability density distribution. It can

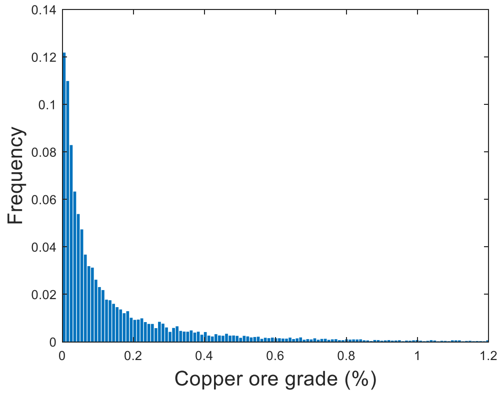


FIGURE 5. Histogram of ore grade frequency distribution.

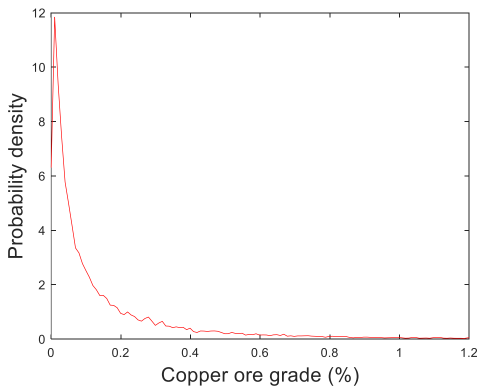


FIGURE 6. Ore grade probability density distribution.

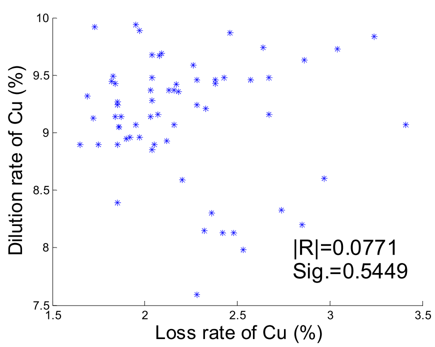


FIGURE 7. Scatter plot of loss rate and dilution rate.

be seen from the two figures that the ore grade distribution is well fitted by the probability density function.

3) RELATION MODEL BETWEEN LOSS RATE AND DILUTION RATE

Figure 7 shows the scatter plot of the loss rate and dilution rate. The correlation coefficient between the loss rate and dilution rate is −0.0771, and the significance level is 0.5499. Since the significance level value 0.5499 is bigger than 0.05, it indicates that there is no relationship between the loss rate and dilution rate. Therefore, the loss rate and dilution rate are two independent variables in this case.

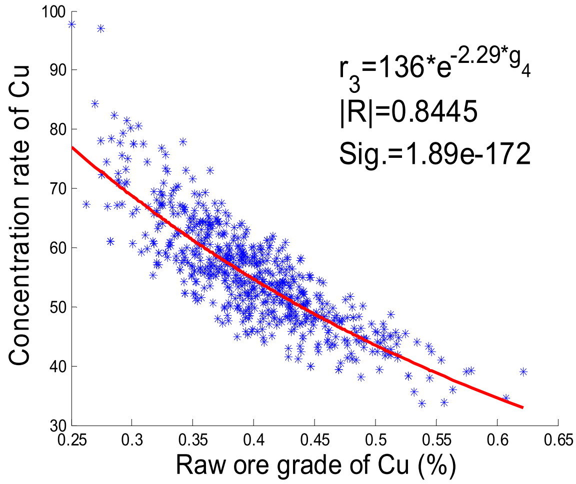


FIGURE 8. Exponential fits concentration rate and grade of raw ore.

4) RELATION MODEL BETWEEN CONCENTRATION RATE AND GRADE OF RAW ORE

Figure 8 illustrates the scatter plot of the concentration rate and grade of raw ore. As shown in Figure 8, the relationship between the concentration rate and grade of raw ore meets the exponential distribution function and the correlation coefficient is -0.8445. The significance level is 1.89e-172, smaller than 0.05. Therefore, we use an exponential function to fit this relation. The concentration rate function can be expressed:

$$r_3 = 136^* e^{-2.29^* g_4} \tag{22}$$

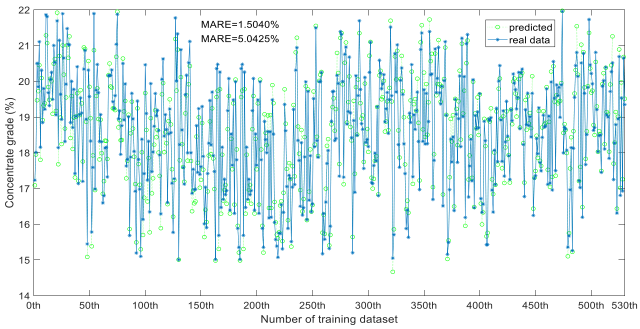
5) RELATION MODEL BETWEEN ORE CONCENTRATE GRADE AND SOME IMPACT INDICATORS

The relationship between ore concentrate grade and some impact indicators (concentration rate and grade of raw ore) is very complex and highly nonlinear [14]. It is very hard to establish this relationship by regression analysis. Therefore, we take the back-propagation neural networks (BPNN) [44], [45] to establish the relationship model.

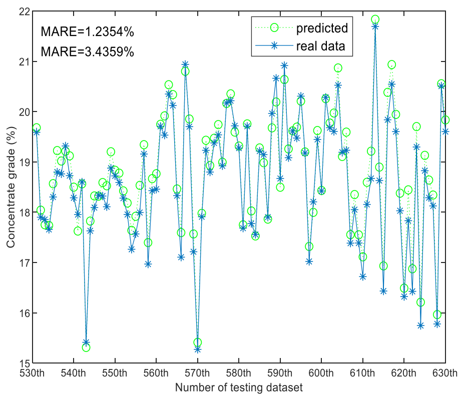
The BPNN takes the concentration rate and grade of raw ore as inputs, and the concentrate grade as output. The BPNN comprises 2 input nodes, 1 output node. The transfer functions of the hidden and the output layer choose the 'tansig' and 'purelin', respectively. The learning algorithm chooses 'traingdm'. The maximum number of iterations is 5000, and the precision is 0.0001. The 1st to 530th sets are used as training dataset, and the 531th to 630th sets are taken as testing dataset. We find that the prediction result shows better with the one hidden layer and we select it. To get the best number of hidden nodes, we try some different hidden nodes to establish the neural network. The results obtained using different hidden nodes are compared in Table 6. The MARE and AMRE are respectively abbreviations of Mean Absolute Relative Error and Absolute Maximum Relative Error. The compared results in Table 6 show that the hidden node of 3 is superior to the others. Therefore, the hidden node is selected

TABLE 6. Results obtained with different hidden nodes.

Hidden nodes	Concentration grade			
	Train MARE	Train AMRE	Test MARE	Test AMRE
1	1.6722%	10.5560%	2.3903%	17.0018%
2	1.5140%	5.2889%	1.2705%	3.6983%
3	1.5040%	5.0425%	1.2354%	3.4359%
4	1.5186%	4.4228%	1.3049%	7.5396%
5	1.5405%	7.3940%	1.3072%	4.1756%



(a) Predicted **concentrate grade** of training dataset.



(b) Predicted concentrate grade of testing dataset.

FIGURE 9. Predicted model of ore concentrate grade by BPNN.

to be 3. Figure 9 shows the precision of the BPNN in predicting the ore concentrate grade. It is clearly indicated from Figure 9 that the BPNN has a good prediction precision in predicting the ore concentrate grade.

C. MULTI-OBJECTIVE OPTIMIZATION OF YINSHAN COPPER MINES

1) DECISION VARIABLES AND PARAMETERS OF RELATED ALGORITHMS

The relationships among production technical indexes of Yinshan copper mines are determined as introduced above. According to Equations (1)-(8), and (20), one can be seen that the independent variables are the geological cutoff grade, the minimum industrial grade, the loss rate, and the dilution rate. The loss rate and dilution rate are mainly related to the mining technology and ore body characteristic. As a result, the two variables do not change for the given metal mines.

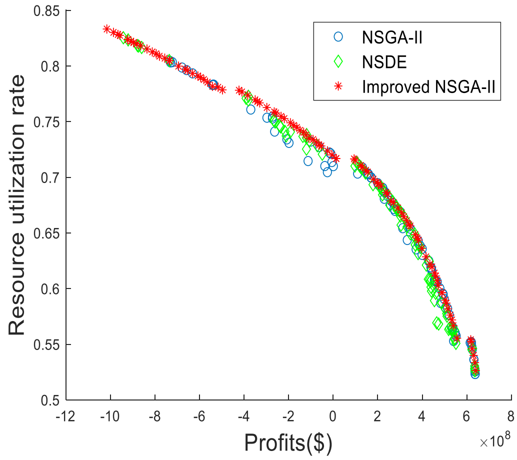


FIGURE 10. Pareto optimal solutions obtained by three algorithms.

Hence, the loss rate and dilution rate are given by optimization as 2% and 9%. Therefore, the geological cutoff grade and minimum industrial grade are finally chosen as the decision variables. The geological cutoff grade and minimum industrial grade both range from 0.05% to 0.45% for most copper mines.

The parameters of the three algorithms are set as follows. The population size is 100, the maximum number of evaluation is 2000, the distribution indices of mutation operator and the crossover operator are both 20, the crossover operator probability is 0.5, the mutation operator probability is $1/D$, the crossover rate is 0.75, the mutation scale factor is 0.5, and the adaptive control parameters m_f, θ_f, m_{cr} and θ_{cr} are respectively 0.75, 0.1, 0 and 1.

2) RESULTS ANALYSIS OF YINSHAN COPPER MINES

The improved NSGA-II, the NSGA-II, and the NSDE are used to optimize the Yinshan copper mines in order to validate the outperformance of the improved NSGA-II. Figure 10 shows the Pareto optimal solutions of the MMPP optimization obtained by the three algorithms. As shown in Figure 10, the improved NSGA-II has better convergence than the NSGA-II and the NSDE on the MMPP optimization in the obtained Pareto optimal solutions.

It can be seen from Figure 10 that the increased resource utilization ratio will lead to the reduction of profits. The Pareto optimal solutions are compromising each other, and no solution is better than the other solutions. The Pareto optimal solutions can meet the different needs of decision-makers. In addition, those solutions provide sufficient information to the decision-making department and enable decision-makers to make better decisions. It is of great importance for achieving sustainable development of mineral resources.

To further validate that the improved NSGA-II has better performance, the mean and standard deviation of the HV of the three algorithms are calculated after running 31 times on the MMPP optimization of the Yingshan Copper Mine. The calculated results of the HV are shown in Table 7. From Table 7, the mean of the HV for the improved NSGA-II is

TABLE 7. ***HV*** **results of NSGA-II, NSDE, and improved NSGA-II.**

Algorithm	Mean of *HV*	Standard deviation of *HV*
NSGA-II	281645872	148637
NSDE	281735371	195146
Improved NSGA-II	281846112	140394

TABLE 8. ***T*-** **test results of** ***HV*** **on a case.**

Algorithm	NSGA-II	NSDE
MMPP	+	+

greater than that of the NSGA-II and the NSDE. It means that the improved NSGA-II has better convergence and diversity than the NSGA-II and the NSDE on the MMPP optimization of the Yinshan Copper mine.

In addition, the standard deviation of the HV for the improved NSGA-II is smaller than the NSGA-II and the NSDE, which proves the reliability of the improved NSGA-II. Further, in order to prove that the improved NSGA-II is significantly superior to the NSGA-II and the NSDE, we perform a statistical analysis of the HV by the one-tailed t-test. The results of the one-tailed t-test of the HV are listed in Table 8. In Table 8, the meaning of "+" is the same as that in Table 4. As shown in Table 8, the improved NSGA-II is significantly better than the NSGA-II and the NSDE on the optimization of the production process of the Yinshan copper mine. In light of these, the improved NSGA-II is more effective and useful for optimizing the MMPP.

VI. CONCLUSION

Based on the results presented above, the following conclusions can be made:

1) The improved NSGA-II outperforms the NSGA-II and the NSDE in diversity and convergence. Four test functions from the ZDT series functions are chosen for experimentation. The experimental results show that the improved NSGA-II is significantly superior to the NSGA-II and the NSDE on four test functions. The outperformance of the improved NSGA-II can be attributed to the SLHD, the mutation and crossover of the differential evolution algorithm, and the adaptive adjustment of mutation scale factor and crossover rate.
2) The improved NSGA-II can achieve better Pareto optimal solutions than the NSGA-II and the NSDE in optimizing the MMPP. The Pareto optimal solutions can meet different needs of decision-makers. In addition, those solutions provide more sufficient information to the decision-making department and enable decision-makers to make better decisions. Thus, the improved NSGA-II is a reliable method that can facilitate sustainable development of metal mineral resources.

The above study provides an effective multi-objective optimization method for optimizing the MMPP with maximizing economic and resource benefits. Nevertheless, the MMPP also involves safety, environmental and uncertainty. These objectives can also be included in the improved NSGA-II method of this study and will be considered in a future study.

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